

**CHAPTER-V**  
**TESTING LINDER**  
**HYPOTHESIS**

# CHAPTER-V

## TESTING LINDER HYPOTHESIS

### 5.1. Linder Hypothesis (Linder Effects)

Linder stated that consumer demand is determined strongly by income levels. Countries with high per capita incomes will demand high quality manufactured goods and nations with low per capita income will demand lower quality goods. Consequently, countries with similar per capita income will have overlapping demand structure and will likely demand similar manufactured goods. The more similar the demand structures of two countries, the more intensive, potentially is the trade between these two countries. The level of average income is one of the most important forces influencing the demand structure of a country. There is strong relationship between the level of per capita income and the types of consumer or capital goods demanded. According to the Linder's theory, the Linder effect implies that similarity of per capita income levels among trading partners affect trade positively. In this study, Linder Hypothesis will be tested in Fixed-Random Effects model, Gravity model A and Gravity model B, through three effects (Linder effects) which are given as follows:

*LINDER1: This variable shows the degree of dissimilarity of per capita GDP among trading partners.*

*LINDER2: This variable shows the absolute differences in Logarithm of per capita GDP among trading partners.*

*LINDER3: This variable shows the Logarithm of the share of the absolute differences in per capita GDP among trading partners from aggregate per capita GDP.*

### 5.2. Classification of Countries

To test the validity of the Linder hypothesis among Iran and its trading partners, data related to 152 countries has been collected. Even though 152 countries are taken for

study, twenty-five cross-sections were omitted due to the lack of related data. In this study, 127 cross-sections are being analyzed. These countries will be divided into 5 groups. The first group (Base group) includes all cross-sections and the rest four groups are divided based on their GNI per capita levels according to the World Bank Atlas method (2012) classification. Countries classified according to GNI per capita levels are low income (23 countries), lower middle income (27 countries), upper middle income (36 countries) and high income (41 countries). The classification has been made as follows:

**d. Base group**

Base group includes 127 countries: Afghanistan, Albania, Algeria, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahrain, Bangladesh, Belarus, Belgium, Benin, Bosnia, Brazil, Brunei, Bulgaria, Burkina Faso, Cameroon, Canada, Central African Republic, Chile, China, Colombia, Congo, Costa Rica, Croatia, Cuba, Cyprus, Czech Republic, Denmark, Djibouti, Dominican, Ecuador, Egypt, Estonia, Ethiopia, Finland, France, Gabon, Gambia, Georgia, Germany, Ghana, Greece, Guinea, Hong Kong, Hungary, India, Indonesia, Iraq, Ireland, Italy, Ivory Coast, Japan, Jordan, Kazakhstan, Kenya, Kuwait, Kyrgyz Republic, Lebanon, Libya, Lithuania, Luxemburg, Macedonia, Madagascar, Malaysia, Malta, Mali, Mauritania, Mauritius, Mexico, Moldova, Morocco, Mozambique, Myanmar, Namibia, Nepal, Nigeria, Netherlands, New Zealand, Norway, Oman, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Republic of Korea, Romania, Russia, Saudi Arabia, Senegal, Sierra Leon, Singapore, Slovak Republic, Slovenia, Somalia, South Africa, Spain, Sri Lanka, Sudan, Sweden, Switzerland, Syria, Tajikistan, Tanzania, Thailand, Togo, Tunisia, Turkey, Turkmenistan, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Uzbekistan, Venezuela, Vietnam, Yemen, Zambia and Zimbabwe.

**e. Low Income (LI)**

LI group includes twenty-three countries: Afghanistan, Bangladesh, Benin, Burkina Faso, Central African Republic, Ethiopia, Gambia, Guinea, Kenya, Kyrgyzstan, Madagascar, Mali, Mauritania, Mozambique, Myanmar, Nepal, Sierra Leone, Somalia, Tajikistan, Tanzania, Togo, Uganda and Zimbabwe.

#### **f. Lower Middle Income (LMI)**

LMI group includes twenty-seven countries: Albania, Armenia, Cameroon, Congo, Ivory Coast, Djibouti, Egypt, Georgia, Ghana, India, Indonesia, Iraq, Moldova, Morocco, Nigeria, Pakistan, Paraguay, Philippines, Senegal, Sri Lanka, Sudan, Syria, Ukraine, Uzbekistan, Vietnam, Yemen and Zambia.

#### **Upper Middle Income (UMI)**

UMI group includes thirty-six countries: Algeria, Argentina, Azerbaijan, Belarus, Bosnia, Brazil, Bulgaria, Chile, China, Colombia, Costa Rica, Cuba, Dominican, Ecuador, Gabon, Jordan, Kazakhstan, Lebanon, Libya, Lithuania, Macedonia, Malaysia, Mauritius, Mexico, Namibia, Panama, Peru, Romania, Russia, South Africa, Thailand, Tunisia, Turkey, Turkmenistan, Uruguay and Venezuela.

#### **High Income (HI)**

HI group includes forty-one countries: Australia, Austria, Bahrain, Belgium, Brunei, Canada, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, Hungary, Ireland, Italy, Japan, Korea, Kuwait, Luxemburg, Malta, Netherlands, New Zealand, Norway, Oman, Poland, Portugal, Qatar, Saudi Arabia, Singapore, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Arab Emirates, United Kingdom, and United States.

### **5.3. Scope of Study**

For the analysis of Linder hypothesis, Fixed-Random effects model (Model I) includes time series variables as; RTRADE, GDPP, GDPIRI, REXCHANGE and LINDER1. Before using this model, Unit Roots test is computed to determine if time series variables are stationary or not. The Co-integration test is estimated to test whether there are long-run relationships among time series variables. While estimating model I, Poolability test is applied to determine whether regression is pool or not. If it is not pool, it must be determined, whether it is fixed or random. Hausman test is one, which determines Fixed or random effects. Tobit Model (Censored Regression Model) performs to determine the

effects of countries that have zero trade with Iran and excluded from the Base group in Model I.

Gravity model A (Model II) includes time series variables as; LTRADE2, LOG (SUM2), LNDIS, LINDER2, LOG (POPP) and LOG (REXCHANGE<sub>P</sub>). Gravity model B (Model III) includes time series variables as; LTRADE, LOG (SUM2), LNDIS, LINDER3, LOG (POPP) and LOG (REXCHANGE<sub>P</sub>). Before Estimating the Model II and III, Unit roots and Contigeration tests are performed. For analysis of these variables in all three models, data is used for period 1992 to 2012.

## 5.4. Model Specification<sup>1</sup>

Three models, Fixed-Random Effect model, gravity model A and gravity model B have been used. Each model Included Linder variable that computed Linder effect, called LINDER1, LINDER2 and LINDER3

### a. Fixed-Random (FE-RE) Effect Model(Model I)

Panel data models can measure the effects of observable and unobservable variables on dependent variables. A fixed effects or random effects models will be selected depend upon whether or not an unobservable variables is correlated with dependent variables. In a fixed effects model, a time-invariant variable such as distance cannot be used. In order to determine the special effects, Model I based on Mcpherson *et al.*'s model has been applied. Mcpherson *et al.* <sup>2</sup>(2000) developed a model to examine the Linder hypothesis, which is as follows:

Model I Specification:

$$RTRADE_{ij} = \beta_1 + \beta_2 GDPP_{jt} + \beta_3 GDPIRI_{it} + \beta_4 REXCHANGE_{jt} + \beta_5 LINDER1_{ij} + \varepsilon_{ij} \quad (1)$$

Where,

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<sup>1</sup> Note that in all models, which are under estimation in this study, indice i refer to Iran, indice j refer to trade partners and indice t refer to time. Further , C in all models shows constant/ intercept

<sup>2</sup> Mcpherson *et al.* (2000) have examined the Linder trade thesis in two studies. First among 19 OECD countries for 1990-1995 and got approval for Linder hypothesis. In second study, they tested Linder thesis among six east African countries for years 1984-1992 and got acceptance for Linder trade thesis.

$RTRADE_{ij}$  = Dollar value of total trade between Iran and potential trading partner in constant 2005 US \$

$GDPP_{jt}$  = Gross domestic products of potential trading partner in constant 2005 US \$

$GDPIR_{it}$  = Gross domestic products of Iran in constant 2005 US \$.

$$REXCHANGE_{jt} = \frac{e_{jt} P_{jt}}{P_{it}} = \text{Real exchange rate}$$

$e_{it}$  is the exchange rate of potential trading partner (measured in units of the currency of Iran per unit of the currency of potential trading partner);  $p_{jt}$  is the GDP deflator of potential trading partner and  $p_{it}$  is the GDP deflator of Iran.

$LINDERI_{ij}$  = The absolute difference in the level of real per capita GDP of Iran and potential trading partner in constant 2005 US \$

*LINDERI* variable shows the degree of dissimilarity of Per Capita GDP among trading partners. If the Linder hypothesis is supported by the data of this model then the coefficient on this variable should be negative and statistically significant.

$\varepsilon_{itj}$  = Error term

### **b. Gravity Model Approach**

In the area of international trade flows, Timbergen (1962) and Pöyhönen (1963) were the first to introduce the gravity model into economics studies on international trade. The origin of the gravity model is the gravity equation that is brought from physics<sup>1</sup>. The results provide an explanation of bilateral trade flows by using an analytical relation that is very similar to the “Universal Law of Gravitation” proposed by Newton in 1687<sup>2</sup>. As reproduced by Timbergen and Pöyhönen, the volume of trade between two countries is positively related with their economic “mass” and negatively with distance between them:

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<sup>1</sup> Since the early 1940s, the gravity model has been applied to explain the determinants of different types of flows, such as migration, flows of buyers to shopping centers, commuting flows, patient flows to hospitals and etc. (Serlenga, L. and Shin, Y 2004)

<sup>2</sup> For further information, see (De Blasi, G. et al. 2007)

$$trade_{ij} = A \cdot \frac{GDP_i \times GDP_j}{dist_{ij}} \quad (2)$$

Where,

$trade_{ij}$  is the bilateral trade flow value between country i and country j,  
 $GDP_i$  and  $GDP_j$  are country i and j's respective national incomes, and  
 $dis_{ij}$  is the physical distance between country i and j.

A is a constant of proportionality.

After taking logarithms, equation (1) is transferred to:

$$\log(trade_{ij}) = A + b_1 \log(GDP_i \cdot GDP_j) - b_2 \log(dist_{ij}) + \varepsilon_{ij} \quad (3)$$

Where,

A is the constant,

$b_1$  and  $b_2$  are coefficients to be estimated,

and  $\varepsilon_{ij}$  is a random error term.

This equation explained that the amount of bilateral trade is positively related to the two countries' GDP values and inversely related to the physical distance between them.

Linnemann (1966) has added several additional variables to the basic gravity model, called the "augmented gravity model":

$$\log(Trade) = b_0(\log GDP_{it}) + b_1(\log GDP_{jt}) - b_2(\log Dist_{ij}) - b_3(\log PCGDP_{it} - \log PCGDP_{jt}) + b_4d_1 + b_5d_{2+...} + b_n d_m + \varepsilon_{ijt} \quad (4)$$

Deardorff (1995) has also added other variables to the basic model such as population, income per capita, exchange rates, and dummy variables (for the presence of common language, common currency, colonial links, infrastructures, migration flows, bilateral

tariff barriers, commercial agreements among the trading countries and etc)<sup>1</sup>. According to empirical studies, the geographic distance ( $Dist_{ij}$ ) is an important determinant of trade. The distance can be analyzed in terms of geography, culture, language and adjacency (Border). Usually geographic distance measures the cost of transportation. Review of literatures showed that there is an increase in trade flows if transportation cost decreases. The theory asserts that there is a negative correlation between distance and the trade. The Linder effect ( $PCGDP_{it} - PCGDP_{jt}$ ) is estimated by a variable that measures the degree of dissimilarity between the per capita income levels of potential trading partners. This variable is calculated as an absolute difference in the level of real per capita GDP in “j” and potential trading partner “i” at time “t”. If the Linder hypothesis is supported by the data of this analysis then the coefficient on this variable should be negative and statistically significant<sup>2</sup>.

### **b.1 .Gravity Model A(Model II)**

Model II is an augmented gravity model. The equation No.4 developed by Linnemann is inadequate in explaining the trade and economic atmosphere of Iran. Therefore this equation requires some modification and extension in respect to Iran’s total trade and economic conditions by considering some other variables such as population, income per capita, exchange rates, and dummy variables for the presence of common language, colonial links, adjacency, Institutions, infrastructures, migration flows, bilateral tariff barriers, commercial agreements among the trading countries and the political factors.

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<sup>1</sup> The gravity model was earlier criticized due to the lack of theoretical foundations. However, since the seminal paper by Anderson (1979) it has accepted that the prediction of the gravity model can be derived from different structural models such as Ricardian models, Heckscher-Olin (H-O) models and increasing returns to scale (IRS) models of the New Trade Theory (Serlenga,L. and Shin,Y 2004) . Empirically, the gravity model has been well suited for trade policy analysis and has been widely used to estimate the impact of different policy issues regarding regional trading groups, currency unions and various trade distortions (Serlenga,L. and Shin,Y 2004). Nowadays, the gravity model has become one of the standard tools to analysis trade patterns. According to the gravity model hypothesis, the larger, the richer, the closer together two countries are, the more they trade. And they trade more intensively the more things they have in common, such as currency, language, shared political histories or colonial connections, a border, etc.( Ciuriak,D. and Kinjo,S. 2006).

<sup>2</sup> For more details, see (Leitão,N.C. 2010:93-04) and (Vollrath,T *et al.* 2007)



The modified model that is given below adequately covers required variables in the equation for Iran's trade and economic conditions.

$$LTRADE2_{ij} = \alpha_1 + \alpha_2 LOG(SUM1_{ij}) + \alpha_3 LNDIS_{ij} + \alpha_4 LINDER2_{ij} + \alpha_5 LOG(POPP_j) + \alpha_6 LOG(REXCHAMGEP_j) + d_1 DUM1 + d_2 DUM2 + d_3 DUM3 + \omega_{ij} \quad (5)$$

Where,

$LTRADE2_{ij}$  = Logarithm of Dollar value of total trade between Iran and potential trading partner in constant 2005 US \$

$$SUM1_{ij} = GDPP + GDPIRI$$

$LNDIS_{ij}$  = Logarithm of geographic distance between countries i and j that is calculated by distance between capital cities of Iran and potential trading partner in kilometers.

$LOG(REXCHAMGEP)_j$  = Logarithm of real exchange rate

$$LINDER2_{ij} = |LOG(PCGDPIRI_{it}) - LOG(PCGDPP_j)|$$

PCGDPIRI = Per capita gross domestic products of Iran in constant 2005 US \$

PCGDPP = Per capita gross domestic products of potential trading partner in constant 2005 US \$

*LINDER2* variable shows the absolute differences in Logarithm of per capita income GDP among trading partners. If the Linder hypothesis is supported by the data of this model then the coefficient on this variable should be negative and statistically significant.

$LOG(POPP_j)$  = Logarithm of total population of potential trading partners

DUM1 is a time dummy variable stand for the period of 2005-2012. This variable is included in model to consider economic and political uncertainties, shocks and instability.

DUM2 is dummy variable stands for countries with common border with Iran includes Afghanistan, Armenia, Azerbaijan, Iraq, Kuwait, Oman, Pakistan, Qatar, Russia, Saudi Arabia, Turkey, Turkmenistan ,and United Arab Emirates.

DUM3 is dummy variable stand for membership in OPEC. This variable includes Algeria, Angola, Ecuador, Iraq, Kuwait, Libya, Nigeria, Qatar, Saudi Arabia, United Arab Emirates and Venezuela

$\omega_{ij}$  = Error term

### **b.2 .Gravity Model B(Model III)**

Model III is an augmented gravity model. The equation No.4 developed by Linnemann also found inadequate in explaining the ratio of trade as dependent variable. This equation needs some modification and extension in order to see the effect of explanatory variables (such as SUM2 and LINDER3 in addition to the independent variables in equation No.18) on share of trade from aggregate GDP. The modified model that properly covers necessary variables in the equation shown as follows:

$$LTRADE_{ij} = \alpha_1 + \alpha_2 LOG(SUM2_{ij}) + \alpha_3 LNDIS_{ij} + \alpha_4 LINDER3_{ij} + \alpha_5 LOG(POPP_j) + \alpha_6 LOG(REXCHAMGEP_{jt}) + d_1 DUM1 + d_2 DUM2 + d_3 DUM3 + \omega_{ij} \quad (6)$$

Where,

$$LTRADE_{ij} = LOG\left(\frac{RTRADE_{ij}}{SUM1_{ij}}\right)$$

$$SUM2_{ij} = PCGDPP_{ij} + PCGDPIRI_{it}$$

$LNDIS_{ij}$  = Logarithm of geographic distance between countries i and j that is calculated by distance between capital cities of Iran and potential trading partner in kilometers.

$LOG(REXCHAMGEP)_{jt}$  = Logarithm of real exchange rate

$$LINDER3_{ij} = LOG\left(\frac{|PCGDPIRI_{it} - PCGDPP_{ij}|}{SUM2_{ij}}\right)$$

*LINDER3* variable shows the Logarithm of the share of the absolute differences in per capita income GDP among trading partners from aggregate per capita income GDP. If the Linder hypothesis is supported by data of this model then the coefficient on this variable should be negative and statistically significant.

$LOG(POPP_{jt})$  = Logarithm of total population of potential trading partners

DUM1 is a time dummy variable stand for the period of 2005-2012. This variable is included in model to consider economic and political uncertainties, shocks and instability.

DUM2 is dummy variable stands for countries with common border with Iran includes Afghanistan, Armenia, Azerbaijan, Iraq, Kuwait, Oman, Pakistan, Qatar, Russia, Saudi Arabia, Turkey, Turkmenistan ,and United Arab Emirates.

DUM3 is dummy variable stand for membership in OPEC. This variable includes Algeria, Angola, Ecuador, Iraq, Kuwait, Libya, Nigeria, Qatar, Saudi Arabia, United Arab Emirates and Venezuela.

$\omega_{ij}$  =Error term

## **5.5. Approach to Data Analysis**

In this part, first the Panel Data method will be studied. In addition, to study the individual effects (that can capture unobservable, time-invariant effects, which may be correlated with the observable variables) Fixed and Random effects method will be reviewed, and the related tests (Poolability and Hausman) to determine the nature of effect will be studied. Unit root test is performed on time series variables to determine if they are stationary or not. Due to the existence of time dimension in Panel Data, testing for unit roots is necessary. Further, in this part the structure of the unit root tests for Panel Data will be discussed.

### ***5.5.1. Panel Data Method***

A panel data set consists of a set of time-series observation on a set of cross-sectional units. The term “panel data” refers to the pooling of observations on a cross-section of Individuals, households, countries, regions, firms, etc. over several time periods. This can be achieved by surveying a number of households or individuals and following them over time. Panel data usually contains a large number of cross sectional units, which, are repeated observed over time. The modeling of panel data approaches distinguishes in the time dependence, in the assumptions of the error term and in the measurement of the dependent variables. Due to the specific assumption, consequences for the estimation methods follow. When the cross sectional data are only pooled over T periods, the coefficients can be estimated by OLS under classical assumption about the error term. The main objective of panel data analysis is the consideration of unobserved heterogeneity and its estimation. The methods, which are developed for this purpose,

depend on the assumptions of the error term, the regressand, the regressors and the coefficients of the model<sup>1</sup>.

Standard panel data analysis starts with a linear model. A panel data regression differs from a regular time-series or cross-section regression in that it has a double subscript on its variables.

$$y_{it} = \alpha + X'_{it}\beta + u_{it} \quad i = 1, \dots, N : t = 1, \dots, T \quad (1)$$

The  $i$  subscript, denotes the cross-section dimension (households, individuals, firms, countries, etc) whereas  $t$  denotes the time-series dimension.  $\alpha$  is a scalar,  $\beta$  is  $K \times 1$  and  $X_{it}$  is the  $it$  th observation on  $K$  explanatory variables. Most of the panel data applications utilize a one-way error component model for the disturbances as follows:

$$U_{it} = \mu_i + v_{it} \quad (2)$$

Where,

$\mu_i$  denotes the unobservable individual-specific effect and  $v_{it}$  denotes the remainder disturbance.  $\mu_i$  is time-invariant and it accounts for any individual-specific effect that is not included in the regression as the individual's unobserved ability (that captures the individual heterogeneity). The remainder disturbance  $v_{it}$  varies with individuals and time as the usual disturbance in the regression.

The equation (1) in vector form can be written as follows:

$$y = \alpha \iota_{NT} + X\beta + u = Z\delta + u \quad (3)$$

Where,

$y$  is  $NT \times 1$ ,  $X$  is  $NT \times K$ ,  $Z = [\iota_{NT}, X]$ ,  $\delta' = (\alpha', \beta')$  and  $\iota_{NT}$  is a vector of ones of dimension  $NT$ . In addition, equation(2) can be written as follows:

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<sup>1</sup> For more information, see (Baltagi 2005 and Hubler 2005)

$$u = Z_{\mu}\mu + v \quad (4)$$

### 5.5.2. Fixed and Random Effects Models

In this section, the fixed and random effects methods will be studied.<sup>1</sup>:

Fixed effects assume that individual group/time have different intercept in the regression equation, while random effects hypothesize individual group/time have different disturbance. When the type of effects (group versus time) and property of effects (fixed versus random) combined, there are several specific models: fixed group effect model (one-way), fixed time effect model (one-way), fixed group and time effect model (two-way), random group effect model (one-way), random time effect (one-way), and random group and time effect model (two-way)<sup>2</sup>

Five forms of Panel data models are given as follow:

The equation (1), as given in Panel Data method has been reproduced again as follows:

$$y_{it} = \alpha + X'_{it}\beta + u_{it} \quad (1)$$

In equation (1), neither its intercept nor its slope varies

$$y_{it} = \alpha + X'_{it}\beta_i + u_{it} \quad (5)$$

In equation (5), only slope (  $\beta_i$  ) varies.

$$y_{it} = \alpha_i + X'_{it}\beta + u_{it} \quad (6)$$

In equation (6), only intercept (  $\alpha_i$  ) varies within estimator.

$$y_{it} = \alpha_i + X'_{it}\beta_i + u_{it} \quad (7)$$

In equation (7), both intercept (  $\alpha_i$  ) and slope (  $\beta_i$  ) vary across units

$$y_{it} = \alpha_{it} + X'_{it}\beta_{it} + u_{it} \quad (8)$$

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<sup>1</sup> The Linear panel data model may appear overly restrictive because  $\beta$  is the same in each time period. However, by appropriately choosing  $X_{it}$ , changing parameters over time is possible. In addition, some of the elements of  $X_{it}$  may not be time varying, such as gender dummies when  $i$  indexes individuals, or industry dummies when  $i$  indexes firms, or state dummies when  $i$  indexes cities (Wooldridge 2002:169). In the panel data models, there is possibility to allow for “individual “effects that can capture unobservable, time-invariant effects which may be correlated with the observable variables. These effects may be fixed or random (Kruiniger 2002).

<sup>2</sup> For more information, see (Park 2011).

In equation (8), both intercept ( $\alpha_{it}$ ) and slope ( $\beta_{it}$ ) vary across units and time.

These five models can be studied through two general fixed and random effects models. Standard pooled linear regression models assume that residuals are independently and identically distributed (IID). From equations (1) and (2):

$$y_{it} = \alpha + X'_{it}\beta + \mu_i + v_{it} \quad (9)$$

$$\text{for } i = 1, \dots, N \quad \text{and} \quad t = 1, \dots, T, \text{ let } E(\mu_i) = E(v_{it}) = 0$$

$$\text{var}(\mu_i) = \sigma_\mu^2, \text{var}(v_{it}) = \sigma_v^2 \quad \text{and} \quad E(\mu_i, v_{it}) = 0$$

Where,

$\mu_i$  is an individual-specified effect, and  $v_{it}$  is an idiosyncratic error term that is iid. If model (9) is correctly specified and regressors are uncorrelated with the error then it can be consistently estimated using pool OLS. A simple variant of the model (9) permits intercept to vary across individuals while slope parameters do not, like in model (6). In the later model,  $v_{it}$  is iid and  $\alpha_i$  are random variables that capture unobserved heterogeneity. If this  $\alpha_i$  (as an unobserved random variable) is potentially correlated with the observed regressors  $X_{it}$ , this model is called fixed effect (FX). If the fixed effects exist and is correlated with  $X_{it}$ , then pool OLS estimator is inconsistent<sup>1</sup>.

Fixed-effects model (FE) is used whenever only analyzing the impact of variables that vary over time is the case. Fixed-effects models are designed to study the causes of changes within a person (or entity). A time-invariant characteristic cannot cause such a change, because it is constant for each person. Under the fixed effect model, all studies share a common true effect size. In other words, all factors, which could influence the effect size, and therefore the effect size is the same in all the study populations. In the random effects model, the individual-specific effect is a random variable that is uncorrelated with the explanatory variables. The random effects or multilevel model assumes that the individual effects are captured by the intercept and a random component  $\mu_i$ . This random component is not associated with the regressors. Any unobserved individual heterogeneity that is being distributed independently of the

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<sup>1</sup> For more information, see (Baltagi 2005:12)

regressors is random effects. Under the random effects model, the true effect could vary from study to study and the mean of a distribution of true effects is estimated. In other words, the combined estimate is not an estimate of one value, but rather the average of a distribution of values. Large studies may yield more precise estimates than small studies, but each study is estimating a different effect size, and each of these effect sizes serves as a sample from the population whose mean is to be estimated. In a random effects model there are two levels of sampling and two levels of error. First, each study is used to estimate the true effect in a specific population. Second, all of the true effects are used to estimate the mean of the true effects. Therefore, as compared with the fixed effect model; the weights assigned under random effects are more balanced.<sup>1</sup>

In model (6), if the  $\mu_i$  can be assumed random, then  $\mu_i \approx \text{IID}(0, \sigma_\mu^2)$ ,  $v_{it} \approx \text{IID}(0, \sigma_v^2)$  and the  $\mu_i$  are independent of the  $v_{it}$ . In addition, the  $X_{it}$  are independent of the  $\mu_i$  and  $v_{it}$ , for all t and i. The random effects model is an appropriate specification if N individuals are drawn from a large population<sup>2</sup>.

### 1. Test for Poolability

F test will be used to test the individual effects to choose between pool OLS model and FX model<sup>3</sup>.

$$\begin{cases} H_0 : \alpha_0 = \alpha_1 = \alpha_2 = \dots \alpha_N \\ H_1 : \alpha_i \neq \alpha_j \end{cases}$$

Null hypothesis says intercept is common for all individuals and there is no special effect so that, Pool OLS estimator is consistent. Alternative hypothesis declares that every individuals have own intercept or its own special effects. In this condition FX model or Least Dummy Variable (LSDV) estimator is consistent.

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<sup>1</sup> For more information, see (Johnston & Dinardo 1997; Schmidheiny 2013 ;Parlow 2010 ; Cameron & Trivedi 2005; Borenstein et al. 2007 and Reyna 2007)

<sup>2</sup> For more information, see (Baltagi 2005:14)

<sup>3</sup> For more details, see (Johnston and Dinardo 1997)

$$F = \frac{(RSS - URSS)/(N-1)^{H_0}}{URSS(NT - N - K)} \approx F(N-1, N(T-1) - K) \quad (10)$$

Equation (10) is a simple Chow test with the restricted residual sums of squares (RRSS) that is OLS on the pooled model, and the unrestricted residual sums of squares (URSS) that is the LSDV regression<sup>1</sup>. To determine the nature of the especial effect (fixed or random), Hausman test is necessary.

## 2. The Hausman Test

To choose between FX and RE models, Hausman test is applied. If the individual-specific effect really is an unrelated effect, RE estimator will be used. This is usually tested by a (Durbin-Wu-) Hausmann test.

The Hausman test statistic is given by:

$$m = n\hat{q}'[\text{var}(\hat{q}_1)]^{-1}\hat{q}_1 \quad (11)$$

Where,

$$\hat{q}_1 = \hat{\beta}_{RE} - \beta'_{FE}$$

$$\begin{cases} H_0 : RE \\ H_1 : FE \end{cases}$$

Under  $H_0$ ,  $m$  is asymptotically distributed as  $\chi_K^2$  where,  $K$  denotes the dimension of slope vector  $\beta$ . Null hypothesis shows that  $\hat{\beta}_{RE}$  is efficient and  $\beta'_{FE}$  is consistent though typically not efficient. The alternative hypothesis declares that only the fixed effect model is consistent<sup>2</sup>.

### 5.5.3. Panel Data Unit Root Test

In a regression analysis of the time series, it is expected that the distribution of a time series variable in terms of mean and variance will not change over time. Unit root tests are used to determine if variables are weakly stationary (which is zero mean and constant variance) and if otherwise, to determine their order of integration (that is number of times they are to be differenced to be stationary). It must be done to avoid; 1)Spurious regression: modeling relationship between two random walk series, such as two I(1)

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<sup>1</sup> For more information, see (Baltagi 2005)

<sup>2</sup> For more information, see (Baltagi 2005)



series ,and 2) Meaningless regression: regressing two variables of different order of integration on each other, like  $I(0)$  on  $I(1)$  series. Recently, time series econometrics and panel data analysis have focused on studying the macro panels with large number of cross-sections (N) and large length of the time series (T). Adding the cross-sectional dimension to the usual time dimension is very important in the context of non-stationary series. Indeed, unit root tests generally have low power in small sample sizes to distinguish non-stationary from stationary series that are persistent. In order to increase the power of unit root tests, a solution is to increase the number of observations by including information relating to various individuals or countries. Panel-based unit root tests have higher power than unit root tests based on individual time series. The tests such as Dickey-Fuller (DF), augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) lack power to distinguish the unit root null from stationary alternatives.<sup>1</sup>

Since Levin and Lin (1993) established the foundations for panel unit root tests, a few tests for panel unit roots have been proposed. Among those, the most common tests in practice are Levin-Lin (LL), Im-Pesaran-Shin (1997) (IPS) and Maddala-Wu (1999) (MW).<sup>2</sup>

Im-Pesaran-Shin introduced a power comparison of the LL and IPS tests and argued that the IPS test is more powerful than the LL test. Although the null hypothesis is the same in the two tests, the alternative hypothesis is different. The LL tests are based on homogeneity of the autoregressive parameter (although there is heterogeneity in the error variances and the serial correlation structure of the errors). Thus, the tests are based on pooled regressions. The IPS test, on the other hand, is based on heterogeneity of the autoregressive parameter<sup>3</sup>.

According to whether unit root tests allow for potential correlations across residuals of panel units, two generations of tests can be distinguished, as listed below:

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<sup>1</sup> For more information, see (Maddala.& Wu, 1999;Analysts' Data Services and Resources Ltd ? ,Hurlin & V Mignony 2000 and Breitung & Pesaran 2005)

<sup>2</sup> For more information, see ( Hoang and Mcnown2006)

<sup>3</sup> For more information, see (Maddala and Wu 1999:637)

<b>Table 5.1: Panel Unit Root Test</b>	
<b>First Generation</b>	Cross-sectional independence
1. Nonstationarity tests	Levin and Lin (1992, 1993) Levin, Lin and Chu (2002) Harris and Tzavalis (1999) Im, Pesaran and Shin (1997, 2002, 2003) Maddala and Wu (1999) Choi (1999, 2001)
2- Stationarity test	Hadri (2000)
<b>Second Generation</b>	Cross-sectional dependencies
1- Factor structure	Bai and Ng (2001, 2004) Moon and Perron (2004a) Phillips and Sul (2003a) Pesaran (2003) Choi (2002)
2- Other approaches	O.Connell (1998) Chang (2002, 2004)
<i>Source: Hurlin ,C. and Mignony,V. (2006)</i>	

As Breitung and Pesaran (2005) assumed, a simple first-order autoregressive model, AR (1) is given by:

$$y_{it} = (1 - \alpha_i)\mu_i + \alpha_i y_{i,t-1} + \varepsilon_{it} \quad (1)$$

Where,

$\{y_{i0}, \dots, y_{iT}\}$  on the cross-section units  $i=1, 2, \dots, N$

The initial values,  $y_{i0}$ , are given, and the errors  $\varepsilon_{it}$  are identically, independently distributed (idd) across  $i$  and  $t$  with  $E(\varepsilon_{it}) = 0, E(\varepsilon_{it}^2) = \sigma_i^2 < \infty$  and  $E(\varepsilon_{it}^4) < \infty$   
Equation (12) can be written as simple Dickey-Fuller (DF) regressions as follows:

$$\Delta y_{it} = -\phi_i \mu_i + \phi_i y_{i,t-1} + \varepsilon_{it} \quad (2)$$

Where,

$$\Delta y_{it} = y_{it} - y_{i,t-1}, \phi_i = \alpha_i - 1$$

By developing (1) and (2) in mean-deviation forms  $\tilde{y}_{it} = \alpha_i \tilde{y}_{i,t-1} + \varepsilon_{it}$  where,  $\tilde{y}_{it} = y_{it} - \mu_i$ , DF regression in  $\tilde{y}_{it}$  is as follows:

$$\Delta \tilde{y}_{it} = \phi_i \tilde{y}_{i,t-1} + \varepsilon_{it} \quad (3)$$

$$\left\{ \begin{array}{l} H_0 : \phi_1 = \dots = \phi_N = 0 \\ H_{1a} : \phi_1 = \dots = \phi_N = \phi \quad \text{and} \quad \phi < 0 \\ H_{1b} : \phi_1 < 0, \dots, \phi_N < 0, N_0 \leq N \end{array} \right.$$

The null hypothesis  $H_0$  declares all time series are independent random walks. There is two alternatives,  $H_{1a}$  and  $H_{1b}$ . Under  $H_{1a}$ , it is assumed that the autoregressive parameter is identical for all cross section units, which called the homogeneous alternative.  $H_{1b}$  assumes that  $N_0$  of the  $N$  ( $0 < N_0 \leq N$ ) panel units are stationary with individual specific autoregressive coefficients. This is referred to as the heterogeneous alternatives. For the consistency of the test, it is assumed that  $N_0 / N \rightarrow k > 0$  as  $N \rightarrow \infty$ . Different panel testing procedures can be developed depending on which of the two alternatives is being considered.

## 5.6. Results and Analysis<sup>1</sup>

### 5.6.1. Results from Panel Data Unit Roots Test

Unit root test is performed on time series variables to determine if they are stationary<sup>2</sup> or non-stationary. Moreover, if the variables are not stationary, unit root test will be used to determine the order of integration that is number of times that variables must be differenced to be stationary. Since most panel data models have a time dimension, it is necessary to look for unit roots in panel data. To test whether or not the time series variables are stationary, Im-Pesaran-Shin (IPS), Augmented Dickey- Fuller (ADF), and Phillips-Perron (PP) have been performed .

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<sup>1</sup> For econometric analysis and estimations, Eviews 7 has been employed. Results of models are taken from Eviews software

<sup>2</sup> Stationary means that time series variables must have zero mean and constant variance.

Results of panel data unit root tests (Table 5.2) show that according to three methods of IPS, ADF and PP, time series variables: RTRADE, GDPIR, REXCHANGE, LINDER1, LINDER2, LINDER3 and LOG (REXCHANGE) are stationary on level, I(0). Under ADF and PP, LOG (POPP) is stationary however; IPS is not supporting the result. According to all three methods, among times series variables, GDPP, LOG (SUM1) and LOG (SUM2) are non-stationary which, after one time difference will be stationary that is integrated of order unity, I(1). The following results are obtained by data estimation made by Eviews.

Table 5.2: Unit Root Test						
Name of Variables	RTRADE	GDPP		GDPIR	REXCHAGNEP	LINDER1
D	Level	Level	1th difference	Level	Level	Level
Pesaran et. Al	-11.5135	24.3270	-18.6271	-13.4580	-115.473	-22.2103
P-value	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000
ADF	711.895	59.8746	1078.99	571.571	3257.68	1095.10
P-value	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000
PP	809.264	59.8746	1237.63	543.958	3272.56	1159.75
P-value	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000

Table 5.2: Unit Root Test, Continued						
Name of Variables	LTRADE	LTRADE2	LOG(SUM1)		LOG(SUM2)	
d	Level	Level	Level	1th difference	Level	1th difference
Pesaran et. al	-14.1463	-12.6213	15.2798	-16.8206	8.53729	-21.8031
P-value	0.0000	0.0000	1.0000	0.0000	1.0000	0.0000
ADF	710.344	672.559	89.1646	739.265	207.150	1090.11
P-value	0.0000	0.0000	1.0000	0.0000	0.9858	0.0000
PP	915.154	932.025	55.2681	1101.03	152.804	1437.53
P-value	0.0000	0.0000	1.0000	0.0000	1.0000	0.0000

Table 5.2: Unit Root Test, Continued				
Name of Variables	LINDER2	LINDER3	LOG(REXCHANGE P)	LOG(POPP)
d	Level	Level	Level	Level
Pesaran et. al	-28.9950	-23.8708	-18.6605	-0.05464
P-value	0.0000	0.0000	0.0000	0.4782
ADF	1440.33	1114.42	853.841	771.263
P-value	0.0000	0.0000	0.0000	0.0000
PP	1526.17	1202.39	1315.53	1592.69
P-value	0.0000	0.0000	0.0000	0.0000
<i>Source: Own analysis by using Eviews</i>				

### 5.6.2. Results of Cointegration Test<sup>1</sup>

Cointegration test will be applied to test whether there are long-run relationships among time series variables. The existence and the nature of the long-run relationships are investigated by cointegration techniques developed by Engle and Granger (1987), Johansen (1991,1995) and Phillips (1991)<sup>2</sup>.

Eviews uses Pedroni, Kao and a Fisher-type test using Johansen methodology. The Pedroni and Kao tests are based on Engle-Granger (1987) two-step residual-based cointegration tests. The Fisher test is a combined Johansen test<sup>3</sup>. (Analysts' Data Services and Resources Ltd)

Johanson Fisher Panel Cointegration Test is performed to test whether there are long-run relationships among time series variables in models. The results among all three models of the study show that the null hypothesis (lack of the cointegration) is rejected. The alternative hypothesis (existence of cointegration) is accepted, consequently there are long-run relationship among time series variables in models I, II and III. (See Tables 5.3, 5.4 and 5.5)

<b>Table 5.3: Model I, Johansen Fisher Panel Cointegration Test</b>				
Series: RTRADE, GDPP, GDPIRI, REXCHANGE, LINDER1				
Unrestricted Cointegration Rank Test (Trace and Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Fisher Stat. (from trace test)	Prob.	Fisher Stat. (from max-eigen test)	Prob.
None	4259.	0.0000	2763.	0.0000
At most 1	2310.	0.0000	1323.	0.0000
At most 2	1275.	0.0000	814.7	0.0000
At most 3	737.4	0.0000	580.7	0.0000
At most 4	566.3	0.0000	566.3	0.0000
<i>Source: Own analysis by using Eviews</i>				

<sup>1</sup> Cointegration is the idea that the linear combinations of two non-stationary series can be stationary, implying a long-run relationship, so that they can be modeled. If the cointegration relationship exists, and then the long-run parameters can be estimated efficiently.

<sup>2</sup> For more details, see (Breitung & Pesaran 2005)

<sup>3</sup> For more information see (Analysts' Data Services and Resources Ltd)

<b>Table 5.4: Model II, Johansen Fisher Panel Cointegration Test</b>				
Unrestricted Cointegration Rank Test (Trace and Maximum Eigenvalue)				
Hypothesized	Fisher Stat.		Fisher Stat.	
No. of CE(s)	(from trace test)	Prob.	(from max-eigen test)	Prob.
None	5038.	0.0000	3534.	0.0000
At most 1	3278.	0.0000	1974.	0.0000
At most 2	1930.	0.0000	1225.	0.0000
At most 3	1106.	0.0000	835.1	0.0000
At most 4	741.8	0.0000	741.8	0.0000
<i>Source: Own analysis by using Eviews</i>				

<b>Table 5.5: Model III, Johansen Fisher Panel Cointegration Test</b>				
Series: LTRADE, LOG(SUM2) ,LINDER3, LOG(POPP) ,LOG(REXCHANGE)				
Unrestricted Cointegration Rank Test (Trace and Maximum Eigenvalue)				
Hypothesized	Fisher Stat.		Fisher Stat.	
No. of CE(s)	(from trace test)	Prob.	(from max-eigen test)	Prob.
None	5052.	0.0000	3550.	0.0000
At most 1	3315.	0.0000	2004.	0.0000
At most 2	1952.	0.0000	1229.	0.0000
At most 3	1152.	0.0000	870.6	0.0000
At most 4	759.8	0.0000	759.8	0.0000
<i>Source: Own analysis by using Eviews</i>				

### 5.6.3. Estimation Results of Model I<sup>1</sup>

Model I, as mentioned in this chapter, is estimated for five groups including ,one Base group (including all cross-sections), and other 4 groups as, High Income (HI),Upper Middle Income (UMI),Lower Middle Income (LMI), and Low Income (LI).

#### 5.7.3.1. Estimation Results for Base Group

Before estimation the Model I (Base Group), it is necessary to test whether there are the individual effects to choose between pool OLS and FX model. The result of F test shows that the null hypothesis of poolability is rejected, this implies that a separate intercept is required for each individual in the sample, and there are special effects so that OLS estimator is not consistent. (See Table 5.6)

<sup>1</sup> For further analysis, Model I is computed in a Dynamic Panel Data (DPD) approach. See the appendix II for the results of Generalized Method of Moments (GMM) for DPD

<b>Table 5.6: Model I, Base group, Redundant Fixed Effects Tests</b>			
Test cross-section fixed effects			
Effects Test	Statistic	d.f.	Prob.
Cross-section F	33.087731	(126,2536)	0.0000
Cross-section Chi-square	2593.053534	126	0.0000
<i>Source: Own analysis by using Eviews</i>			

To test whether the individual-specific effect really is an unrelated effect, Hausman test is applied. The result of this test approves the null hypothesis of the efficiency of the random effect model. (See Table 5.7)

<b>Table 5.7: Model I, Base group, Correlated Random Effects - Hausman Test</b>			
Test cross-section random effects			
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	0.000000	4	1.0000
<i>Source: Own analysis by using Eviews</i>			

Generalized Least Square<sup>1</sup>(GLS) estimator of the random effect model is used to estimate the Model I (Base group). Estimation results of Model I (Base group) imply that, if GDPP one-unit increases, RTRADE will increase by 2.58 in an average. If GDPIRI changes by one unit, RTRADE will change by 1.27 in the same direction. **LINDER1** and **REXCHANGEP** are statistically insignificant. (See Table 5.8)

<b>Table 5.8: Model I, Base group, Pooled EGLS (Cross-section random effects)</b>				
Dependent Variable: RTRADE				
Total pool (balanced) observations: 2667				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-431838.8	711462.4	-0.606974	0.5439
GDPP	2.58E-06	3.70E-07	6.973921	0.0000
GDPIRI	1.27E-05	2.05E-06	6.186925	0.0000
REXCHANGEP	-0.637140	1.341723	-0.474867	0.6349
<b>LINDER1</b>	<b>-0.000296</b>	<b>0.000743</b>	<b>-0.399110</b>	<b>0.6898</b>
R2 : 0.037		F : 26.7		
<i>Source: Own analysis by using Eviews</i>				

<sup>1</sup> Generalized least squares (GLS) is applied when there is heteroscedasticity (when the variances of the observations are unequal) or correlation between the observations.



### 5.6.3.1.1. Tobit Model (Censored Regression Model)<sup>1</sup>

The Tobit model can be shown in the terms of a latent variable  $y_{ijt}^*$ .

$$y_{ijt}^* = x_{ijt} \beta_j + \varepsilon_{ijt} \quad (19)$$

$$y_{ijt} = \begin{cases} y_{ijt}^* & \text{if } y_{ijt}^* > 0 & (a) \\ 0 & \text{if } y_{ijt}^* \leq 0 & (b) \end{cases}$$

It is assumed that total trade must be non-zero quantity of goods and services.

(a): If the measure of ability or desire for trade is positive, trade will be zero.

(b): If the measure of ability or desire for trade is zero or negative, trade will be zero.

The use of the censored dependent variable  $y_{ijt}^*$  provides a significant improvement on the validity of the Linder hypothesis. The Table (5.9) shows results of Tobit model. Estimation of censored regression model implies that, if LINDER1 increases one unit, RTRADE will decrease by 0.001 in an average. If GDPP changes by one unit, RTRADE will change by 3.47 in an average. If GDPP increases by one unit, RTRADE will raise by 0.00016 in an average. All variables are statistically significant. REXCHANGEP does not show any significant effect on RTRADE in this model.

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<sup>1</sup> Theoretically, it is assumed that trade must be positive in values for goods and services. However, in actual trade analysis, total trade will have significant number of zero observation as well as many positive observations. In process of estimation, data from countries that trade zero amounts of goods and services to the country under investigation will be excluded. From an econometric perspective, such omission surely leads to biased results. Practically this omission overestimate effects of countries that have non-zero trade with the country under investigation and underestimate effects of those countries that have zero trade with the country. In particular, if the omitted countries have per capita incomes similar to the country under investigation, there will be a bias toward accepting the Linder hypothesis. Conversely, if the omitted countries have per capita incomes very different from the country under investigation, then there will be a bias toward rejecting the Linder hypothesis. The appropriate econometric approach would be the one, which recognizes the censored nature of the dependent variable, and include data on all potential trading partners, whether or not a non-zero amount of goods and services is actually exchanged. (Mcpherson *et al.* 2000) To include the related data from all trading partners, Tobit model will be performed. James Tobin (1958) proposed this statistical model to calculate the relationship between a non-negative dependent variable  $y_{jii}$  and an independent variable  $x_{jii}$ .

<b>Table 5.9: Model I, Base Group, Method: ML - Censored Extreme Value (Quadratic hill climbing)</b>				
Dependent Variable: RTRADE Included observations: 2667				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
REXCHANGEP	-0.050317	0.759962	-0.066210	0.9472
<b>LINDER1</b>	<b>-0.001068</b>	<b>0.000420</b>	<b>-2.544873</b>	<b>0.0109</b>
GDPP	3.47E-06	1.23E-06	2.811692	0.0049
GDPIRI	0.000161	3.05E-05	5.267197	0.0000
C	-21922277	4708302.	-4.656090	0.0000
<i>Source: Own analysis by using Eviews</i>				

### 5.3.3.2. Estimation Results of High Income Group

Before estimation the Model I (HI Group), it is necessary to test whether or not there are the individual effects to choose between pool OLS and FX model. F test result shows the null hypothesis of poolability is rejected. This implies that a separate intercept is required for each individual in the sample, and there are special effects so that OLS estimator is not consistent. (See Table 5.10)

<b>Table 5.10: Model I, High Income, Redundant Fixed Effects Tests</b>			
Test cross-section fixed effects			
Effects Test	Statistic	d.f.	Prob.
Cross-section F	40.242490	(39,796)	0.0000
Cross-section Chi-square	914.866998	39	0.0000
<i>Source: Own analysis by using Eviews</i>			

To test whether the individual-specific effect really is an unrelated effect, Hausman test is applied. The result of this test rejects the null hypothesis of the efficiency of the random effects model. So then, the fixed effect model is consistent. (See Table 5.11)

<b>Table 5.11: Model I, High Income, Correlated Random Effects - Hausman Test</b>			
Test cross-section random effects			
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	45.882695	4	0.0000
<i>Source: Own analysis by using Eviews</i>			

After the Hausman test, which showed the fixed effects model is consistent; Pooled Least Square estimator of the fixed effect model is used. Results imply that, if GDPIRI one unit increases, RTRADE increases by 6.47 in an average. One unit change occurs in LINDER1, RTRADE changes by -814.8. This implies that there is the Linder effect in this model. GDPP and REXCHANGE are statistically insignificant. (See Table 5.12)

Table 5.12: Model I , High Income, Pooled Least Squares				
Dependent Variable: RTRADE Total pool (balanced) observations: 840				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	16142846	1914270.	8.432898	0.0000
GDPP	-1.07E-06	9.62E-07	-1.109291	0.2676
GDPIRI	6.47E-05	8.06E-06	8.029747	0.0000
REXCHANGE	-73.23571	92.62144	-0.790699	0.4294
<b>LINDER1</b>	<b>-814.8061</b>	<b>84.46752</b>	<b>-9.646383</b>	<b>0.0000</b>
R2: 0.67		F: 38.6		
<i>Source: Own analysis by using Eviews</i>				

### 5.6.3.3. Estimation Results of Upper Middle Income Group

Before estimation the Model I (UMI group), it is necessary to test whether or not there is the individual effects to choose between pool OLS and FX model. F test result shows that, the null hypothesis of poolability is rejected. This implies that a separate intercept is required for each individual in the sample, and there are special effects so that OLS estimator is not consistent. (See Table 5.13)

Table 5.13: Model I, Upper Middle Income, Redundant Fixed Effects Tests			
Test cross-section fixed effects			
Effects Test	Statistic	d.f.	Prob.
Cross-section F	17.189048	(30,616)	0.0000
Cross-section Chi-square	395.940810	30	0.0000
<i>Source: Own analysis by using Eviews</i>			

To test whether the individual-specific effect really is an unrelated effect or not, Hausman test is carried out. The result under this test rejects the null hypothesis of the efficiency of the random effects model, and so fixed effects model is consistent. (See Table 5.14)

<b>Table 5.14: ModelI, Upper Middle Income, Correlated Random Effects - Hausman Test</b>			
Test cross-section random effects			
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	31.797628	4	0.0000
<i>Source: Own analysis by using Eviews</i>			

To estimate the Model I (UMI group), Pooled Least Square estimator of the fixed effect model is used. Estimation results of Model I (UMI group) describe that, if GDPP one-unit increases, RTRADE raises by 1.64 in an average. GDPIRI, REXCHANGEP and LINDER1 are statistically insignificant. (See Table 5.15)

<b>Table 5.15: Model I, Upper Middle Income, Pooled Least Squares</b>				
Dependent Variable: RTRADE				
Total pool (balanced) observations: 651				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-312869.9	420314.1	-0.744372	0.4569
GDPP	1.64E-05	5.37E-07	30.55424	0.0000
GDPIRI	-3.26E-06	2.30E-06	-1.416297	0.1572
REXCHANGEP	-0.979686	0.721053	-1.358688	0.1747
<b>LINDER1</b>	<b>-0.000317</b>	<b>0.000478</b>	<b>-0.663791</b>	<b>0.5071</b>
R2: 0.82		F: 83.0		
<i>Source: Own analysis by using Eviews</i>				

#### 5.6.3.4. Estimation Results of the Lower Middle Income Group

Before estimation the Model I (LMI Group), it is necessary to test whether or not there are the individual effects to choose between pool OLS and FX model. F test result shows that the null hypothesis of poolability is rejected. This implies that a separate intercept is

required for each individual in the sample, and there are special effects so that OLS estimator is not consistent. (See Table 5.16)

<b>Table 5.16 : Model I ,Lower Middle Income, Redundant Fixed Effects Tests</b>			
Test cross-section fixed effects			
Effects Test	Statistic	d.f.	Prob.
Cross-section F	13.023300	(25,516)	0.0000
Cross-section Chi-square	267.090796	25	0.0000
<i>Source: Own analysis by using Eviews</i>			

To test whether the individual-specific effect really is an unrelated effect, Hausman test is applied. The result of this test approves the null hypothesis of the efficiency of the random effects model. (See Table 5.17)

<b>Table 5.17: Model I, Lower Middle Income, Correlated Random Effects - Hausman Test</b>			
Test cross-section random effects			
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	0.000000	4	1.0000
<i>Source: Own analysis by using Eviews</i>			

To estimate the Model I (LMI group), Generalized Least Square (GLS) estimator of the random effect model is used. Estimation results imply that, if GDPP one unit increases, RTRADE increases by 1.09 in an average. One unit change in GDPIRI will changes RTRADE by 1.13 positively. REXCHANGEPI and LINDER1 do not show any significant effects on RTRADE in this model. (See Table 5.18)

<b>Table 5.18: Model I ,Lower Middle Income , Pooled EGLS (Cross-section random effects)</b>				
Dependent Variable: RTRADE				
Total pool (balanced) observations: 546				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1275026	587418.1	-2.170561	0.0304
GDPP	1.09E-05	3.97E-06	2.748644	0.0062
GDPIRI	1.13E-05	4.08E-06	2.767614	0.0058
REXCHANGEPI	-9.724434	10.92395	-0.890194	0.3738
<b>LINDER1</b>	<b>-179.1339</b>	<b>476.7237</b>	<b>-0.375760</b>	<b>0.7072</b>
R2: 0.082		F: 12.16		
<i>Source: Own analysis by using Eviews</i>				

#### 5.6.3.5. Estimation Results of Low Income Group

Before estimation the Model I (LI Group), it is necessary to test whether or not there are the individual effects to choose between pool OLS and FX model. The result of F test describes that the null hypothesis of poolability is rejected. This implies that a separate intercept is required for each individual in the sample, and there are special effects so that OLS estimator is not consistent. (See Table 5.19)

<b>Table 5.19: Model I , Low Income, Redundant Fixed Effects Tests</b>			
Test cross-section fixed effects			
Effects Test	Statistic	d.f.	Prob.
Cross-section F	1857.068500	(18,376)	0.0000
<i>Source: Own analysis by using Eviews</i>			

To test whether the individual-specific effect really is an unrelated effect, Hausman test is applied. The result of this test rejects the null hypothesis of the efficiency of the random effects model. Thus fixed effect model will be consistent. (See Table 5.20)

Table 5.20: Model I , Low Income , Correlated Random Effects - Hausman Test			
Test cross-section random effects			
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	8.533113	4	0.0739
<i>Source: Own analysis by using Eviews</i>			

SUR<sup>1</sup> Generalized Least Square estimator of the fixed effect model is used to estimate the Model I (LI group). Results imply that, if one unit of GDPIRI increases, RTRADE increases by 5.05 in an average. If GDPP changes by one unit, RTRADE changes by -2.51. One unit change occurs in REXCHANGE, RTRADE decreases by -6.11 and likewise one unit change happens in LINDER1, RTRADE decreases by -4531.5 in an average. All independent variables used in this model are statistically significant. (See Table 5.21)

Table 5.21: Model I, Lowe Income , Pooled EGLS (Cross-section SUR)				
Dependent Variable: RTRADE Total pool (balanced) observations: 399				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1720013.	26200.67	65.64768	0.0000
GDPP	-2.51E-05	2.49E-07	-100.7409	0.0000
GDPIRI	5.05E-05	3.12E-07	162.1504	0.0000
REXCHANGE	-6.113315	0.102193	-59.82150	0.0000
<b>LINDER1</b>	<b>-4531.587</b>	<b>27.22448</b>	<b>-166.4527</b>	<b>0.0000</b>
R2: 0.98		F: 1630.9		
<i>Source: Own analysis by using Eviews</i>				

<sup>1</sup>Cross-section SUR generalized least squares is the feasible GLS estimator for systems where the residuals are both cross-sectionally heteroskedastic and contemporaneously correlated.

#### 5.6.4. Estimation Results of Gravity Model A (Model II)

GLS estimator is applied to test the Model II (gravity model A) for Base group, UMI group, LMI group and LI group. By using cross-section weight in GLS in this model, FGLS<sup>1</sup> is performed by assuming the presence of cross-section heteroskedasticity. In case of HI group, the Pooled LS method is computed.

##### 5.6.4.1. Estimation Results of Base Group

Results of Mode II (Base group) imply that LOG (SUM1) will affect LTRADE2 by 0.56 percent positively. If LNDIS changes by one percent, LTRADE2 will change by 1.31 negatively. If LINDER2 increases by one percent, LTRADE2 will decline by 1.4 percent more than proportionally. LINDER2 is significant and negative for Base group and this approves the validity of the Linder hypothesis. If LOG (POPP) increases by one percent, LTRADE2 will change by 0.68 percent less than proportionally. One percent change in DUMMYG will affect LTRADE2 adversely by 0.14, and likewise one percent change in INGRP (OPEC) will affect LTRADE2 by -1.48 in an average. One percent change in INGRP (BORDER) will affect LTRADE2 by 0.91 positively. All these variables in this model are statistically significant. However, LOG (REXCHANGE) does not show any significant effect on LTRADE2. The autoregressive process of order one AR (1) is included in this model<sup>2</sup> to transform serial correlation into serially uncorrelated classical errors. (See Table 5.22)

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<sup>1</sup> Cross-section heteroskedasticity allows for a different residual variance for each cross section. Residuals between different cross-sections and different periods are assumed zero. GLS for this specification is straightforward. So firstly, a preliminary estimation to obtain cross-section specific residual vectors is performed, and then these residuals are used to form estimates of the cross-specific variances. The estimates of the variances are then used in a weighted least squares procedure to form the feasible GLS estimates

<sup>2</sup> The classical error component disturbances ( $U_{it} = \mu_i + V_{it}$ ) assume that the only correlation over time is due to the presence of the same individual across the panel. This may be a restrictive assumption for economic relationships, where an unobserved shock of this period will affect the behavioral relationship for at least the next few periods. This type of serial correlation is not allowed for in the simple error component model. Ignoring present serial correlation resulted in consistent but inefficient estimates of the regression coefficients and biased standard errors. For more information see also (Baltagi 2005: 84).



Table 5.22: Model II, Base group, Pooled EGLS (Cross-section weights)				
Dependent Variable: LTRADE2				
Total pool (unbalanced) observations: 2388				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.982841	3.730314	-0.799622	0.4240
LOG(SUM1)	0.565499	0.182975	3.090576	0.0020
LNDIS	-1.312021	0.169961	-7.719529	0.0000
<b>LINDER2</b>	<b>-1.408546</b>	<b>0.204783</b>	<b>-6.878228</b>	<b>0.0000</b>
LOG(POPP)	0.680356	0.097028	7.011937	0.0000
LOG(REXCHANGE)	0.041807	0.028647	1.459375	0.1446
@INGRP(BORDER)	0.914956	0.292793	3.124928	0.0018
@INGRP(OPEC)	-1.484355	0.326645	-4.544243	0.0000
DUMMYG	-0.145270	0.062979	-2.306632	0.0212
AR(1)	0.822035	0.010889	75.48920	0.0000
R2: 0.91		F: 2799.3		
<i>Source: Own analysis by using Eviews</i>				

#### 5.6.4.2. Estimation Results of High Income Group

Table (5.23) shows results of HI group. If LOG (POPP) increases by one percent, LTRADE2 will increase more than proportionally by 1.29 percent. LNDIS affects LTRADE2 by -0.86 percent less than proportionally, and **LINDER2** affect LTRADE2 by -1.96 percent more than proportionally. LOG (SUM1), LOG (REXHCANGEP) and DUMMYG do not show any significant effect on LTRADE2. Further, the autoregressive process of order one AR (1) is included in the model to remove serial correlation.

Table 5.23: Model II, High Income ,Method: Pooled Least Square				
Dependent Variable: LTRADE2				
Total pool (unbalanced) observations: 791				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	12.37786	8.301952	1.490957	0.1364
LOG(SUM1)	-0.552507	0.458420	-1.205243	0.2285
LNDIS	-0.869169	0.315701	-2.753143	0.0060
<b>LINDER2</b>	<b>-1.965530</b>	<b>0.713017</b>	<b>-2.756640</b>	<b>0.0060</b>
LOG(POPP)	1.296561	0.264363	4.904466	0.0000
LOG(REXCHANGE)	0.129251	0.100610	1.284676	0.1993
DUMMYG	-0.123409	0.143351	-0.860883	0.3896
AR(1)	0.836133	0.020399	40.98942	0.0000
R2: 0.87		F: 807.8		
<i>Source: Own analysis by using Eviews</i>				

#### 5.6.4.3. Estimation Results of Upper Middle Income Group

Results of UMI group imply that one percent change in LOG (SUM1) affects LTRADE2 by 1.04 more than proportionally, and one percent change in LOG (POPP) affects LTRADE2 by 0.7 percent less than proportionally .One percent increase in LNDIS will decline LTRADE2 by 1.77 percent in average. If LINDER2 increases by one percent, LTRADE2 declines by 1.75 percent more than proportionally. LINDER2 is significant and negative which approves the Linder hypothesis. LNDIS is negative and significant which implies that there is a negative effect of distance on bilateral trade between Iran and potential trading partners. LOG (REXCHANGE) and DUMMYG do not show any significant effect on LTRADE2 in this model. In addition, the autoregressive process of order one AR (1) is included in the model to solve the serial correlation problem. (See Table 5.24)

Table 5.24: Model II, Upper Middle Income ,Method: Pooled EGLS (Cross-section weights)				
Dependent Variable: LTRADE2				
Total pool (unbalanced) observations: 579				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-12.13134	6.636878	-1.827868	0.0681
LOG(SUM1)	1.043044	0.339191	3.075093	0.0022
LNDIS	-1.779394	0.154509	-11.51644	0.0000
<b>LINDER2</b>	<b>-1.754222</b>	<b>0.362931</b>	<b>-4.833487</b>	<b>0.0000</b>
LOG(POPP)	0.700207	0.160521	4.362094	0.0000
LOG(REXCHANGE)	0.028597	0.046176	0.619316	0.5360
DUMMYG	-0.130217	0.129260	-1.007397	0.3142
AR(1)	0.768725	0.024802	30.99431	0.0000
R2: 0.91		F: 836.1		
<i>Source: Own analysis by using Eviews</i>				

#### 5.6.4.4. Estimation Results of Lower Middle Income Group

Results of Model II (LMI group) describe that if LOG (SUM1) changes by one percent, LTRADE2 will change by 2.33 percent more than proportionally, and if LOG (POPP) changes by one percent, LTRADE2 will change by 0.67 percent less than proportionally. If LNDIS increases by one percent, LTRADE2 will decline by 2.13 percent more than proportionally. If LOG (REXCHANGE) increases, LTRADE2 will decline by 0.1 percent. If DUMMYG changes by one percent in, LTRADE2 will change by 0.45 percent in an average. LNDIS is statistically significant that shows the negative effect of distance between Iran and potential trading partners on bilateral trade. **LINDER2** does not show any significant effect on LTRADE2. The autoregressive process of order one AR (1) is included in this model to correct the serial correlation. (See Table 5.25)

<b>Table 5.25: Model II, Lower Middle Income ,Method: Pooled EGLS (Cross-section weights)</b>				
Dependent Variable: LTRADE2				
Total pool (unbalanced) observations: 467				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-42.08351	14.48895	-2.904523	0.0039
LOG(SUM1)	2.334729	0.607731	3.841713	0.0001
LNDIS	-2.137014	0.235631	-9.069317	0.0000
<b>LINDER2</b>	<b>-0.901582</b>	<b>0.912194</b>	<b>-0.988366</b>	<b>0.3235</b>
LOG(POPP)	0.679202	0.145128	4.680007	0.0000
LOG(REXCHANGE)	-0.108258	0.058437	-1.852538	0.0646
DUMMYG	-0.456887	0.214194	-2.133052	0.0335
AR(1)	0.725780	0.027018	26.86311	0.0000
R2: 0.85		F: 383.8		
<i>Source: Own analysis by using Eviews</i>				

#### 5.6.4.5. Estimation Results of Low Income Group

Results of Model II (IL group) imply that if LOG (SUM1) changes by one percent, LTRADE2 will change by 1.54 percent more than proportionally, and if LOG (POPP) changes by one percent, LTRADE2 will change by 0.78 percent less than proportionally. These effects are statistically significant. Moreover, If LNDIS increases by one percent, LTRADE2 will decline by 4.3, and likewise if LINDER2 increases by one percent, LTRADE2 declines by 3.4 more than proportionally. Both variables have negative and significant effect on LTRADE2 that approves the model's hypothesis. LOG (REXCHNAGEP) and DUMMYG do not show any significant effects on dependent variable. The autoregressive process of order one AR (1) is included in this model to transform serial correlation into serially uncorrelated classical errors. (See Table 5.26)

Table 5.26: Method: Pooled EGLS (Cross-section weights)				
Dependent Variable: LTRADE2				
Total pool (unbalanced) observations: 338				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.653252	15.82638	-0.230833	0.8176
LOG(SUM1)	1.540381	0.628106	2.452421	0.0147
LNDIS	-4.330080	0.313967	-13.79151	0.0000
<b>LINDER2</b>	<b>-3.433659</b>	<b>0.842238</b>	<b>-4.076829</b>	<b>0.0001</b>
LOG(POPP)	0.788825	0.102466	7.698440	0.0000
LOG(REXCHANGE)	0.018942	0.067819	0.279301	0.7802
DUMMYG	-0.064046	0.276640	-0.231515	0.8171
AR(1)	0.549751	0.040624	13.53266	0.0000
R2: 0.83		F: 240.6		
<i>Source: Own analysis by using Eviews</i>				

### 5.6.5. Estimation Results of Gravity Model B (Model III)

To test the Model III (gravity model B), GLS estimator is applied for five groups- Base group, HI group, UMI group, LMI group and LI group. In this method, FGLS is also performed by using cross-section weight in GLS.

#### 5.6.5.1. Estimation Results of Base Group

Results of Mode III (Base group) imply that LOG (SUM2) will affect LTRADE by 0.67 percent in the same direction in an average. If LNDIS changes by one percent, LTRADE2 will change by -1.41 percent more than proportionally. **LINDER3 is insignificant which implies that in this group there is no valid Linder effect.** If LOG (POPP) changes by one percent, LTRADE will change by 0.57 percent, and likewise if LOG (REXCHANGE) changes by one percent, LTRADE will change by 0.06 percent less than proportionally. One percent change in DUMMYG and INGRP (OPEC) will affect LTRADE adversely by -0.24 and -1.3 respectively in an average. If INGRP (BORDER) changes by one percent, LTRADE will change by 0.87 positively. The

autoregressive process of order one AR (1) is included in this model to transform serial correlation into serially uncorrelated classical errors. (See Table 5.27)

Table 5.27: Model III , Base group, Method: Pooled EGLS (Cross-section weights)				
Dependent Variable: LTRADE				
Total pool (unbalanced) observations: 2388				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-17.94935	1.511529	-11.87496	0.0000
LOG(SUM2)	0.672858	0.082502	8.155616	0.0000
LNDIS	-1.414051	0.175529	-8.055947	0.0000
<b>LINDER3</b>	<b>0.115739</b>	<b>0.101647</b>	<b>1.138631</b>	<b>0.2550</b>
LOG(POPP)	0.571424	0.058003	9.851621	0.0000
LOG(REXCHANGE)	0.060184	0.028442	2.116049	0.0344
@INGRP(BORDER)	0.878429	0.282939	3.104656	0.0019
@INGRP(OPEC)	-1.304411	0.329444	-3.959434	0.0001
DUMMYG	-0.241423	0.060147	-4.013899	0.0001
AR(1)	0.824126	0.010788	76.39323	0.0000
R2: 0.86		F: 1748.9		
Source: Own analysis by using Eviews				

#### 5.6.5.2. Estimation Results of High Income Group

Results of HI group imply that variables LOG (SUM2), **LINDER3** and LOG (POPP) do not show any significant effect on LTRADE. If LNDIS changes by one percent, LTRADE will change by -0.59 percent, and likewise if LOG (REXHCANGEP) changes by one percent, LTRADE will change by 0.29 percent less than proportionally. If DUMMYG changes by one percent , LTRADE will change by -0.16 percent. The autoregressive process of order one AR (1) is included in this model to remove serial correlation. (See Table 5.28)

Table 5.28: Model III ,High Income ,Method: Pooled EGLS (Cross-section weights)				
Dependent Variable: LTRADE Total pool (unbalanced) observations: 791				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-10.67434	5.105204	-2.090874	0.0369
LOG(SUM2)	-0.310026	0.354813	-0.873772	0.3825
LNDIS	-0.597935	0.360799	-1.657250	0.0979
<b>LINDER3</b>	<b>2.372033</b>	<b>2.313257</b>	<b>1.025408</b>	<b>0.3055</b>
LOG(POPP)	0.205913	0.160427	1.283535	0.1997
LOG(REXCHANGE)	0.296310	0.080122	3.698255	0.0002
DUMMYG	-0.167904	0.082676	-2.030869	0.0426
AR(1)	0.907822	0.015089	60.16582	0.0000
R2: 0.85		F: 642.8		
<i>Source: Own analysis by using Eviews</i>				

### 5.6.5.3. Estimation Results of Upper Middle Income Group

Results of Model III (UMI group) show that if LOG (SUM2) changes by one percent, LTRADE will change by 0.82 percent, and likewise if LOG (POPP) changes by one percent, LTRADE will change by 0.71 percent less than proportionally. One percent change in LNDIS will change LTRADE by -1.71 percent more than proportionally. LNDIS is negative and significant which implies the negative effect of distance on bilateral trade between Iran and potential trading partners. LINDER3 is insignificant which implies that there is no Linder effect in this model. LOG (REXCHANGE) and DUMMYG do not show any significant effects on LTRADE in this model. The autoregressive process of order one AR (1) is included in this model to solve the serial correlation problem. (See Table 5.30)

<b>Table 5.29: Model III: Upper Middle Income ,Method: Pooled EGLS (Cross-section weights)</b>				
Dependent Variable: LTRADE				
Total pool (unbalanced) observations: 579				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-18.71114	1.752768	-10.67520	0.0000
LOG(SUM2)	0.822511	0.099900	8.233347	0.0000
LNDIS	-1.714812	0.146978	-11.66714	0.0000
<b>LINDER3</b>	<b>0.106655</b>	<b>0.117570</b>	<b>0.907161</b>	<b>0.3647</b>
LOG(POPP)	0.715183	0.071789	9.962304	0.0000
LOG(REXCHANGEP)	0.021074	0.044592	0.472590	0.6367
DUMMYG	-0.152093	0.110905	-1.371385	0.1708
AR(1)	0.767811	0.025183	30.48894	0.0000
R2: 0.8		F: 571.9		
<i>Source: Own analysis by using Eviews</i>				

#### 5.6.5.4. Estimation Results of the Lower Middle Income Group

Results of Model III (LMI group) show that if LOG (SUM2) changes by one percent, LTRADE will change by 2.47 percent, and likewise If LNDIS increase by one percent, LTRADE will decline by -2.12 percent more than proportionally. If LOG (POPP) changes by one percent, LTRADE will change by 0.84 percent less than proportionally. If LOG (REXCHANGEP) increases by one percent, LTRADE will decline by -0.12 percent less than proportionally. If LINDER3 increases by one percent, LTRADE will change by 1.5 percent more than proportionally. The positive sign of LINDER3 implies that in this model, Heckscher–Ohlin effect is dominated by Linder effect. These variables are statistically significant. If DUMMYG increases by one percent, LTRADE will decline by 0.55 percent significantly. The autoregressive process of order one AR (1) is included in this model to change serial correlation into serially uncorrelated classical errors. (See Table 5.30)



Table 5.30 : Model III, Lower Middle Income ,Method: Pooled Least Squares				
Dependent Variable: LTRADE				
Total pool (unbalanced) observations: 467				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-30.10412	8.019978	-3.753642	0.0002
LOG(SUM2)	2.479984	0.935056	2.652232	0.0083
LNDIS	-2.128057	0.253082	-8.408561	0.0000
<b>LINDER3</b>	<b>1.531966</b>	<b>0.770461</b>	<b>1.988376</b>	<b>0.0473</b>
LOG(POPP)	0.841797	0.127929	6.580208	0.0000
LOG(REXCHANGE)	-0.126220	0.063839	-1.977158	0.0486
DUMMYG	-0.556830	0.222449	-2.503186	0.0127
AR(1)	0.745052	0.026518	28.09651	0.0000
R2: 0.83		F: 324.7		
<i>Source: Own analysis by using Eviews</i>				

#### 5.6.5.5. Estimation Results of Low Income Group

Results of Model III (LI group) show that if LNDIS changes by one percent, LTRADE will change by -4.3 percent. Similarly, if **LINDER3** changes by one percent, **LTRADE** will change by -9.8 percent more than proportionally. These results imply that there are adverse effects between these two variables-LNDIS and LINDER3, and LTRADE. Further, results show that these effects are statistically significant. In addition, results imply that if LOG (POPP) increases by one percent, LTRADE will increase by 0.81 percent less than proportionally. Such change in LTRADE is statistically significant. LOG (SUM2), LOG (REXCHANGE) and DUMMYG do not show any significant effect on LTRADE in this group. The autoregressive process of order one AR (1) is also included in this model to solve the serial correlation problem. (See Table 5.31)

<b>Table 5.31, Model III, Low Income, Method: Pooled EGLS (Cross-section weights)</b>				
Dependent Variable: LTRADE				
Total pool (unbalanced) observations: 338				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.582874	7.812469	0.202609	0.8396
LOG(SUM2)	0.512179	0.929247	0.551177	0.5819
LNDIS	-4.313742	0.347273	-12.42176	0.0000
<b>LINDER3</b>	<b>-9.888474</b>	<b>3.362585</b>	<b>-2.940735</b>	<b>0.0035</b>
LOG(POPP)	0.810441	0.101939	7.950218	0.0000
LOG(REXCHANGE <sub>P</sub> )	0.013697	0.072850	0.188012	0.8510
DUMMYG	0.028754	0.290589	0.098952	0.9212
AR(1)	0.577343	0.039228	14.71760	0.0000
R2: 0.82		F: 220.0		
<i>Source: Own analysis by using Eviews</i>				

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