# CHAPTER 4

# RESEARCH METHODOLOGY

## 4.1. Gravity Model

Gravity model has been extensively utilized in explaining bilateral trade patterns. It can explicate the impact of various variables affecting the volume of trade between two countries. The basic framework of the model states that trade is positively related to the product of the countries' GDP while it has negative relationship with distance which represents transport cost. Gravity model may take in other variables influencing trade such as common border, common language, custom union, etc.

### 4.1.1. Foundation of Gravity Model

Anderson (1979) elaborated the theoretical foundation for the gravity equation. The simplest derivation of the gravity equation is formed from a Cobb-Douglas expenditure system. It is also assumed that there is perfect specialization of good by each country and that there are no tariffs or transport cost. The last assumption states that every country has similar preferences. The value of imports of goods *i* to country *j* is

$$M_{ij} = b_i Y_j \qquad (4.1)$$

where $Y_j$ is income in country *j*.

Using the condition that income equals sales means that:

$$Y_i = b_i (\sum_j Y_j)$$

$$\Leftrightarrow b_i = \frac{Y_i}{\sum_j Y_j}$$

Solving (1) with $b_i$ , we obtain:

$$\Leftrightarrow M_{ij} = \frac{Y_i Y_j}{\sum Y_j} \qquad (4.2)$$

Equation (4.2) is the basic form of gravity model. It shows that trade is determined by income from the origin country and the destination country.

Anderson also shows that gravity model works under the condition that there is traded and non-traded goods in the economy. Assuming that $\theta_i$ is the expenditure on country *i*'s traded goods divided by the total expenditure in country *j* on tradeables and letting $\phi_j$ as the share of expenditure of country *j* and $\phi_j = F(Y_j, N_j)$. The value of imports of *i*'s good to country *j* is:

$$M_{ij} = \theta_i \phi_j Y_j \tag{4.3}$$

Taking into account the condition of trade imbalance due to long term capital account transaction is a function of $(Y_i, N_i)$, the balance of trade of country *i* implies

$$Y_i \phi_i m_i = (\sum_j Y_j \phi_j)\theta_i \tag{4.4}$$

where $m_i = m(Y_i, N_i)$. Thus, we obtain

$$\theta_i = \frac{m_i \phi_i Y_i}{\sum_j Y_j \phi_j}$$

Solving (3) with $\theta_i$, we obtain

$$M_{ij} = \frac{m_i \phi_i Y_i \phi_j Y_j}{\sum_i \sum_j M_{ij}} \tag{4.5}$$

Equation (4) is another deterministic gravity equation which may work as the foundation of gravity model. It shows that trade is not only determined by the income of the origin and destination country but also by the size of the origin and destination country. Here, size is reflected by population.

Anderson also shows that gravity model is also workable if we let trade is available for many goods. We let the model work under the assumption that there are tariffs and distance between countries. He elaborates the model with the condition that any kind of transit costs has an increasing function of distance and is the same across commodities. His derivation produces the following gravity equation:

$$M_{ij} = \frac{m_i \phi_i Y_i \phi_j Y_j}{\sum_j \phi_j Y_j} \cdot \frac{1}{f(d_{ij})} \cdot \left[ \sum_j \frac{\phi_j Y_j}{\sum_j \phi_j Y_j} \cdot \frac{1}{f(d_{ij})} \right]^{-1} U_{ij} \qquad (4.6)$$

where $f(d_{ij})$ is the function of all costs regarding all variables of economic distance between country *i* and *j*, and $U_{ij}$ is a log-normal disturbance with $E(\ln U_{ij}) = 0$.

Equation (4.6) has some differences compared to prior forms of gravity equation derived by Anderson. The first difference is that equation (4.6) defines trade as aggregate trade rather than commodity-specific trade. Therefore, this research needs to base its foundation concerning the use of gravity model with other basis due to the research aim in defining the pattern of commodity-specific bilateral trade. The second difference is that equation (4.6) affirms that $1/f(d_{ij})$ is not a log-linear function. This statement allows this research to integrate other variables regarded as economic distance of trade into the gravity model. Moreover, it asserts also that these other variables of economic distance may be integrated into the equation as their natural measurement or form rather than being restricted to use the form of log-linear variable. Lastly, equation (4.6) comprises the square bracket term which is not incorporated in equation (4.2) and (4.5). This means that equation (4.6) states that the flow of trade between country *i* and *j* is influenced by the economic distance between country *i* and *j* relative to other countries in the observed economy. This implies that we should take into account the whole system of the economy in using the gravity model.

Contrast to Anderson which strictly assumes that there is perfect specialization among countries. Evenett and Keller (2002) derive the gravity equation under the assumption of imperfect specialization among countries. Furthermore, Evenett and Keller also show that bilateral volume of trade is higher the more the product is specialized[6]. Thus, based on this statement, gravity model

[6] Evenett and Keller argue that the volume of trade in the case In which the production of both goods is perfectly specialized ($M_S$) is more than the volume of trade in the case with

is workable to perform analysis in this research which allows bilateral trading partners to be able to trade in the same sector of commodities.

In accordance with what Anderson states that we should take into account the whole system of the economy in using the gravity model, Feenstra et al (2001) shows that the term of the world income or the total world trade can be treated as a constant when gravity model is run over a cross-section of countries[7]. This research performs an estimation of bilateral trade data over a cross-section of trade sector and trading partners. Therefore, this research incorporates the variable of the total trade of the system which is Indonesia's total international trade as a constant.

### 4.1.2. Critiques to Gravity Model

Gravity model assumes that trade is mainly determined by the level of income of trading partners and the distance between these two trading partners. However in reality, international trade occurs due to differences in comparative advantage. A country has a comparative advantage in producing a good if the opportunity cost in producing the good in that country is lower than in other countries. As we can see from the form of gravity model, these differences in comparative advantage is not explicitly shown.

International trade may also prevail due to differences of factor endowment among countries. These differences in endowment cannot be seen only by seeing its level of income solely which the basic gravity model explicates.

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specialization for one good but not the other good ( $M_{IH}$ ). Moreover, $M_{IH}$ is argued to be more than the volume of trade in the case in which both countries produce both goods ( $M_H$ ). These inequalities are concluded below:

$M_S > M_{IH} > M_H$ .

[7] Feenstra et al define $M_{ij}$ as total imports of country *j* from country *I*, $Y_i$ as the income of country *I*, $Y_j$ as the income of country *j*, and $Y_w$ as the world income. They explains that the total imports of country *j* from country *i* is $M_{ij} = Y_i Y_j / Y_w$ . This equation can also be derived into: $\log(M_{ij}) = -\log(Y_w) + \log(Y_i) + \log(Y_j)$ . Furthermore, they assert that $-\log(Y_w)$ can be treated as a constant in the model.

Gravity model also does not see the differences in supply condition a country has. Two countries for example may have the same level of income but not the same level of the volume of trade to another particular country. This condition may happen due to differences in capacity utilization, etc.

However, gravity model is an easy tool to explicate several factors affecting international trade simultaneously in a model. These factors do not take the form of quantity variable but also quality variable such as custom union, currency union, preferential trade arrangement, common language, common border, etc.

## 4.2. Exchange Rate Uncertainty

This research uses the measure of exchange rate uncertainty proposed by Perée and Steinherr (1989). Specifically

$$U_t = U^1 + U^2 = \frac{\max X_{t-k}^{t} - \min X_{t-k}^{t}}{\min X_{t-k}^{t}} + \left[1 + \frac{\left|X_t - X_t^p\right|}{X^p}\right]^2 \tag{4.7}$$

Perée and Steinherr define $X$ as the nominal exchange rate at time $t$, $\max X_{t-k}^{t}$ and $\min X_{t-k}^{t}$ as maximum and minimum values of nominal exchange rate over time interval of $k$ up to time $t$, $X^p$ as the 'equilibrium' exchange rate. Moreover, they also propose various value of $k$ to capture medium term uncertainty. These values are 10, 5 and 3 years respectively.

The first term, $U^1$, captures accumulated experiences. Perée and Steinherr postulate that the largest spread occurred in a given time interval forms the state of uncertainty. This means that people would still remember and consider the bad or good experiences happened in the past to judge the level or stability or uncertainty in the present time. This $U^1$ term is naturally a proxy for uncertainty. Therefore, it is expected that this term would be negatively correlated with trade.

The second term, $U^2$, tells more about the recent condition in period $t$. Perée and Steinherr postulate that uncertainty grows exponentially rather than linearly as misalignment does. Therefore, this second term may represent uncertainty, just like the first term does, but it may also represent nonlinear responses to misalignment. Thus, Perée and Steinherr also argue that $U^2$ may correlate negatively with trade if it does represent uncertainty, but it may correlate positively with trade if the second interpretation of $U^2$ dominates.

In the calculation of $U^2$, we use the approach made by Cho et al (2002) in interpreting the 'equilibrium' exchange rate denoted by $X_t^p$ in Perée and Steinherr's measure of exchange rate uncertainty. Cho et al (2002) use the mean of exchange rate of the previous $k$ years as the proxy of the 'equilibrium' exchange rate.

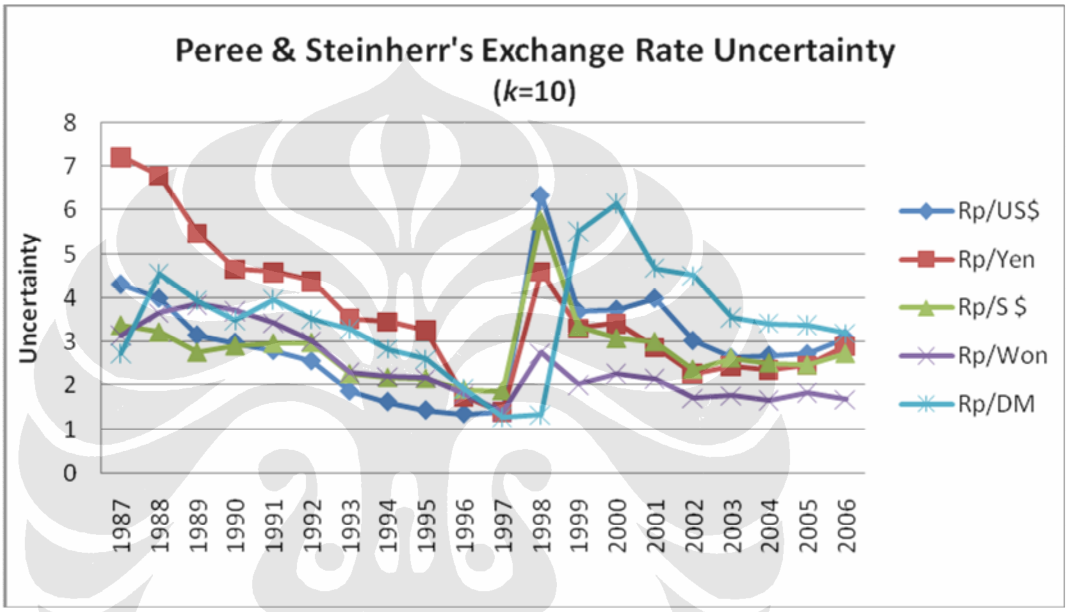
This research assumes that RER is more relevant in affecting trade and that PPP does not hold. Therefore, the research applies the RER into the exchange rate uncertainty measurement proposed by Perée and Steinherr elaborated above. Specifically,

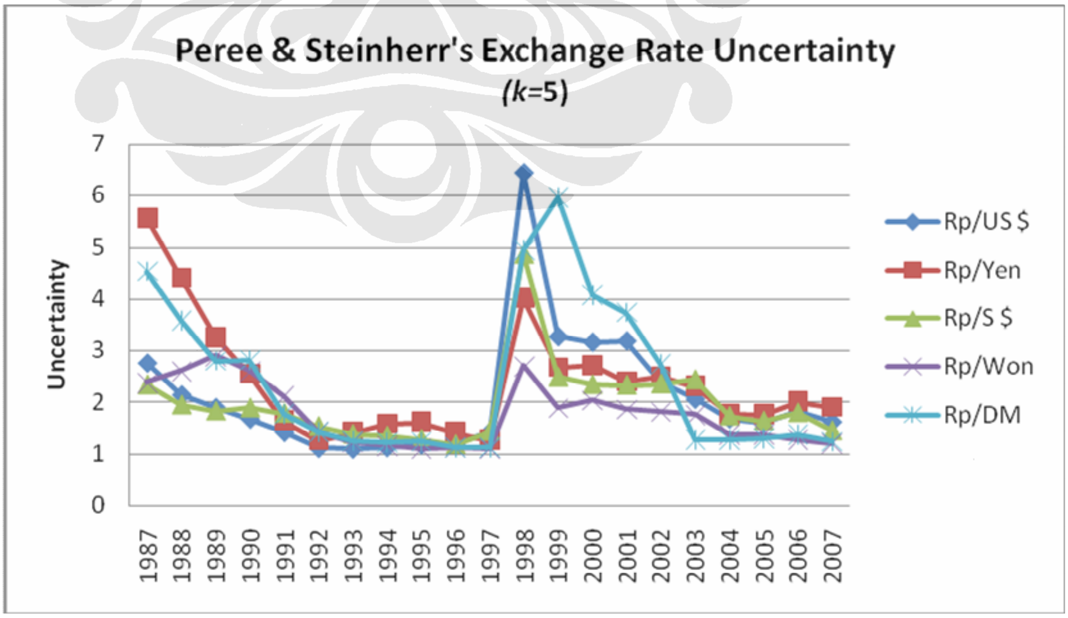
$$RER = \frac{e.P^*}{P} \qquad (4.8)$$

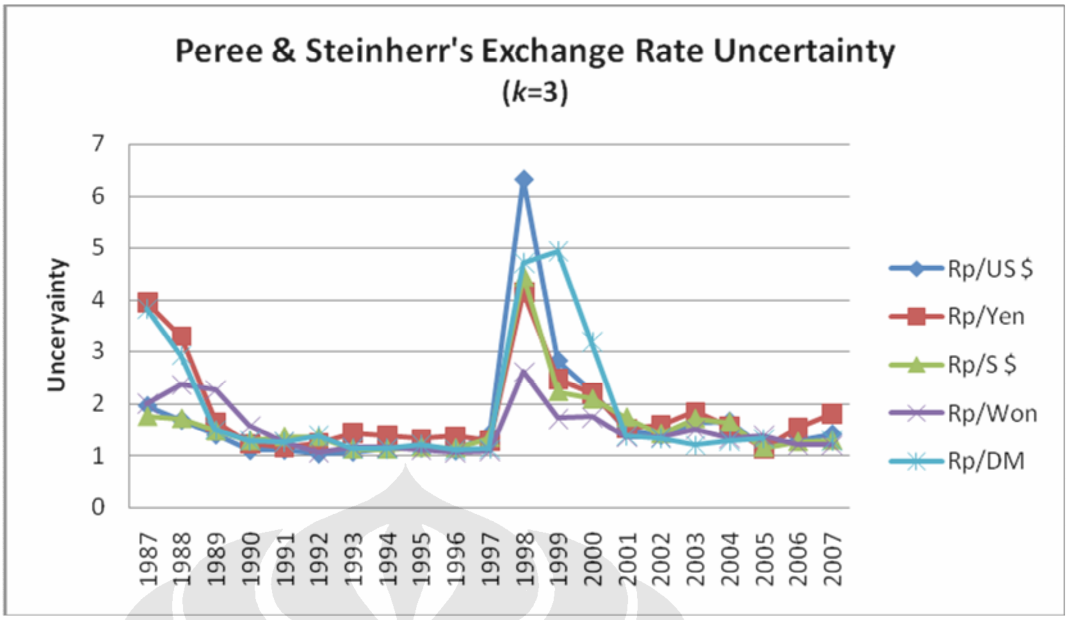
where $e$ is nominal exchange rate between country *i* and *j* (in terms of Rp/US \$, Rp/Yen, Rp/Euro, and so forth), $P^*$ is price level in country *j* (foreign country or Indonesia's trading partner), $P$ is price level in country *i* (home country or Indonesia).

This research calculates medium term exchange rate uncertainty for Indonesia and its main trading partners with different values of $k$. In accordance with Perée and Steinherr's calculation, these values are 10, 5 and 3 years. However, this research takes the value of 3 years for $k$ as the default model. Below is the figure of those calculated exchange rate uncertainty for real exchange rate of Indonesia and its five main trading partners for the period of 1987 to 2006.

Chart 4.1. Calculated Perée and Steinherr Exchange Rate Uncertainty






As we can see from the charts above, period of fixed-exchange rate regime in Indonesia is not characterized by lower level of exchange rate uncertainty compared to period of free-floating exchange rate regime. During fixed-exchange rate regime, high level of exchange rate uncertainty may occur due to rapid devaluation policies. Moreover, throughout the years observed, highest level of exchange rate uncertainty coincides with times of economic crisis. This calculated measure of exchange rate uncertainty which is presented on charts above is available in the Appendix.

### 4.3. Sample and Data

The sample of the research is Indonesia's bilateral trade data with its five main trading partners in the period of year 1987 to 2006. Indonesia's main trading partner is defined as country which has biggest percentage of Indonesia's total bilateral trade (export plus import). The data is a panel data with trade sector and trading partners as the cross-section variable and year as the time-series variable. The cross-section variable is defined as a system of code consists of trade sectors and trading partners. This cross-section is named coding. The time span used for this research is the period of the year 1987 to 2006. This time range allows for 10 years period of the fixed exchange rate regime and 10 years period of free-floating exchange rate regime.

Five main trading partners for the whole period are included to sample because they are assumed to be able to represent the pattern of Indonesia's bilateral trade. In this research, Indonesia's main trading partners are Japan, United States, Korea, Singapore and Germany.

Exports and imports data were taken from Badan Pusat Statistik (BPS). This data is preserved in nominal value in US $. These nominal value of trade data were then converted into real value of trade using annual exchange rate data and consumer price index data from the International Monetary Fund (IMF) series International Financial Statistics (IFS). Specifically

$$Trade^t_{real} = \frac{Trade^t_{nominal} . e^t}{CPI^t} \qquad (4.9)$$

where $Trade^t_{real}$ is real value of trade in period $t$, $Trade^t_{nominal}$ is nominal value of trade in period $t$, $e^t$ is annual nominal exchange rate in period $t$, and $CPI^t$ is the Indonesia's consumer price index (CPI) as the price level in period $t$. The annual nominal exchange rate variable converts the nominal value of trade from US $ into rupiah (Rp). The consumer price index variable deflates the nominal value of trade into real value of trade.

The data of real Gross Domestic Product (GDP) and population were obtained from the IFS series from IMF. Real GDP per capita data is obtained by dividing GDP of each country with the number of population of the respective country. The measure of distance was the same as those used by Rose[8]. Cho et al.(2002) also use Rose's data for the variable of distance. Meanwhile, the measure of uncertainty was calculated using the Perée and Steinherr's exchange rate uncertainty measure. The nominal annual exchange rate data obtained from the IFS were converted into real annual exchange rate using consumer price index data taken from the same series.

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[8] Rose's data can be accessed on his website: http://haas.berkeley.edu/~arose.

Sectors of international trade are defined by the classification of 1 digit Standard International Trade Classification Revision 3 (SITC Rev.3). The research includes 9 from 10 sectors defined by SITC as follows:

Table 4.1. Code for Trade Sector Classification

| SITC Digit | Description | sector *c* |
|---|---|---|
| 0 | Food and Live Animals | 1 |
| 1 | Beverages and Tobacco | 2 |
| 2 | Crude Material, Inedible | 3 |
| 3 | Mineral Fuel/Lubricants | 4 |
| 4 | Animal/Veg Oil/Fat/Wax | 5 |
| 5 | Chemicals/Products N.E.S | 6 |
| 6 | Manufactured Goods | 7 |
| 7 | Machinery/Transportation Equipment | 8 |

The cross-section variable, coding, has 40 individuals which represent 8 trade sectors with 5 trading partners[9]. Meanwhile, the time-series variable has 20 years as observation. Hence, this research has a sample of 800 observations.

## 4.4. Model Specification

### 4.4.1. Model

This research uses gravity model in order to explain the volume of trade between Indonesia and its five main trading partners. It is specifically formed in order to indicate different impact that the exchange rate uncertainty imposes toward different trade sectors. Therefore, the research specifies the model on trade data over a time-series of years and over a cross-section of trade sectors and trading partners. The gravity equation is then augmented to allow the prior conditions as stated below:

$$\ln TRADE_{ij,t}^{s} = \delta + \beta_1 \ln GDPPC_t + \beta_2 \ln POP_t + \beta_3 \ln dist + \beta_4^s U_{ij,t} + \varepsilon_{ij,t}^{s} \quad (4.10)$$

[9] Details on this variable is available in Appendix.

where $TRADE_{ij,t}^{s}$ is real gross bilateral trade (imports plus exports) between countries *i* and *j* in year *t* for each sector *k*. The independent variables are therefore *GDPPC* as the product of country *i*'s GDP per capita and country *j*'s GDP per capita, *POP* as the product of country *i*'s population and country *j*'s population, *dist* as the measure of distance between country *i* and *j*, $U_{ij,t}$ as the measure of exchange rate uncertainty between country *i* and *j* in year *t*. Whereas, $\varepsilon_{ij,t}^{s}$ is log-normal disturbance with $E(\ln\varepsilon_{ij,t}^{s}) = 0$.

The utilization of product of GDP per capita and product of population is also found in the gravity model formed by Rose (2000) and Cho et al. (2002).

This research uses the econometric program Stata 10.0. in estimating the model. Moreover, the research also uses Stata 10.0 in running various econometric tests to produce the most credible estimation and results.

### 4.4.2. Fixed-Effects Estimators

The utilization of panel data with year as the time-series variable and coding as the cross-section variable gives advantages in estimating different impacts of one or more variables toward different individuals. The research uses fixed-effects estimators to pursuit that aim. As Baltagi (2005) notes, the fixed effect model or also known as the Least Square Dummy Variable (LSDV) model is an appropriate specification if we are concentrating on a specific set of individuals, which in this research are trade sectors.

The fixed-effect estimators allow the dependent variable to have different sensitivity toward its independent variables. However, Baltagi states that the fixed effect estimators can only estimate the time-variant variables.

This research generates dummy interactive variables for each trade sector *c* and the observed independent variables which is the exchange rate uncertainty. The variable of exchange rate uncertainty is a time-variant variable which fulfills the requirement of a fixed effect estimator.

### 4.4.3. Ordinary Least Square (OLS)[10]

The model specified in equation (4.10) is estimated under the Ordinary Least-Square (OLS) method. Estimation under OLS follows the least-square criterion stating that the minimum square of the residual is attained. Residual is defined as the difference between the actual value and the estimated value of a variable.

In estimating a model, we need to ensure that an estimator fulfills the requirement to be a best linear unbiased estimator (BLUE). Therefore, the model has to be linear in parameters. The estimation has to be able to produce unbiased and efficient estimators as well.

As already shown in equation (4.10), the model specified in this research is already linear in parameters. For the relationship between the trade as the independent variable and GDP per capita, POP and distance as the dependent variable, the estimated parameters of these dependent variables act can be directly interpreted as the elasticity of trade to GDP per capita or POP or distance. It means that these parameters represent the relative change of trade due to changes in GDP per capita or POP or distance. Since the measure of exchange rate uncertainty is included not in logarithmic form, the estimated parameter of exchange rate uncertainty is not the elasticity of trade to exchange rate uncertainty. However, the parameter of exchange rate uncertainty is able to represent the percentage change of trade due to an increase of one unit exchange rate uncertainty.

Moreover, there are some other assumptions necessary to hold in order to get unbiased and efficient estimators. These assumptions are no-multicollinearity, homoscedasticity, and no-autocorrelation. Assumption of no-multicollinearity is hold under the condition that there is no exact linear relationship between independent variables. Homoscedasticity prevails if the all the residuals have the

[10] More on OLS, See: Gujarati, Damodar N.. *Basic Econometrics*.

same variance. On the other hand, no-autocorrelation or no-serial correlation prevails if the residuals do not have any correlation.

Using the Stata 10.0 program, the research tests the data based on the assumptions elaborated above. Test of multicollinearity is run through the Variance-Inflating Factor (VIF). No-multicollinearity exists under the value of Mean VIF of 1. Moreover, the research also measures the correlation among the independent variables using the correlation matrix. A correlation between two independent variables that exceeds a value of 0,8 indicates a relatively high multicollinearity. Test of heteroscedasticity is run through the Breusch-Pagan/Cook-Weisberg test of heteroscedasticity. This test uses the null hypothesis of constant variance which implies homoscedasticity. If the probability of chi-square exceeds the confidence interval of 5%, the null hypothesis is accepted. Test of autocorrelation is run through the Wooldridge test for autocorrelation in panel data. This test uses the null hypothesis of no-first order autocorrelation. If the probability of F test exceeds the confidence interval of 5%, the null hypothesis is accepted.

## 4.5. Panel Data Regression Models[11]

There are several methods in regressing a panel data. Most of them differ in assuming or treating the residuals factor. These regression models are chosen also according to the characteristics of data. This includes the condition fulfillment of OLS's assumptions.

### 4.5.1. Pooled Least Square Model

The pooled-least square model seems to be the simplest panel data regression model. As Gujarati (2003) argues this approach does not take into

[11] More on Panel Data Estimation Method, see: Wooldridge, Jeffrey M. *Econometric Analysis of Cross Section and Panel Data*; Gujarati, Baltagi, Badi. *Econometric Analysis of Panel Data*; Gujarati, Damodar N. *Basic Econometrics*.

account the dimensions of space and time. Therefore, the data is estimated under the usual OLS regression.

Wooldridge (2002) elaborates several assumptions in pooled OLS. The first assumption to be hold is the condition in which there is no correlation between the independent variables and the residuals[12]. The second assumption states that there cannot be any perfect linear collinearity among the independent variables[13]. The last assumption applied in pooled OLS implies that homoscedasticity and no-serial correlation should prevail[14].

Wooldridge also explains the main condition of this pooled OLS in terms of the model residuals. In a panel data, an unobserved and time-constant variable defined as the unobserved effect $c_i$ is assumed to have no correlation with the independent variables. He also emphasized this condition as strict exogeneity assumption.

### 4.5.2. Fixed-Effects Model

The fixed-effect model allows the unobserved effects to be correlated with the independent variables. Therefore, this model takes out the unobserved effects from the residuals and positions it as independent variable as well.

This model also has the assumption of strict exogeneity of independent variables. However, this assumption is conditional on the observed variables[15]. Wooldridge also assures the main objection to estimate the parameters under this assumption is to convert the model to eradicate the unobserved effects.

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[12] This assumption can be expressed as follows: $E(x_t^{'}u_t) = 0, t = 1,2,...,T$

[13] This assumption can be expressed as follows: $\left|\sum_{t=1}^{T} E\left(x_t^{'}x_t\right)\right| = K$

[14] The assumption of homoscedasticity can be expressed as follows: $E\left(u_t^2 x_t^{'} x_t\right) = \sigma^2 E\left(x_t^{'} x_t\right), t = 1,2,....,T$, where $\sigma^2 = E\left(u_t^2\right)$ for all *t*. The assumption of no-serial correlation can be expressed as follows: $E\left(u_t u_s x_t^{'} x_s\right) = 0, t \neq s\ ,\ t,s = 1,....,T$ .

[15] This assumption can be expressed as follows: $E\left(u_{it} \mid x_i, c_i\right) = 0, t = 1,2,...,T$ .

Technically, Gujarati gives examples about how to incorporate fixed-effects estimators into the equations. In general, these fixed-effects estimators can take form of different intercepts across individuals or different slopes across individuals.

### 4.5.3. Random-Effects Model

The random-effects model incorporates the unobserved effect under the residuals. This is quiet similar to the pooled OLS. However, in random-effect model, the error term consists of unobserved effects, $c_i$, and the idiosyncratic error, $u_{it}$. This new error term is defined as the composite errors, $v_{it}$ [16]. The main aim of random-effect model is to make use of the serial correlation that the error term has due to the incorporation of the unobserved effects.

However, as Gujarati explains briefly, this random-effect model assumes this composite error to be homoscedastic. Although, it allows the error terms of the cross-section variables at two different times to be correlated, no matter how far these two times are from one to another. Hence, the random-effects model cannot be estimated under OLS, because OLS does not take into account these correlation structures. As Gujarati affirms as well, this condition goes hand-in-hand with the aim of random-effect model elaborated above which is workable under the Generalized Least-Square (GLS) model.

### 4.5.4. Hausman Test

The Hausman Test works to decide whether the unobserved effects are correlated with the independent variables. In fixed-effect model, the unobserved variables are allowed to be correlated with the independent variables. On the other hand, the random-effect model takes the condition of no-correlation between the unobserved effects and the independent variables.

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[16] The composite error can be expressed specifically : $v_{it} = c_i + u_{it}$

The null hypothesis of the Hausman test states that the fixed-effects model's and the random-effects model's parameters are not significantly different. If the null hypothesis is accepted, the fixed-effects model is preferable to be used or the data estimated. If the null hypothesis is rejected, the random-effects model more appropriate to be used for the data estimated.

### 4.5.5. Generalized Least Square (GLS) Model

Under the condition of heteroscedasticity, OLS estimators can no longer produces and efficient parameters. This condition may happen because the parameter cannot produce the minimum variance due to the presence of heteroscedasticity.

In order to overcome heteroscedasticity, we can regress the equation under the Generalized Least Square (GLS) method. This approach of estimation gives less weight to parts of the sample which has greater variability and gives more weight to parts of the sample which has less variability. This condition is not applied under the OLS because OLS treats all parts of the sample equally.

The estimation of GLS can be explained in simple way as follows. Consider a two-variable model:

$$Y_i = \beta_1 + \beta_2 X_i + u_i \qquad (4.11)$$

Which can also be written as :

$$Y_i = \beta_1 X_{0i} + \beta_2 X_i + u_i \qquad (4.12)$$

Where $X_{0i} = 1$ for each *i*.

If we assume that the heteroscedastic variances are known to be $\sigma_i^2$, we can divide (4.12) with $\sigma_i$ and obtain:

$$\frac{Y_i}{\sigma_i} = \beta_1\left(\frac{X_{0i}}{\sigma_i}\right) + \beta_2\left(\frac{X_i}{\sigma_i}\right) + \left(\frac{u_i}{\sigma_i}\right) \qquad (4.13)$$

Equation (4.13) can also be expressed:

$$Y_i^* = \beta_1^* X_{0i}^* + \beta_2^* X_i^* + u_i^* \qquad (4.14)$$

Now, the transformed equation which becomes the equation (4.14) already has constant variances. This condition indicates that the error term is already homoscedastic.

### 4.5.6. Feasible Generalized Least Square (FGLS) Model

The feasible generalized least square (FGLS) is basically similar to GLS model. The FGLS takes the weights that are used to transform the equation to be homoscedastic by taking estimated weights. These estimated weights may not exactly similar to the true weights.

Moreover, the FGLS can also be used in solving the problem of autocorrelation. In this case, the FGLS takes the estimated residuals in order to transform the model into a generalized difference equation.

## 4.6. Significance Testing

Each parameter of the independent variables in the model is tested in order to determine its significance in influencing the dependent variable. Here, we use the t-test with confidence interval of 5 %. If the null hypothesis is rejected, the independent variable has significant influence to the dependent variable.

The research also tests the model as whole using F-test or Wald-Test. If the null hypothesis is rejected at a 95% level of confidence, the parameters of all independent variables can significantly explain the dependent variable simultaneously.

Moreover, if available, the research also uses the value of R-square of the estimated model. This value of R-square shows us the percentage of the dependent variable’s variances can be explained by the independent variables’ variances.