DETERMINANTS OF UNEMPLOYMENT IN ASIA: CASE STUDY IN CHINA, INDIA, JAPAN, SOUTH KOREA, AND THAILAND

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DECLARATION

We hereby declare that:

(1) This undergraduate FYP is the end result of our own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this FYP has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Equal contribution has been made by each group member in completing the FYP.

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller Test
ADRL	Auto-Regressive Distributed Lagged
AUTO	Automation Level
BLUE	Best Linear Unbiased Estimators
CEIC	Census Economic Information Center
CLRM	Classical Linear Regression Model
DV	Dependent Variable
FDI	Foreign Direct Investment Net Inflow
FEM	Fixed Effect Model
GDP	Gross Domestic Product
GDPG	Gross Domestic Product Growth
GLS	Generalized Least Squares
IFR	International Federation of Robotics
IMF	International Monetary Fund
IPS	Im-Pesaran-Shin
ILO	International Labor Organization
IV	Independent Variable
LAUTO	Natural Log of Automation Level
LFDI	Natural Log of Foreign Direct Investment Net Inflow

LGDPD	Natural Log of Gross Domestic Product Growth
LM Test	Breusch-Pagan Lagrange Multiplier Test
LPOP	Natural Log of Population Growth
LSDV	Least Square Dummy Variable
LUR	Natural Log of Unemployment Rate
N	Cross-sectional Dimension
OLS	Ordinary Least Square
POLS	Pooled Ordinary Least Square Model
POP	Population Growth
REM	Random Effect Model
SEZs	Special Economic Zones
TOL	Tolerance Factor
UR	Unemployment Rate
VAR	Vector Auto Regression
VIF	Variance Inflation Factor
WLS	Weighted Least Squares

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PREFACE

It is necessary to complete a research project in order to successfully complete studies in Bachelor of Economics (Honours) Financial Economics. Therefore, topic for this research has been chosen as Determinants of Unemployment in Asia: Case study in China, India, Japan, South Korea and Thailand. This research has been carried out to identify the determinants of unemployment and its relationship with the dependent variable in Asia countries.

Unemployment in Asia has always been an important issue, however often disregarded and ignore by many. A nation with steady unemployment rate is beneficial for several parties including government, investors, businesses as well as individuals. Hence, this study able to show determinants or key role of unemployment in Asia focusing on its relationship.

Lastly, the research also able to reveal a better understanding on the reason of high or low unemployment rate in 5 Asia countries that has been selected. This research can help the government and economists figure out how to bring the unemployment rate down to a more manageable level.

ABSTRACT

This study seeks to investigate the relationship between unemployment rate (UR), growth of Gross Domestic Product (GDPG), net inflow of Foreign Direct Investment (FDI), population growth (POP), and automation level (AUTO). This study employs secondary data to conduct the panel analysis by using STATA software. The annual panel data is collected from five Asia countries including China, India, Japan, South Korea, and Thailand from 2005 to 2019. The Fixed Effect Model (FEM) is preferred in this study, and results showed GDPG and FDI both have a significant negative relationship with the unemployment rate, while POP has a significant positive relationship with unemployment. However, AUTO is found to be statistically insignificant to affect the unemployment rate. This study also suggested few implications for policymakers in dealing with the unemployment issues such as monetary and fiscal policy, government intervention on the exchange rate, development of infrastructure, child control policy, and others

Chapter 1 Research Overview

1.0 Introduction

This first chapter of this research introduces the study's issue starting with the 'research background' which provides the outlines for the reader to understand the topic and its importance. Followed by the 'problem statement' which explains the problems this project needs to address. Next, is the 'research objectives' that aim to be achieved at the end of this research and the 'research questions' that point out the specific questions to be answered. Lastly, 'significance of study' explains the reason why this research was needed as well as the 'chapter layout'.

1.1 Research Background

According to Pettinger (2019), unemployment is characterized as individuals who want to be in full-time employment and look for a job diligently but are not able to find a job. The unemployment rate is defined numerically as the proportion coming about because of dividing the total quantity of unemployed of a country by the total number of individuals in the labor force (ILO, 2011). Unemployment is important because it fills in as one of the measures of the economic status of a country and it does address how well our economy is working. Other than that, regardless of how well things are going for the average resident, those without incomes and jobs will suffer in a harder circumstance as it likewise represents a personal expense. There are four types of unemployment basically which are frictional unemployment, structural unemployment, cyclical unemployment, and demand deficient unemployment as shown in figure 1.1.

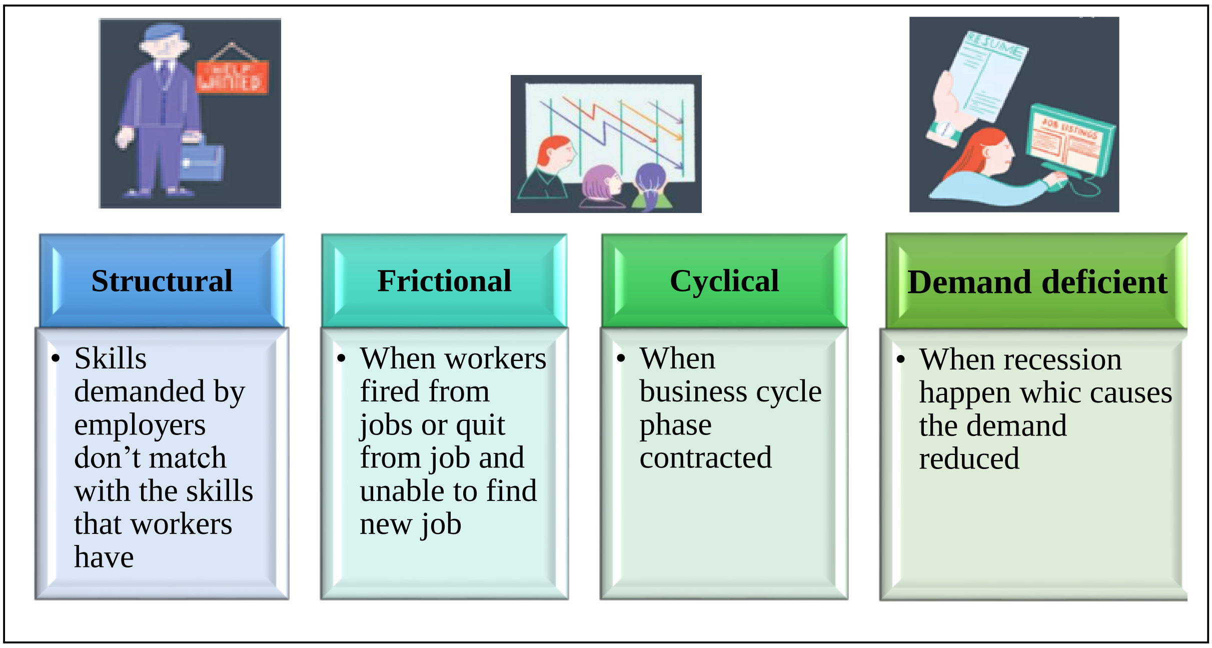

Figure 1.1. Types of Unemployment

1.1.1 Factors Causing Unemployment

The higher unemployment rates are caused because of population increases around the globe where in the present circumstance the demand for work will be higher than the accessible jobs. Employers face difficulties to arrange vacancies for huge numbers of workers as the number of individuals who are searching for jobs is expanding (Maijama’a et al., 2019). A joblessness circumstance proceeds as long as the gap of demand and supply persists. For example, India has an accumulation of joblessness which continues developing with a rapidly expanding population since expanding jobs is not possible in the nonappearance of complementary resources (Agarwal, 2014). Other factors that cause unemployment are lack of skills or education for employment where the mismatch occurs in labor markets that lead to structural unemployment as shown in Figure 1.1. Another cause of unemployment is the rising cost. The increasing expense makes it difficult for the organizations to pay the typical ideal salary for the employees or even the minimum wage sometimes. Additionally, there is a worldwide rapid technological change that plays a major part in the expanded joblessness issue because numerous jobs which were done by hands are being finished by various machines and innovations these days.

1.1.2 Unemployment Rate in Asia Countries

Based on World Bank Data (2021), figure 1.2 shows the unemployment rate of Asia countries from the year 2005 until 2020. The unemployment rate shows decreasing trends for both South and East Asia from the year 2005 until 2007. This decline was mainly strong economic growth from 2006 until 2007 which had reduced working poverty (ILO, 2007). An Asia country's unemployment rate was higher in 2009 because of the closure of factories, reduced working hours, losses in income, forced workers on unpaid leave, and more that were caused by the global financial crisis. For instance, the quantity of joblessness expanded by 28.7 percent in Singapore between March 2008 and March 2009, and the highest increase in Thailand was by 73.3 percent in a similar period (Huynh et al., 2010).

Then, the unemployment rate increased rapidly from 2019 to 2020 in Asia countries because of the Covid-19 crisis that impacted production, foreign and domestic consumer demand, and investment which shows that impact was stronger than the 2008-09 global financial crisis. For example, in the first quarter of 2020, there was a closure of 460,000 companies in China which put pressure on employers and led to the unemployment rate increasing to the highest level of 6.2 percent (CNBC, 2020). South Asia was hit hardest by this covid-19 pandemic as they encountered the most serious consequences where the economic growth was relied upon to be at a negative 7.7 percent in 2020 (ILO, 2020).

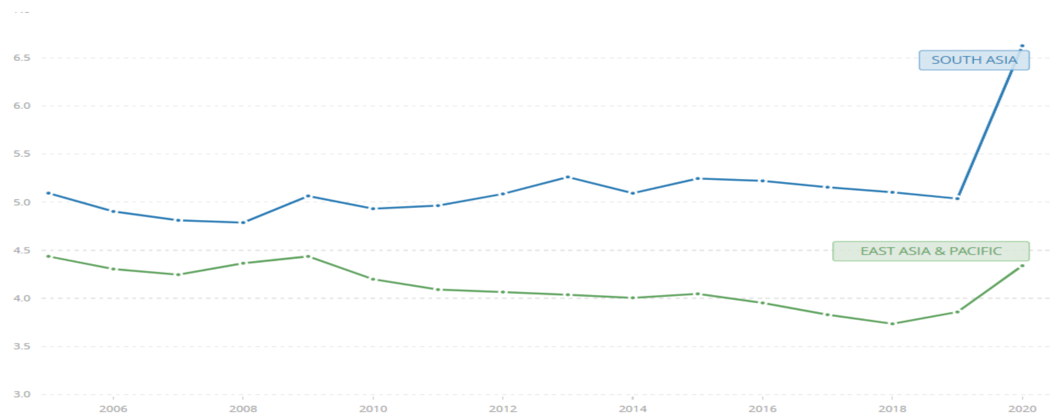

Figure 1.2. Unemployment Rate of South Asia and East Asia & Pacific from the year 2005-2020. Source: World Bank Data (2021). Retrieved from https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS?end=2020&locations=8S-Z4&start=2005

In particular, **China** faced unemployment problems too. The increase in the unemployment rate was major from educated unemployed and it has a positive relationship with GDP growth. This happens because, increasing population growth where it reached 1.98 billion in 2019 and move in foreign companies to China increases competition which causes rises in the quantity of unemployment and laid-off workers (NBER, 2015). There was structural unemployment for educated people in China due to the mismatch between market demand and labor skills which can lead to a youth unemployment crisis in the future. (CNBC, 2014).

Moreover, **India** is listed among BRICS countries where BRIC economies would come to influence the worldwide economy by 2050 (Mallapur, 2019). However, India is appearing to have the greatest pool of jobless individuals on the globe as it is an intricate issue with various overlapping and interweaved causes. According to the International Labor Organization (ILO), the unemployment rate kept increasing day by day with a total of 1.36 billion populations in their country.

Furthermore, **Japan** is known as one of the richest countries with the largest GDP per capita of $40,246.88. However, unemployment still occurs in this county and has been a repetitive issue in Japan for longer than quite a few years. This is because Japan's aging population leads to a fall in the supply of labor as labor participation reduces over time. According to the Population Reference Bureau (2020), Japan was the country with the highest aging population which is 126.8 million compared to other countries. Liu (2014) found that the labor participation rate has a long-term impact on unemployment in Japan.

Nevertheless, **South Korea** is known to have the fourth largest Gross Domestic Product (GDP) among Asia countries but this country faces an unemployment problem that keeps increasing. This is because of a mismatch between job opportunities available and educational level since youths in Korea are overeducated and professional jobs available are lower (Choi, 2017).

Whereas, based on World Bank Data (2021), **Thailand**'s unemployment rate is among the lowest in the world and compared to other Asia countries as shown in Figure 1.3. This is because unemployed persons or those who lose their job may be engaged in the agriculture sector, self-employed by starting their own business in the street, engaged in the informal sector, or work in "grey areas" which is prostitution thus it could count as employed (Fernquest, 2015).

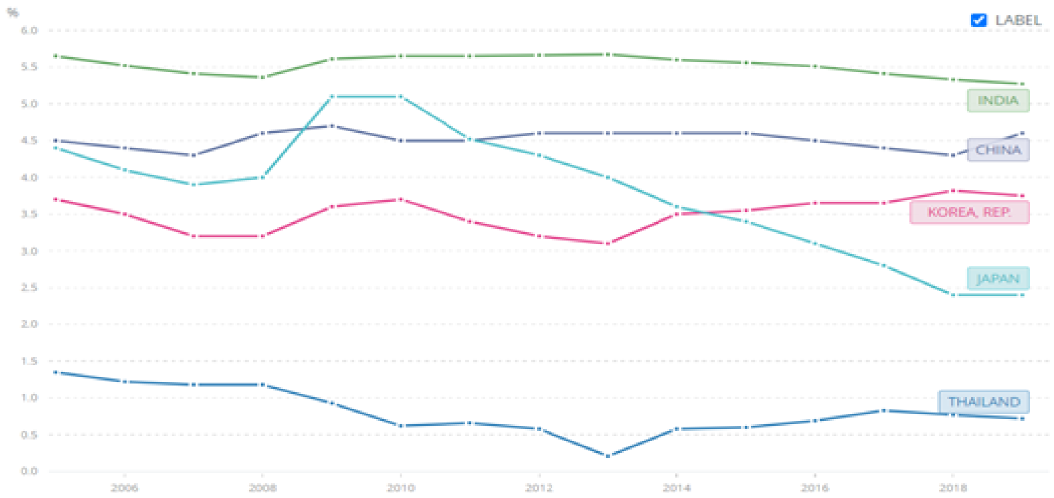

Figure 1.3. Unemployment Rate of China, India, Japan, South Korea, and Thailand from the year 2005-2020. Source: World Bank Data (2021). Retrieved from https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS?end=2019&locations=TH-IN-CN-KR-JP&start=2005

1.1.3 Unemployment Consequences

Unemployment in these five Asia countries leads to many problems in terms of social, moral, and economic aspects. A high unemployment rate can have lasting consequences on individuals and families where it reduces the standard of living and leads to poverty growth. For example, India is the only country with 800 million in poverty compared to other Asia countries because of no food, no jobs, and no money (Alok, 2020). Then moral consequences are unemployment causes moral degeneration and criminal activities such as gambling, corruption, robberies, and gangsterism will increase especially among youth unemployment and lead to political instability. This is because, at the point when people were on an empty stomach and couldn't procure salaries legally to supply for their families, it was likely to lead them into violent and criminal activity. States like Assam and Kerala in India have detailed crime rates as the highest as well as most elevated joblessness rates (Kishna & Kumar, 2015).

Meanwhile, increases in unemployment give consequences to economic growth because savings of individuals are reduced and future retirement funds also decreased since they cover their today’s cost by using the savings. This causes youth joblessness today will diminish the earnings of future retirees and the burden on the government will increase. Other than that, unemployment affects consumer spending on goods and services which further reduces economic growth. For example, China's economic growth decline because of retail deals in March 2020 fell 15.8 percent year over year, even as organizations reopened due to unemployment lower spending (SCMP, 2020).

As unemployment becomes a most severe economic and social problem for every country, especially Asia countries, this allows us to further investigate determinants of unemployment in Asia countries and to gain a better understanding of it.

1.2 Problem Statement

Gross Domestic Product growth, Foreign Direct Investment net inflow, population growth, and automation level are the variables that strongly affect the unemployment rate of a country.

According to Okun's law, there is a negative relationship between GDP and unemployment. If the GDP growth of a country weakens, it will raise the unemployment rate. According to a case study, the result proves that GDP growth and unemployment rate are negatively correlated, however, the GDP growth impact on the unemployment rate is not meaningful. The authors argue that GDP growth can increase job opportunities, but it might not be powerful enough to lower the unemployment rate in a country (Haririan et al., 2010). Hence, this study plans to find out the exact correlation of GDP growth and unemployment rate in the selected Asia countries including China, India, Japan, South Korea, and Thailand.

Besides, the FDI net inflow is an important part of a country's economy. The FDI net inflow benefits the country by allowing technology spillovers, enhancing business competition, and boosting domestic business. However, the net inflow of FDI has both positive and negative relationships with the unemployment rate. According to Zdravković and Bradić (2017), the authors argue that FDI net inflow impacted on the unemployment rate is different based on the sample, applied methodology, and observed period. Hence, the relationship between FDI net inflow and unemployment rate needs to be further explored in this study to get the most accurate findings.

Furthermore, the growing population in a country also leads to an increase in the unemployment rate. According to a case study of Nigeria, the authors prove that there is a positive relationship between the unemployment rate and population growth. When the laborers are underutilized, it indicates that there is a mismatch between labor supply and labor demand in the market. The population is referring to the labor supply, while the country's economic situation is referring to the labor demand. When there are insufficient job opportunities in the market to match the growing population, it will lead to an increase in the unemployment rate (Maijama'a et al,2019). As many of the findings proved a positive relationship between population growth and unemployment rate, this study would like to further clarify the issue in the selected countries.

Moreover, issues that raise unemployment in a country were the fast development of high technology, automation, and digitalization in the workplace. A positive relationship between automation and the unemployment rate was proved by many studies. (Falaton & Safarzadeh, 2017; Hedvičáková & Král, 2018; Acemoglu & Autor, 2011). However, according to Postel-Vinay (2002), the author argues that the development of high technology would reduce the level of employment in the long run, but it shows a positive effect on the level of employment in the short run. In other words, the development of high technology will increase the level of unemployment in the long run and reduce the level of unemployment in the short run. Meanwhile, Cords and Prettner (2018) argue that automation positively impacted the unemployment of the low-skilled labor market, but negatively impacted the unemployment of the high-skilled labor market. Therefore, the relationship between automation and the unemployment rate needs to be well-explored to justify the most accurate answer in the selected countries.

Overall, the researchers of this study are concerned about the correlation between Gross Domestic Product growth, Foreign Direct Investment net inflow, population growth, automation level, and unemployment rate in the five chosen Asia countries. Therefore, the following chapters are conducted to answer the research questions below.

1.3 Research Objectives

This research explores the unemployment rate in the context of Asia countries using five samples that include China, India, Japan, South Korea, and Thailand. The general objective of this study is to investigate the determinants of the unemployment rate over 15 years in five selected Asia countries based on the automation level. To achieve the aim of this research, the specific objectives of this study are:

1. To study the relationship between GDP growth and the unemployment rate.
2. To study the relationship between FDI net inflow and the unemployment rate.
3. To examine the relationship between population growth and the unemployment rate.
4. To examine the relationship between automation level and the unemployment rate.

1.4 Research Question

To further understand the unemployment issue well, there are several research questions asked in this study which are:

1. Is there any significant relationship between GDP growth and the unemployment rate?
2. Does the FDI net inflow in a country have a significant relationship with the unemployment issue?
3. How does population growth affect the unemployment rate?
4. Is automation an advantage or drawback for the unemployment issue?

1.5 Significance of Study

Unemployment among Asians has become a major concern for developing countries in Asia that lead to social and economic challenges. Since prior research has focused solely on the relationship between macroeconomic variables and unemployment rates, other crucial factors such as automation and population expansion have been overlooked. Hence, these concerns led us to conduct this study, which included not only macroeconomic factors (GDPG, FDI, and population growth) but also automation levels.

The goal of this study is to fill in the gaps and find out whether chosen independent variables have a significant relationship with unemployment rates. Any significant relationship between variables is proven using the panel data analysis approach. Therefore, this would be essential for future scholars who intend to further understand and investigate the issue using the panel data analysis approach.

Besides, automation levels and population growth are often disregarded by researchers when analyzing the unemployment rate in Asia. As 15 years of data are employed to analyze the significances, future economists gain the latest information and data on unemployment in Asia.

Finally, this research provides policymakers with recommendations on how to reduce unemployment in Asia which will help them to construct and adjust new or existing policies as well as strategies in their decision-making.

1.6 Chapter Layout

The first chapter demonstrates the outline of the study that comprises the background of the study and a problem statement that explains the reasons for the research area chosen in this study. Besides, research questions, research objectives, the significance of the study, and chapter layout are discussed in this chapter.

Chapter 2 consists of a literature review. This chapter explains the underlying theories, concepts, and models, previous empirical studies, theoretical framework. Lastly, the hypothesis of the study and the gap of the literature review is also presented in this chapter.

Chapter 3 addresses the methodology used in this study. This chapter explains the research design, data collection method, diagnostic tests, and method selection.

Chapter 4 discusses the result of various tests generated by STATA software which include descriptive analysis, diagnostic checking test, and panel data analysis. Lastly, are the model selection tests to choose the best model that best fits this study.

Chapter 5 explains the conclusion of the study. This chapter includes a summary of statistical analysis results from the previous chapter, a discussion of findings, as well as limitations of this study. Other than that, implications for policymakers and suggestions for future investigators are also included in this chapter.

1.7 Conclusion

Overall, the outline of this study has been explained in this chapter. The main motive of this study is to investigate the relationship between Gross Domestic Product growth, Foreign Direct Investment net inflow, population growth, automation level, and unemployment rate in the five selected countries. The following chapter discusses the literature review.

Chapter 2: Literature Review

2.0 Introduction

The first part of this chapter discusses the underlying theories, models, and concepts of the variables. Besides, review of different opinions and research on the previous studies about the correlation between Gross Domestic Product Growth (GDPG), Foreign Direct Investment net inflow (FDI), population growth (POP), and automation level (AUTO) (independent variable), and unemployment rate (UR) (dependent variable) that has been published by international scholars to support this study. Next, is the 'proposed theoretical framework', 'hypothesis of the study,' followed by the 'gap of literature review.'

2.1 Review of Theories, Model, and Concepts

2.1.1 Okun's Law – Gross Domestic Product (GDP) and Unemployment

Okun's Law by Arthur Okun in 1960 is a significant theory that focuses on understanding and interpreting the negative relation between a country's GDP and its unemployment. The theory explains that the unemployment rate will decline by 1 percent when GDP growth increases by 4 percent (Dankumo et al., 2019). The authors point out that Okun's law shows a reduction in the percentage of a country's GDP when the rate of unemployment is above the natural rate of unemployment which is between 4.5 percent and 5 percent.

2.1.2 Endogenous Growth Theory– Foreign Direct Investment and Unemployment

Foreign Direct Investment is defined as a venture made by a business or investor in one country into a potential business interest in another country. Chella and Phiri (2017), explain that the inverse relationship between the two variables can be demonstrated through the endogenous growth theory. The authors and De Mello (1997), further elaborate that by using the theory, FDI appeared to diminish unemployment endogenously as it creates return to production through externalities and productivity.

2.1.3 Malthusian Theory – Population Growth and Unemployment

Human resources are one of the main factors of production, thus high and low population growth directly or indirectly determines the labor supply in an economy. Fertility, mortality, life expectancy, and migration are among the key roles in determining a country's population growth. According to Chowdhury and Hossain (2018), Malthus's theory found that population growth and unemployment are positively correlated and assume population causes diminishing returns to labor. Since unemployment is one of the consequences of an increasing population without a corresponding rise in livelihood. However, some authors point that the theory is irrelevant to the modern era since the influence of automation advancements was ignored in this theory (Montano & García-López, 2020).

2.1.4 Solow-Swan Model – Automation Level and Unemployment

According to Barbieri (2019), the adoption of automation helps to spike up productivity and reliability as well as the speed of numerous errands that were previously conducted by people. This can be described by using neoclassical theory by Solow (1956), who introduces a Solow-Swan Model that explores the changes in an economy's production over the long haul due to the shift in population growth, saving rate, and automation advancements. This theory is used by Cords and Prettner (2018) to describe how automation is a production factor that may completely replace labor because it generates similar final goods and services. In other words, as technology advances, it will gradually replace current labor in an economy, resulting in a positive correlation between automation and unemployment.

2.2 Review of Variables/ Past empirical Studies

2.2.1 Gross Domestic Product (GDP) and Unemployment Rate

The GDP growth of a nation, directly and indirectly, contributes to job opportunities and income levels. Some researchers may claim that Okun's law is valid in identifying the negative correlation between GDP and the unemployment rate while some argue it is vice versa.

In the case of Asia countries, Chand et al. (2017), point that India has a strong negative correlation between GDP and unemployment rate from the period 2011 to 2018 as when GDP increases, the unemployment rate decreases which is in line with Okun's law. The authors used correlation and regression analysis in which they found 48 percent change in the unemployment rate in the Indian economy is caused by their GDP. Chowdhury and Hossain (2014) found a similar result in India as Chand et al. (2017), by using the Simple Single Equation Linear Regression Model from 2000 to 2011. Moreover, Wakatabe (2020), the Bank of Japan's Deputy Governor points that Japan's GDP growth, and the rate of unemployment are negatively correlated as an increase in GDP growth leads to the rate of unemployment shrinking and vice versa. He proves this by analyzing the relationship using Okun's law where he demonstrates a negative relationship between the two variables in Japan's economy from 1956 to 1995 and 1996 to 2018.

Meanwhile, by using the Augmented Dickey-Fuller Test (ADF), Phillips Perron Test, and Auto-Regressive Distributed Lagged (ADRL), (Karikari-Apau & Abeti, 2019) point a negative correlation with GDP growth and the rate of unemployment in China from 1991 to 2018. Besides, Li and Liu (2012), also found the two variables have a long-term negative relationship by using time series data from 1978 to 2010 in China which the data employed using Vector Auto Regression (VAR) model with Unit Root Test and Granger Causality Test. Similarly, Irpan et al. (2016), reveal that Okun's law validates the relationship in Malaysia by proving a rise of 3.5 percent in GDP growth will cause a 1 percent decline in unemployment rate using regression analysis. Besides, Arslan and Zaman (2014), determine a significant negative relationship between the two variables in Pakistan from 1990 to 2010 using Ordinary Least Square (OLS) analysis.

However, in the short run, their findings are contradictory since the variables have a positive relationship which is similar to Aurangzeb and Khola (2013). They explained that high GDP growth and the rate of unemployment could be present in the short term, and it will refute Okun's law. Aurangzeb and Khola (2013), claim that using Ordinary Least Square analysis, Cointegration procedures, and Granger causality test shows the relationship between the two variables in India, Pakistan, as well as China between 1980 to 2009 is positive. Besides, a study from 1995 to 2019 in Bangladesh by Alam et al. (2020) also shows a positively correlated relationship between the two factors by employing the ADF, Collinearity, Cointegration, and OLS. The author explains that GDP growth increases at the same time unemployment rises and this may result due to higher uneducated citizens, poor human resource management, and ineffective monetary and fiscal policy over the long haul.

2.2.2 Foreign Direct Investment (FDI) and Unemployment Rate

FDI is known as an activity to direct investment by an individual or organization from the nation of origin to another country. FDI inflow is a significant factor that affects a nation's unemployment rate.

The correlation between FDI and the rate of unemployment has been previously investigated by some researchers and most researchers have concluded negative effects. Firstly, the global financial crisis in 2008 caused Japan's unemployment to be increased and FDI to reduces in the year 2009 and founds that FDI has significantly negative effects on the unemployment rate in Japan (Palat, 2011). Nevertheless, according to Sjoholm (2008), he reported FDI inflow in China will increase employment in other words unemployment will reduce because domestic firms become more competitive which enable to expand of employment and production, this indicates that there are negative significant effects between unemployment and FDI by conducting an econometric study on 15 Chinese firm-level data for the period 1998-2004. Similarly, in China where the unemployment increases and FDI inflows reduced to US$95 billion in 2009 because of the global financial crisis of 2007-2008 (Chen, 2017).

According to Ghosh & Parab (2021), he conducts analysis and proved that there are negative effects between FDI and unemployment by using Endogenous Growth Theory from the year 1970 until 2017 in India where an increase in FDI increases productivity together with employment and this leads the unemployment rate to reduce. Meanwhile, Lin and Wang (2004), Matthew and Johnson (2014), Joshi (2009), and Irpan et al. (2016) also found FDI reduces unemployment by generating more new jobs. Similarly, in the case of Malaysia, it shows significant negative effects between FDI and unemployment by used the ordinary least square method to examine the impact from 1980 to 2010. It shows that an increase in FDI by 1 percent causes the rate of unemployment reduced by 0.09 percent (Sarwar et al., 2012). In addition, Mucuk and Demirsel (2013) have determined a significant negative effect was found between FDI and unemployment in the case of Thailand by using the panel data technique from 1981 to 2009.

Conversely, FDI also causes a rise in unemployment indirectly in India which is also known as significantly positive effects between two variables in the host country as they only will hire efficient and skilled enough workers at the point when foreign organizations are permitted to set up their endeavor in the host country (Mishra, 2020). Nevertheless, a significant positive effect between FDI and unemployment was shown in the analysis conducted by Alam and Hoque (2020) based on the least square regression results by using the data set of 1995 until 2019. It also shows that FDI contributes to the long-run impact on the joblessness rate of Bangladesh.

In contrast, by using Statistical Analysis System which is AUTO REG procedure to test from 1985 until 2011 and the results conclude that FDI and unemployment have no significant relationship in the case of China because other variable predictors such as loan interest rate influence the unemployment rate more than FDI (Wei, 2013).

2.2.3 Population Growth and Unemployment Rate

Population growth of a nation or region changes over time, while new job opportunities are still limited to occupy the entire population eventually creates unemployment. Population growth can best describe as an annual proportion of a nation's population size, which is measured by fertility, mortality, and migration rates.

Singh and Sandeep (2014), point that rise in India's rural and urban population has a beneficial influence on the country's rate of unemployment using data from 2001 to 2011. Similarly, Aurangzeb and Khola (2013), found a positive correlation between the two variables in India and China as their regression analysis shows that as a result of population expansion, a rise in joblessness rate occurred which is also similar to the Malthus theory. The author reveals that a high population contributes to lower job opportunities to cover the entire population resulting in a higher unemployment rate. Besides, a study reveals that from 1981 to 2016, the two factors have a long-term positive effect in Nigeria using Multiple Regression Mode which validates the theory of Malthus. Meanwhile, Heliati (2019), also points that Indonesia has a positive correlation between population growth and unemployment from 1984 to 2016 by using the OLS test that proves when the population expands to one percent, the joblessness rate will rise to 0.605l points. Similarly, Sadikova et al. (2017), proves that a significant relationship exists between the two components in Russia from 1992 to 2015 by using Johansen Cointegration. Besides, Arslan and Zaman point that in Pakistan, a positive correlation between the population growth and rate of unemployment in the long term determines using the OLS method. As a largely populated nation, the increasing population growth rate significantly raises the unemployment rate, thus becoming the prime factor of unemployment in the country.

However, a case study by Aqil et al. (2014), found an inverse relationship between the two variables in Pakistan by using time series data from 1983 to 2010 using regression analysis. The study points out that if population growth rises by a percentage point, the unemployment rate may reduce by three percentage points. Besides, urban population growth also causes a decline in the unemployment rate in Bangladesh (Akter, 2018). He demonstrates the pattern from 1991 to 2016 by using ADF and OLS test in which he found that an insignificant negative relationship as a rise in population growth by 1 percent will decrease the unemployment rate by 0.134 percent. Urrutia et al. (2017), also points that population growth may negatively affect the unemployment rate in the Philippines from 1988 to 2014 by using Pearson Correlation despite the regression analysis shows a rise in population growth will lead unemployment to increase as well.

2.2.4 Automation Level and Unemployment Rate

Automation is known as the creation and utilization of technology to convey services and products and control and monitor production. For instance, countries like Japan and China induced automation in their daily life.

Based on the previous research, Yixiao and Tyers (2017) stated that automation impacts unemployment positively in China using the Cobb-Douglas framework from the year 1995 until 2015. They explained that unemployment will increase extraordinarily when automation increases, especially low-skilled labor. Similarly, studies were found by another researcher by analyzing one of the Asia countries which are Malaysia, by using a Univariate General Linear model of 20 years period (Thek, 2018). He found that there is a positive effect between automation and unemployment as a rise in automation leads to an increase in unemployment. This is because 57 percent of all jobs are influenced by robotization in Malaysia and high risk has been faced by 7.8 million workers of being automated. Ramaswamy (2017), also point that automation is positively affecting unemployment in India based on the time-based model framework. He claimed that as robotics replaced human work it causes the unemployment rate to increase as a lot of professions are being attacked because of automation and low-skilled workers suffer job losses in India.

Furthermore, Lee (2016) has examined the impact of automation on future employment for the next 15 years in Singapore. He observed that automation has a positive impact on unemployment where an increase in automation will increase unemployment by 25 percent, but this number is relatively lower compared to other countries. The same results are reported by other authors where an increase in automation level will lead to wage inequality increases and unemployment increases among low-skilled workers by using Solow-Swan Model for China and India. These findings are in line with the Solow-Swan model as the results from the analysis show positive effects between two variables (Schlogl & Sumner, 2020; Cords & Prettner, 2018).

While Mutascu (2021) who studied about 23 countries including China, Japan, India, South Korea, and other developed countries by using panel threshold estimations for the year 1998-2016. He claimed different effects which are significant negative effects between automation and unemployment, and he suggests that even under high paces of inflation the automation does not influence compensation, with unemployment consequently being diminished due to the 'Phillips’s effect'. Furthermore, a study by Adachi et al. (2020) found a similar negative relationship between automation level and unemployment in the case of Japan from 1978 to 2017. Their findings show that the adaptation of automation reduces unemployment, as it increases salary, decreases the cost of production, and rises in productivity led the demand for labor to increase.

However, many researchers found that the automation level has no effect on unemployment in Japan since automation benefits the country by fills the labor shortage gap whereas a consequence of this output increases, and it helps productivity and economic growth of Japan in the long term (Ziaei Nafchi & Mohelská, 2018; Frey & Osborne, 2017; and Schneider et al., 2018).

The contradicting relationship of GDP, FDI, population growth, and automation towards the unemployment rate are found based on the results in the literature review, so this triggers us to further analyze the relationship between these variables in Asia countries.

2.3.1 Existing Conceptual Framework

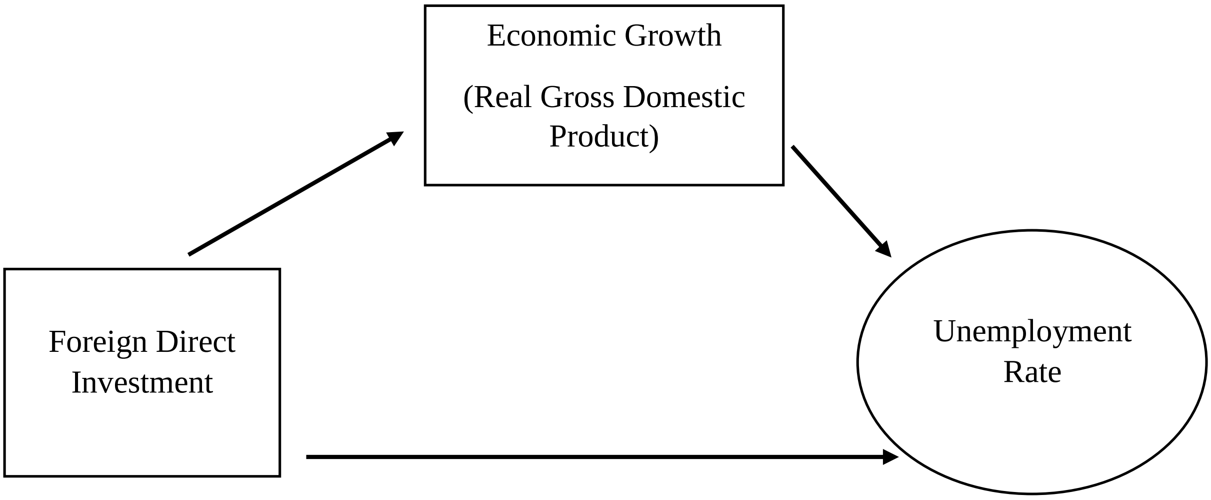

Figure 2.1. Existing Framework of Direct and Indirect Factors affecting Unemployment Rate in Sri Lanka

Source: Thirunavukkarasu, V., Achchuthan, S., & Rajendran, K. (2014). Foreign direct investment, economic growth, and unemployment: Evidence from Sri Lanka. *Velnampy, T., Achchuthan, S., & Kajananthan*, 74-78.

Thirunavukkarasu et al. (2014), reveal the direct and indirect factors that strongly associate with the unemployment rate in Pakistan. The authors discovered a long-term correlation between FDI and unemployment. While GDP has a significant impact on the unemployment rate, with GDP having a 40% influence on the unemployment rate. According to their study, FDI has a critical role in influencing economic growth and reducing unemployment. As a result, the authors recommend that future studies examine FDI as a driver of unemployment in emerging nations.

2.3.2 Adjusted Conceptual Framework

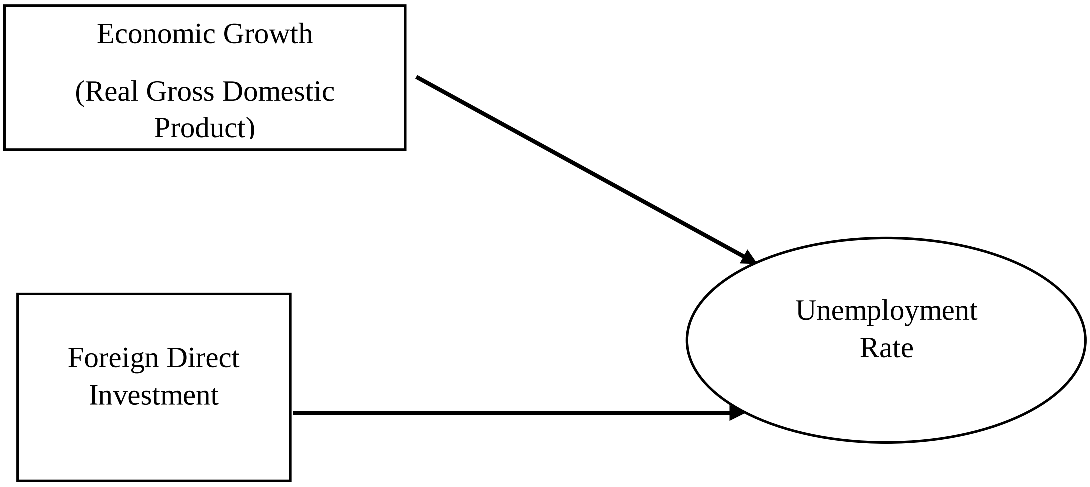

Figure 2.2. Adjusted Framework of Direct Influence of GDP and FDI on the Unemployment Rate.

Figure 2.2 is a modified framework that has been derived from the existing framework. The framework demonstrates the direct influence of GDP and FDI on the unemployment rate. From this figure, a proposed conceptual model is constructed that is relevant to this research.

2.3.3 Conceptual Framework of the Study

Macroeconomics Variable **Non - Macroeconomics Variable**

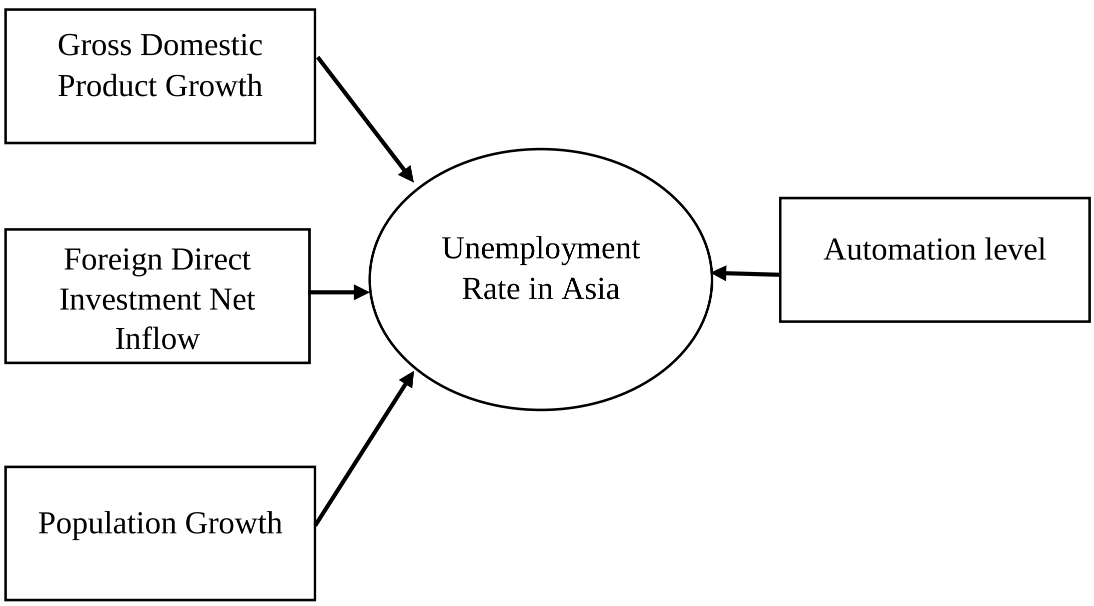

Figure 2.3. Factors Affecting the Unemployment Rate in Asia from 2005 to 2019.

Figure 2.3 is the conceptual framework for this research that has been derived using the literature reviews, existing and modified framework. In addition to macroeconomic variables (GDP growth and FDI) as suggested in the existing and modified framework, this study also intends to discover the connection and relationship between population growth and automation level on the unemployment rate in Asia focusing on Japan, China, India, South Korea, and Thailand.

2.4 Hypothesis of the Study

There are four chosen hypotheses used to determine the correlation between macroeconomic variables (GDPG, FDI, and population growth) and non-macroeconomic variables (automation level) towards the unemployment rate in five observed Asia countries which are China, Japan, India, South Korea, and Thailand. The hypothesis below is the expected relationship found based on the previous studies.

Gross Domestic Product Growth

H1: There is a negative relationship between Gross Domestic Product growth and the unemployment rate.

Foreign Direct Investment

H2: There is a negative relationship between Foreign Direct Investment net inflow and the unemployment rate.

Population Growth

H3: There is a positive relationship between population growth and the unemployment rate.

Automation Level

H4: There is a positive relationship between automation level and the unemployment rate.

2.5 Gap of Literature Review

This research is investigating the correlation between unemployment rate (dependent variable) and GDP growth, FDI net inflow, population growth, and automation level (independent variable) based on the selected countries which are China, India, Japan, South Korea, and Thailand. After reviewing the previous studies, researchers found that there is a limited study examining the automation level and population growth which also play crucial roles in affecting countries' unemployment rates. Besides, most of the research is focusing on the correlation between the unemployment rate and population growth in large population nations such as India, Pakistan, and China, only a few research examines in small population nations such as Japan and South Korea. Therefore, it brings the researchers of this study to explore and fill up the gap on this topic to clarify the relationship of the stated variables on the selected Asia countries.

2.6 Conclusion

In conclusion, the proposed topic of this study has been supported by many findings from the previous study by different researchers. It also led the researchers of this study to develop hypothesis testing. The next chapter discusses the methodologies used to answer the research question of this study.

Chapter 3: Methodology

3.0 Introduction

Chapter 3 introduced the type of method used in this research. There are four sections in this chapter. First is the research design discussing the research method and technique to be used in this study. Secondly, is the data collection method. Thirdly, the researchers applied four diagnostic tests for data checking, and lastly method selection which includes several tests to choose the best equation for this study.

3.1 Research Design

The research design refers to the framework of research methods and techniques chosen by a researcher to analyze and evaluate data in a study. Researchers should choose the most suitable research design and research method for the topic to achieve the research objectives and answer the research questions. There are a variety of research designs a researcher can use to obtain an evidence-relevant result for the study.

The main objective of this study is to investigate the relationship between the unemployment rate and independent variables such as Gross Domestic Products growth (GDPG), Foreign Direct Investment net inflow (FDI), population growth (POP), and automation level (AUTO) in China, India, Japan, South Korea, and Thailand within the period of 2005 to 2019. The data used in this research is annually based.

There are two methods used for data analysis which are qualitative and quantitative methods. According to McCusker and Gunaydin (2015), the qualitative method is used to answer questions about ‘what’, ‘how’ or ‘why’, while the quantitative method is used to answer questions about ‘how many’, or ‘how much’.

Qualitative research emphasizes analysis and evaluation of the data collected from the specific interviewees' viewpoints and opinions, while quantitative research emphasizes statistical information and is required to extract data in a larger volume. This study uses solely quantitative data that aims to attain the research objectives and provide answers to the research questions. Furthermore, STATA software is the main tool to assist the researchers of this study in doing diagnostic checking and regression models.

3.2 Data collection method

This research uses secondary data as the only source to conduct the panel analysis. Secondary data refers to the historical or previous research data that has been collected by other researchers in their works such as journal articles, books, and government publications. In this study, the data for variables cannot be collected through interviews or surveys done by the researchers themselves because the variables are economic variables.

In this study, the panel data collected ranges from the year 2005 to the year 2019 on an annual basis for 15 years, and the countries have chosen are China, India, Japan, South Korea, and Thailand which accounted for 75 observations. This study planned to conduct panel analysis from the year 2006 to the year 2020 initially, but there is a limitation of data sources for the year 2020. Therefore, the data collection period is amended according to the availability of the source. The five countries are selected because they have sufficient data on the automation level. The reason behind this is to examine unemployment behavior regarding the independent variables chosen.

This study has taken the UR as the dependent variable while GDPG, FDI, POP, and AUTO are the independent variables used to examine the impact on unemployment. Table 3.1 shows the sources of data.

Table 3.1

Sources of Data

Variables	Proxy	Unit Measurement	Source
Unemployment rate (DV)	Unemployment rate (UR)	Percentage of the total labor force	World Bank
Gross Domestic Product (IV)	GDP growth (GDPG)	Annual percentage	World Bank
Foreign Direct Investment (IV)	FDI net Inflow (FDI)	Current US$	World Bank
Population (IV)	Population Growth (POP)	Annual percentage	World Bank
Automation level (IV)	Annual installation of industrial robots (AUTO)	Units	IFR World Robotics Reports

Based on Table 3.1, the data for the UR, GDPG, FDI, and POP are collected from the World Bank. At the same time, this study would like to examine the relationship between automation level and unemployment rate. Unfortunately, World Bank does not provide a suitable indicator to measure the automation level. After the research is done on journal articles about automation level (Badiuzzaman & Rafiquzzaman, 2020; Carbonero et al., 2018), this study selected the annual installation of industrial robots from the annual reports published by the

International Federation of Robotics (IFR) as the data collection source because IFR provided sufficient data to suit this study.

3.3 Diagnostics Checking

3.3.1 Panel Unit Root Test

To start a panel data analysis, the panel unit root test is essential to ensure that the data series is stationary. The difference between panel and time series unit root test is that panel unit root test needs to consider the cross-sectional dimension (N). Therefore, the panel unit root test can produce more precise parameter estimates in a model because the consideration of cross-sectional dimension enhances the quality of information obtained (Taylor & Sarno, 1998). Furthermore, stationary is an important assumption to avoid the problem of spurious regression where the statistical result might be inaccurate and shows a non-existent relationship. Spurious regression problems usually arise when regressing economic times series that have an integrated level. When the data series is not stationary, differencing is needed to ensure the data become stationary. This study applied two types of panel unit root tests which are Im-Pesaran-Shin (2003) and Maddala-Wu (1999) test.

Im-Pesaran-Shin (IPS) is less strict in comparison with Levin-Lin-Chu (2002) because it allows some individuals to have unit root (nonstationary). The hypothesis of the IPS test is shown as below:

H_0: $\rho_i = 1$ where i = 1, 2, and 3 (All individual has unit root)

H_1: at least one $\rho_i < 1$ where i = 1,2, and 3 (Some individual has unit root)

The IPS model use the Augmented Dickey-Fuller (ADF) regression separately for each individual as the first step:

$$\Delta Y_{it} = \alpha y_{it-1} + \sum_{k=1}^{\rho i} \beta_{ik} \Delta y_{it-k} + \gamma_{it}\delta + \varepsilon_{it} \qquad (1)$$

where i= 1,2,…, N

t= 1,2,…, T

γ_{it}= fixed/random effect

IPS test considers the average of ADF test statistics calculated when the error term (ε_{it}) is serially correlated with the possibility that the properties of serial correlation are different across the cross-sections. IPS then provides critical values across different numbers of cross-sectional units and time series, and for the equation with intercept, or intercept with the trend. IPS test the average t-statistic for each of the ADF regression by:

$$\underline{t}_{NT} = \frac{1}{N}\sum_{i=1}^{N} t_{iT_i}\,(\rho_i) \qquad (2)$$

where IPS has an assumption on t_{iT} to be i.i.d. which indicates that it is independent and identically distributed and has constant mean and variance.

Another test is the Fisher's test proposed by Maddala and Wu is a test that combines the statistical result of individual unit root test for each of the cross-sectional units, i. Maddala and Wu (1999) suggested using chi-square distributed with the degree of freedom 2N, χ^2(2N) whereby the N represent the number of cross-sections ($T_i \rightarrow \infty$ for all N). The proposed Fisher type test is shown as below:

$$p = -2\sum_{i=1}^{N} lnp_i \qquad (3)$$

The hypothesis is as below:
H_0: All panels contain unit root
H_1: Some or at least one panels contain unit root

According to Maddala and Wu (1999), the benefits of Fisher type test is that an unbalanced panel can be used as compared to the IPS test that requires a balanced panel. Fisher type test also allows different lag lengths to be used in each of the ADF regressions.

3.3.2 Multicollinearity

Multicollinearity is a problem that arises when there is a high correlation between two or more independent variables in the regression. In effect, the regression results might be unable to produce precise estimation due to the relationship between the independent variables. In the presence of multicollinearity problems, the variance and covariance tend to be larger and thus resulting in larger standard error. In effect, the confidence interval becomes wider and leads to a higher chance of providing a misleading conclusion. Meanwhile, the t-statistic tends to be smaller which indicates an insignificant relationship between the dependent and independent variables that are supposed to be significant (Daoud, 2017). When two independent variables are correlated, R^2 will also be very high, which is likely more than 0.9, and caused the F-test to conclude that the model is significant. Hence, a contrast between the t-test is insignificant while the F-test shows significant results (Daoud, 2017).

Two common tools used to check the presence of multicollinearity problems are Tolerance Factor (TOL) and Variance Inflation Factor (VIF). According to Daoud (2017), VIF is a measurement tool for researchers to see how much the variance is inflated. Below shows the formula to calculate VIF:

$$VIF = \frac{1}{(1-R^2_{X1X2})} \qquad (4)$$

When the VIF is close to 10 indicates that there is high collinearity among the independent variables and the model suffers from a significant multicollinearity problem. Besides, TOL is the inverse of VIF and is calculated using the formula shown below:

$$TOL_j = \frac{1}{VIF_j} \qquad (5)$$

TOL that is close to zero indicates that there is a high correlation between the independent variables, therefore the model will have serious multicollinearity problems. In effect, the result is misleading and inaccurate.

3.3.3 Heteroscedasticity

Heteroscedasticity is a problem that occurs where the error term's variance is different across the explanatory variables where $var(LGDPG_i, LFDI_i, LPOP_i, LAUTO_i) = \sigma_i^2$ (Gujarati & Porter, 2009). The classical linear regression model (CLRM) assumed that there is homoscedasticity in the model which indicates that the error term has a constant variance to ensure that the estimators are the best linear unbiased estimators (BLUE). However, the heteroscedasticity problem will cause the estimators to become inefficient because the variance is no longer minimum. In effect, the standard error of coefficients will violate and lead to a meaningless result because the t-test and F-test are invalid. Therefore, the heteroscedasticity test needed to be conducted to avoid the problem occurring in the model.

There are two methods to detect the heteroscedasticity problem. One of the methods is through the informal way which is a graphical method. Another way is using hypothesis testing which includes White Test, Park test, Glejser Test, and Breusch-Pagan Test (Gujarati & Porter, 2009).

The hypothesis is set as below:
H_0: There is no heteroscedasticity problem.
H_1: There is a heteroscedasticity problem.

Decision Rule: Reject H_0 if the p-value is less than the significance level of 1%/5%/10%. Otherwise, do not reject H_0.

If the heteroscedasticity problem is detected in the model, Generalized Least Squares (GLS) or Weighted Least Squares (WLS) are applied to re-estimate the model.

3.3.4 Autocorrelation

Autocorrelation refers to the degree of resemblance of a dependent variable with its own lagged over the past periods. The CLRM assumes that autocorrelation is absent or the error terms among two periods are independent, where $cov(\mu i, \mu j) = 0, i \neq j$**.** When autocorrelation occurs, indicates that the two error terms are interrelated, where $cov(\mu i, \mu j) \neq 0, i \neq j$. There are two types of autocorrelations which are spatial correlation and serial correlation. Spatial correlation takes place in cross-sectional data, while serial correlation takes place in time series data. Besides, there are two types of serial correlation which are pure serial correlation as well as impure serial correlation. According to Studenmund (2014), pure serial correlation happens when no interrelated observations of the error term are ignored in a right specified equation. Impure serial correlation happens when there is an omitted variable or the wrong functional type. The Wooldridge test is used to determine whether or not autocorrelation exists.

The hypothesis used to detect autocorrelation problem is shown as below:
H_0: The model has no autocorrelation problem.
H_1: The model has an autocorrelation problem.

Decision Rule: Reject H_0 if the p-value is smaller than 5% level of significance. Otherwise, do not reject H_0.

3.4 Panel Data Analysis

Panel data analysis acts as a useful method to conduct analysis when the data series contains cross-sectional and time series data. According to Gujarati and Porter

(2008), panel data analysis is suitable for studying the dynamic of change and a more complex model as well as being able to consider the different characteristics among observations to reduce the chance of multicollinearity. Besides, this research also aims to study unemployment in five selected Asia countries which are China, India, Japan, South Korea, and Thailand over 15 years ranging from 2005 to 2019. Therefore, panel data analysis is conducted in this study.

3.4.1 Pooled Ordinary Least Square Model (POLS)

The POLS model is the simplest and easiest type of panel data regression. To regress the POLS model, three assumptions needed to be fulfilled. POLS model assumes that the intercepts are the same as well as having the same slopes among the observations which indicate that the impact of independent variables on dependent variables is the same (Gujarati & Porter, 2008). The POLS model also assumed that the observations are time-invariant which means no time effect over the period. Meanwhile, POLS model is suitable when the observations are homogeneity where the data possess the same characteristics over time. Another condition that the POLS model needs to fulfill is that the explanatory variable must be independent and uncorrelated with the error term in the sense that the error term might be independent and identically distributed. POLS is also the most suitable model for regression that contains the missing value (Croissant and Millo, 2018). However, there are still some limitations of the POLS model. The POLS model treated the characteristics and effects of different observations the same over time. In the presence of homogeneity objects, the estimated parameters will become biased, inefficient, and inconsistent (Gujarati & Porter, 2008). The POLS model for this study is shown as follows:

$$LUR_{it} = \beta_1 + \beta_2 LGDPG_{it} + \beta_3 LFDI_{it} + \beta_4 LPOP_{it} + \beta_5 LAUTO_{it} + \mu_{it} \quad (6)$$

Where

LUR = natural logarithms of unemployment rate

LGDPG = natural logarithms of GDP growth

LFDI = natural logarithms of FDI net inflow

LPOP = natural logarithms of population growth

LAUTO = natural logarithms of automation level

β_1 = mean for intercept term

$\beta_2, \beta_3, \beta_4, \beta_5$ = Coefficient for the independent variables

μ_{it} = combination of time series and cross-sectional error term

i = China, India, Japan, South Korea, Thailand

t = time period ranging from 2005 to 2019

3.4.2 Fixed Effect Model

Fixed Effect Model (FEM) is used when the characteristics of each observation are different across time. Another name for FEM is Least Square Dummy Variable (LSDV) because the FEM model can include dummy variables to detect different intercepts across observations and time variants. According to Vries (2015), FEM helps to reduce the bias of omitted variables to capture the impact of unobserved time and country. Omitted variables are usually correlated with at least one of the independent variables in the model where $Cor(\varepsilon_i, X_{it}) \neq 0$.

There are three scripts for the FEM model and each of them comes across different assumptions. The first script assumed constant slopes for all countries while different intercepts across the countries, and absence of time effect. The FEM model for the first script regressed as below:

$$LUR_{it} = \alpha_1 + \alpha_2 COUNTRY_{2i} + \alpha_3 COUNTRY_{3i} + \alpha_4 COUNTRY_{4i} + \alpha_5 COUNTRY_{5i} + \beta_2 LGDPG_{it} + \beta_3 LFDI_{it} + \beta_4 LPOP_{it} + \beta_5 LAUTO_{it} + \mu_{it} \quad (7)$$

Where α_1 = mean for intercept term

$\alpha_2, \alpha_3, \alpha_4, \alpha_5$ = intercept for each country

$\beta_2, \beta_3, \beta_4, \beta_5$ = Coefficient for the independent variables

μ_{it} = combination of time series and cross-sectional error term

i= China, India, Japan, South Korea, Thailand

t= time period (2005 – 2019)

China = Base group

$COUNTRY_{2i}$= 1 if the country is India; 0 if otherwise

$COUNTRY_{3i}$= 1 if the country is Japan; 0 if otherwise

$COUNTRY_{4i}$= 1 if the country is South Korea; 0 if otherwise

$COUNTRY_{5i}$= 1 if the country is Thailand; 0 if otherwise

For the second script, the assumption is similar to the first script where there is a constant slope with different intercepts for all countries. The only difference is now the FEM assumes there is a time effect (time-variant). The equation is regressed as follows:

$$LUR_{it} = \alpha_1 + \alpha_2 COUNTRY_{2i} + \alpha_3 COUNTRY_{3i} + \alpha_4 COUNTRY_{4i} + \alpha_5 COUNTRY_{5i} + \lambda_1 DUM_{2005} + \lambda_2 DUM_{2006} + \cdots + \lambda_{14} DUM_{2018} + \beta_2 LGDPG_{it} + \beta_3 LFDI_{it} + \beta_4 LPOP_{it} + \beta_5 LAUTO_{it} + \mu_{it} \quad (8)$$

Where α_1 = mean for intercept term

α_2, α_3 = intercept for each country

$\beta_2, \beta_3, \beta_4, \beta_5$ = Coefficient for the independent variables

$\lambda_1, \lambda_2, \dots, \lambda_{14}$ = Coefficient for time dummy variables

μ_{it} = combination of time series and cross-sectional error term

i= China, India, Japan, South Korea, Thailand

t= time period (2005 – 2019)

China = Base group

$COUNTRY_{2i}$= 1 if the country is India; 0 if otherwise

$COUNTRY_{3i}$= 1 if the country is Japan; 0 if otherwise

$COUNTRY_{4i}$= 1 if the country is South Korea; 0 if otherwise

$COUNTRY_{5i}$= 1 if the country is Thailand; 0 if otherwise

DUM_{2005}= 1 if the value of observation is 1 in year 2005; 0 if otherwise

DUM_{2006}= 1 if the value of observation is 1 in year 2006; 0 if otherwise

⋮

DUM_{2014}= 1 if the value of observation is 1 in year 2014; 0 if otherwise

Another script for FEM is that it assumes that both the intercepts and slopes are inconsistent across countries and there is no time effect (time-invariant). The model is shown as below:

$$LUR_{it} = \alpha_1 + \alpha_2 COUNTRY_{2i} + \alpha_3 COUNTRY_{3i} + \beta_2 LGDPG_{it} + \beta_3 LFDI_{it} + \beta_4 LPOP_{it} + \beta_5 LAUTO_{it} + \gamma_1(COUNTRY_{2i}LGDPG_{it}) + \gamma_2(COUNTRY_{2i}LFDI_{it}) + \gamma_3(COUNTRY_{2i}LPOP_{it}) + \gamma_4(COUNTRY_{2i}LAUTO_{it}) + \gamma_5(COUNTRY_{3i}LGDPG_{it}) + \gamma_6(COUNTRY_{3i}LFDI_{it}) + \gamma_7(COUNTRY_{3i}LPOP_{it}) + \gamma_8(COUNTRY_{3i}LAUTO_{it}) + \gamma_9(COUNTRY_{4i}LGDPG_{it}) + \gamma_{10}(COUNTRY_{4i}LFDI_{it}) + \gamma_{11}(COUNTRY_{4i}LPOP_{it}) + \gamma_{12}(COUNTRY_{4i}LAUTO_{it}) + \gamma_{13}(COUNTRY_{5i}LGDPG_{it}) + \gamma_{14}(COUNTRY_{5i}LFDI_{it}) + \gamma_{15}(COUNTRY_{5i}LPOP_{it}) + \gamma_{16}(COUNTRY_{5i}LAUTO_{it}) + \mu_{it} \quad (9)$$

Where α_1 = mean for intercept term

α_2, α_3 = intercept for each country

$\beta_2, \beta_3, \beta_4, \beta_5$ = Coefficient for the independent variables

$\gamma_1, \gamma_2, \ldots, \gamma_{16}$ = Coefficient for each independent variable with country

μ_{it} = combination of time series and cross-sectional error term

i= China, India, Japan, South Korea, Thailand

t= time period (2005 – 2019)

China = Base group

$COUNTRY_{2i}$= 1 if the country is India; 0 if otherwise

$COUNTRY_{3i}$= 1 if the country is Japan; 0 if otherwise

$COUNTRY_{4i}$= 1 if the country is South Korea; 0 if otherwise

$COUNTRY_{5i}$= 1 if the country is Thailand; 0 if otherwise

One limitation of the FEM is that if the equation contains too many dummy variables, FEM might be unable to examine the impact of the variables that do not have a time effect (Gujarati & Porter, 2008).

3.4.3 Random Effect Model

Unlike FEM, Random Effect Model (REM) assumed that the intercept of each cross-section is randomly chosen from a larger population with a fixed mean value (Gujarati & Porter, 2008). REM is one of the panel data regressions that is most suitable to be used when there is no correlation between the intercept of every individual unit and the independent variables where $Cor(\varepsilon_i, X_{it}) = 0$. The regression of REM is shown as below:

$$LUR_{it} = \beta_1 + \beta_2 LGDPG_{it} + \beta_3 LFDI_{it} + \beta_4 LPOP_{it} + \beta_5 LAUTO_{it} + \varepsilon_i + \mu_{it} \quad (10)$$

Where β_1= mean for intercept term

$\beta_2, \beta_3, \beta_4, \beta_5$ = Coefficient for the independent variables

ε_i= cross-sectional error component

μ_{it}= combination of time series and cross-sectional error term

For REM, a few important assumptions need to be fulfilled. One of the assumptions is REM assumed the error term (ε_i) is random and not fixed. When the error term is not constant where $\varepsilon_i \sim N(0, \sigma^2)$, the model might face a serious autocorrelation problem. Therefore, Generalized Least Square (GLS) is more suitable to estimate REM as compared to the OLS method to ensure obtaining the best linear unbiased estimator (Gujarati & Porter, 2008). The advantage of using REM is because REM has a lower chance to face multicollinearity problems due to the reduction of the number of explanatory variables in the sense that the unknown parameter also becomes lesser as compared to FEM.

3.5 Model Selection

The previous section has discussed the function of each type of the panel data regression model which are POLS, FEM, and REM. In order to select the best equation among them, several tests, such as the Chow test, Breusch, and Pagan Lagrange Multiplier test, and Hausman test must be taken.

3.5.1 Hausman Test

In this study, Hausman test is applying to evaluate the most preferable model that best fits the data among FEM and REM.

H_0: REM is more preferable

H_1: FEM is more preferable

The decision rule is to reject null hypothesis if the p-value is less than the significance level where α = 1%/5%/10%. Otherwise, do not reject H_0.

3.5.2 Chow Test

The Chow test was employed to examine the most favorable model among POLS and FEM.

H_0: POLS is more favorable.

H_1: FEM is more favorable.

The decision rule is to reject null hypothesis if the p-value is less than the significance level where α = 1%/5%/10%. Otherwise, do not reject H_0.

3.5.3 Breusch-Pagan Lagrange Multiplier Test (LM Test)

LM test is used to make comparisons between POLS and REM to investigate which model is most suitable for the variables in this study.

H_0: There is no time difference. (POLS is preferable)

H_1: There is a time difference. (REM is preferable)

The decision rule is to reject null hypothesis if the p-value is less than the significance level where α = 1%/5%/10%. Otherwise, do not reject H_0.

3.6 Conclusion

Overall, the methodologies used for this research are discussed. The next chapter discusses the research results and interpretation.

Chapter 4 Data Analysis

4.0 Introduction

Chapter 4 discuss and interpret the results generated from STATA in regard to the proposed methodologies in Chapter 3. The results generated were summarized into table form to provide a clear and simple overview of the depth of the findings.

4.1 Descriptive Analysis

Table 4.1

Descriptive Statistical Results for Dependent and Independent Variables

VARIABLES	MEAN	MEDIAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
LUR	1.09631	1.39000	0.75432	-1.56065	1.73519
LGDPG	2.03665	2.26000	2.06809	-15.40840	2.97794
LFDI	23.86435	23.63000	1.58900	14.94377	26.40456
LPOP	-0.82496	-0.35000	2.19859	-17.42382	0.58149
LAUTO	9.13993	9.28000	1.47717	6.10925	11.94471

Note. LUR stands for natural log of Unemployment Rate, LGDPG stands for natural log for Gross Domestic Products Growth, LFDI stands for natural log for FDI Net Inflow, LPOP stands for natural log for Population Growth, and LAUTO stands for natural log for Automation Level.

The variables data for this study for the selected ASIA countries: China, India, South Korea, Japan, and Thailand from 2005 to 2019 is collected from World Bank and IFR World Robotics Reports. This study uses natural logarithm for the unemployment rate and the independent variables to minimize the scale measurement problem. There are few negative values in the series of FDI net inflow, GDP growth, and population growth. The country sample might become bias if we drop the observations for a country that are negative or zero values (Busse & Hefeker, 2005). To solve this problem, rescaling the data sets for FDI and population growth with a constant minimum value is needed (Busse & Hefeker, 2005). In effect, the intuition for the original information is not affected and negative observations are not excluded.

Based on Table 4.1, the summary result shows that LFDI has the highest mean value of 23.86435 while LPOP has the lowest mean value of -0.82496. This indicates that LFDI has the highest average value among all the variables. LPOP has the highest standard deviation of 2.19859 which shows that the data point for LPOP is far away from the mean value while LUR has the lowest standard deviation of 0.75432 which shows that the data point for LUR is closest to the mean value. Median is the total value of each variable in the middle of a set of periods. Median for LPOP is -0.35, followed by LUR (1.39), LGDPG (2.26), LAUTO (9.28), and LFDI (23.63).

4.2 Diagnostic Checking

4.2.1 Panel Unit Root Test

Unit Root Test is a test that checks the stationary conditions of the variables. Stationary indicates that the data of the variables are not affected by their past value. In this study, the stationary of variables was tested by using Im-Pesaran-Shin (IPS) test and the Fisher unit root test to check the stationarity of the data. The results are shown in Table 4.2 and Table 4.3.

Table 4.2

Results of Im-Pesaran-Shin (IPS) Test

IPS TEST			
	Level	1st Difference (intercept)	2nd Difference (intercept)
LUR	0.3415	-2.9461	-3.8463
	(0.6337)	(0.0016)***	(0.0001)***
LGDPG	-2.7911	-4.7002	-4.8323
	(0.0026)***	(0.0000)***	(0.0000)***
LFDI	-3.7304	-4.6476	-4.9139
	(0.0001)***	(0.0000)***	(0.0000)***
LPOP	3.8245	1.6529	-1.2312
	(0.9999)	(0.9508)	(0.1091)
LAUTO	0.6884(0.7544)	-3.5992	-4.3449
		(0.0002)***	(0.0000)***

Notes. The figure without bracket represents the value of test statistic, value with bracket represents the p-value, while *, **, ***, represents the rejection of null hypothesis at 10%, 5%, and 1% level of significance respectively.

Table 4.2 displays the result of the IPS test in level form for the dependent variable, the log of the unemployment rate (LUR), and the independent variables which is the log of gross domestic product growth (LGDPG), log of foreign direct investment (LFDI), log of population growth (LPOP), and log of automation (LAUTO). The null hypothesis for the IPS test is the series is non-stationary, while the alternative hypothesis is the series is stationary. If the P-value is less than the significance level, it indicates that the series is stationary.

From Table 4.2, it shows that both LFDI and LGDPG are stationary at the level form at a 1% significance level. However, the result shows LUR, LPOP, and

LAUTO are nonstationary in the level form. Hence, first and second differencing are required in order to achieve stationary for the variables.

The third and fourth column of Table 4.2 shows the result after first differencing and second differencing respectively for the variables. The result shows all variables are significant after the first and second differencing at a 1% significance level except LPOP.

Table 4.3

Results of Fisher's Test

FISHER'S TEST			
	Level	1st Difference (intercept)	2nd Difference (intercept)
LUR	10.2267(0.4208)	40.4071(0.0000)***	78.8317(0.0000)***
LGDPG	50.7862(0.0000)***	124.1777(0.0000)***	171.2966(0.0000)***
LFDI	66.5949(0.0000)***	139.7042(0.0000)***	188.5977(0.0000)***
LPOP	6.9456(0.7306)	26.7930(0.0028)***	50.5711(0.0000)***
LAUTO	3.9292(0.9505)	52.0542(0.0000)***	98.8554(0.0000)***

Notes. The figure without bracket represents the value of test statistic, value with bracket represents the p-value, while *, **, ***, represents the rejection of null hypothesis at 10%, 5%, and 1% level of significance respectively.

Table 4.3 shows the result of Fisher's test in level form. All variables are tested in log form. The null hypothesis for Fisher's test is all panels contain unit root, while the alternative hypothesis is at least one panels contain unit root.
From Table 4.3, it displays that only LFDI and LGDPG are stationary at 1% significance level. However, LUR, LPOP, and LAUTO are non-stationary in the level form. In order to achieve stationary for the variables, the first and second differencing should have proceeded.

The third and fourth column of Table 4.3 shows the results after first differencing and second differencing respectively for the variables. The result shows all variables are significant after the first and second differencing at 1% significance level. This represents that the variables are stationary as the null hypothesis is being rejected.

Overall, by using the IPS test, all variables are significant after first and second differencing at 10%, 5%, and 1%, except LPOP is insignificant throughout the entire IPS test. However, in Fisher test it shows all variables are significant after the first and second differencing. Therefore, we can conclude that LPOP is stationary, and we can proceed with the analysis.

4.2.2 Multicollinearity

Multicollinearity generally happens when at least two dependent variables in a regression model are highly correlated (Vatcheva et al., 2016). In other words, one of the explanatory variables of the regression model can be explained by another explanatory variable. If there is multicollinearity problem occurs in the model, the standard error is unstable and resulting in an inaccurate conclusion and interpretation (Vatcheva et al., 2016).

The researchers of this study used two methods to detect the multicollinearity problem in the regression model which are Variance Inflation Factor (VIF) and Tolerance Factor (TOL). According to Daoud, J. I. (2017), if the VIF value is equal to one, it means that the variables are no correlated if the VIF value is between one to five, it is moderately correlated, and if the VIF value is more than five, it is highly correlated among the variables. TOL values that are less than 0.10 represent collinearity.

Table 4.4

Multicollinearity Test Results

COLLINEARITY STATISTIC		
Independent Variable	VIF	Tolerance
LGDPG	1.03	0.96700
LFDI	1.05	0.95582
LPOP	1.18	0.85105
LAUTO	1.19	0.84370

According to Table 4.4, the VIF value for explanatory variables is between one to five and the TOL value is more than 0.10. This indicates that there is no multicollinearity problem exists in the model. In other words, the independent variables have no relationship with each other.

4.2.3 Heteroscedasticity

Table 4.5

Result of Breusch-Pagan Test

BREUSCH-PAGAN TEST	
Chi-square Statistic	22.73
P-value	0.0000***

A heteroscedasticity problem will affect the efficiency of the estimators in a model and cause the results generated to become meaningless. This study used Breusch-Pagan Test to determine the existence of heteroscedasticity problems in a model. The null hypothesis refers to an absence of heteroscedasticity problem in the model while the alternative hypothesis refers to a presence of heteroscedasticity problem.

According to Table 4.5, the p-value of 0.00 implies to reject the null hypothesis of no heteroscedasticity at a 1% significance level. Hence, it proved that the regression suffers from heteroscedasticity problems. In effect, the standard error of coefficients might be violated.

4.2.4 Autocorrelation

Table 4.6

Result of Wooldridge Test

WOOLDRIDGE TEST	
F-statistic	13.800
P-value	0.0206**

Autocorrelation is an important issue in a panel data analysis. It occurs when there is a similarity of the current variable value with its own lagged version. In this research, Wooldridge test for autocorrelation in panel data is used to estimate the autocorrelation problem. The null hypothesis shows that there is no first-order autocorrelation, while the alternative hypothesis shows there is a first-order autocorrelation.

The Wooldridge test result generated by STATA shows the p-value is 0.0206, hence reject the null hypothesis at 5% significance level. This indicates that there is a first order autocorrelation problem that occurs in the regression.

4.3 Panel Data Analysis

4.3.1 Pooled Ordinary Least Square Model (POLS)

Table 4.7

Result of POLS

VARIABLES	POLS
LGDPG	-0.01683

	(0.01453)
LFDI	0.11688*
	(0.06770)
LPOP	0.04855**
	(0.01841)
LAUTO	0.14225**
	(0.05997)
C	-2.91884*
	(1.58024)
Observations	75
R-squared	0.1508

Notes. Robust standard errors in parentheses. *, **, ***, represents the series is significant at 10%, 5%, and 1% significance level respectively.

$$LUR_{it} = -2.9188 - 0.0168LGDPG_{it} + 0.1169LFDI_{it} + 0.0486LPOP_{it} + 0.1423LAUTO_{it} + \mu_{it} \qquad (11)$$

Robust standard error is included in the panel approaches to deal with the problem of autocorrelation and heteroscedasticity in the data series. According to Table 4.7, the $\hat{\beta}_0$ (-2.9188) indicates when LGDPG, LFDI, LPOP, and LAUTO are zero, the unemployment rate is equal to -2.9188 percent. The result shows that GDP growth has a negative, insignificant, effect on the unemployment rate at 1% significance level. This indicates that every one percent increase in GDP growth will lead to a 0.0168 percent decrease in the unemployment rate. Meanwhile, the FDI is proved to have a positive, statistically significant, effect on the unemployment rate at 1% significance level. This means that for every one percent increase in FDI net inflow, the unemployment rate will increase by 0.1169 percent. Population growth and automation level both have a positive, statistically significant, effect on the unemployment rate at 5% significance level. For every one percent increase in population growth, on average, the unemployment rate will increase by 0.0486 percent. An increase of one percent in automation level will cause the unemployment rate to increase by 0.1423 percent. Therefore, the model confirms three out of four hypotheses in the study which are H1, H3, and H4. An increase in GDP growth will lead to a decrease in the unemployment rate while an increase in automation level and/or population growth will cause the unemployment rate to increase.

4.3.2 Fixed Effect Model (FEM)

Table 4.8

Result of FEM

VARIABLES	**FEM**
LGDPG	-0.01583***
	(0.00159)
LFDI	-0.02502***
	(0.00460)
LPOP	0.03061***
	(0.00158)
LAUTO	-0.05565
	(0.06736)
C	2.25955**
	(0.67805)
Observations	75
R-squared	0.0434

Note. Robust standard errors in parentheses. *, **, ***, represents the series is significant at 10%, 5%, and 1% significance level respectively.

$$LUR_{it} = 2.2596 - 0.0158LGDPG_{it} - 0.0250LFDI_{it} + 0.0306LPOP_{it} - 0.0557LAUTO_{it} + \mu_{it} \qquad (12)$$

Since the model is suffered from autocorrelation and heteroscedasticity problems, robust standard errors is used in the regression to solve the problem. The $\hat{\beta}_0$ (2.2596) shows that the unemployment rate is equal to 2.2596 percent when all the factors are equal to zero. The FEM model provides evidence that GDP growth have a negative, significant, effect on the unemployment rate at 1% significance level. For every one percent increase in GDP growth, the unemployment rate will decrease by 0.0158 percent. Meanwhile, FDI is also proved to have a negative, statistically significant, effect on the unemployment rate at 1% significance level. This indicates that every one percent increase in FDI will lead to 0.0250 percent decrease in the unemployment rate. Population growth has a positive, statistically significant, effect on the unemployment rate at 1% significance level. This means that every one percent increase in population growth will lead to an increase in the unemployment rate by 0.0306 percent. Automation levels have a negative, insignificant, effect on the unemployment rate at 1% significance level. For every one percent increase in automation level, the unemployment rate will decrease by 0.0557 percent. Therefore, this model confirms three of the hypotheses in the study which are H1, H2, and H3, indicates that a certain decrease in FDI net inflow and/or GDP growth will lead to an increase in the unemployment rate, ceteris paribus. When population growth increase will cause the unemployment rate to increase.

4.3.3 Random Effect Model (REM)

Table 4.9

Result of REM

VARIABLES	POLS
LGDPG	-0.01683***
	(0.00507)

LFDI	0.11688
	(0.11810)
LPOP	0.04855***
	(0.01856)
LAUTO	0.14225
	(0.21546)
C	-2.91884
	(3.72062)
Observations	75
R-squared	0.1508

Note. Robust standard errors in parentheses. *, **, ***, represents the series is significant at 10%, 5%, and 1% significance level respectively.

$$LUR_{it} = -2.9188 - 0.0168LGDPG_{it} + 0.1169LFDI_{it} + 0.0486LPOP_{it} + 0.1423LAUTO_{it} + \mu_{it} \qquad (13)$$

Same as the previous panel model approaches, REM also uses robust standard error to deal with the autocorrelation and heteroscedasticity problem. The $\hat{\beta}_0$ (-2.9188) implies that the unemployment rate is equal to -2.9188 percent when all factors are equal to zero. According to Table 4.9, the outcome reflects that GDP growth have a negative, significant, effect on the unemployment rate at 1% significance level. For every one percent increase in GDP growth, on average, the unemployment rate will decrease by 0.0168 percent. Meanwhile, FDI is proved to have a positive, statistically insignificant, effect on the unemployment rate at 1% significance level. This means that a one percent increase in FDI net inflow will cause the unemployment rate to increase by 0.1169 percent. The population growth has a positive, statistically significant, effect on the unemployment rate at 1% significance level. This implies that an increase of one percent in population growth will lead to an increase of 0.0486 percent in the unemployment rate. The automation level has a positive, but insignificant, effect on the unemployment rate at 1% significance level. For every one percent increase in automation level, the unemployment rate will increase by 0.1423 percent. Therefore, the model confirms three out of four hypotheses in the study which are H1, H3, and H4. An increase in GDP growth will lead to a decrease in the unemployment rate while an increase in automation level and/or population growth will cause the unemployment rate to increase.

Table 4.10

Comparison of R-squared for POLS, FEM, and REM

MODEL	POLS	FEM	REM
R-squared	0.1508	0.0434	0.1508

The R-squared is a measurement that uses to identify how well the independent variables can explain the dependent variable. The R-squared for POLS, FEM, REM are 0.1508, 0.0434, and 0.1508 respectively which is counted as a low R-squared. The result in Table 4.10 shows that for POLS and REM, 15.08% of the variation can be explained by the explanatory variables which include FDI net inflow, GDP growth, population growth, and automation level. Meanwhile, there is 4.34% of the variation can be explained by the explanatory variables in FEM. However, a model with a low R-squared does not directly means that the model is worse, but rather that the model is less predictable. This is not a major issue when the variables are related to social and economic factors. This is because the data behavior for these variables is usually hard to predict. Evidence shows that the R-squared is usually being misunderstood by many studies conducted. For instance, high R-squared is believed to shows a good fit of a model while a low R-squared is believed to shows that the dependent and independent variables are not related (Kutner et al., 2005). However, this belief will violate when the actual regression relationship is curvilinear.

4.4 Model Selection

We have discussed the data analysis of POLS, FEM, and REM in the previous section. In order to choose the most suitable model among them, the comparison tests like Hausman test, Chow test, and LM test are needed.

4.4.1 Hausman Test

Table 4.11

Result of Hausman Test

Test	Chi-sq. Statistic	P-value
Hausman Test	63.68	0.0000 ***

Hausman test is conducted to select the best model that fits our study among REM and FEM. The null hypothesis states that REM is endorsed in this study while the alternative hypothesis states that FEM is endorsed. The decision rule is to reject null hypothesis if the p-value is not more than the significance level, otherwise do not reject null hypothesis. The p-value (0.0000) in Table 4.11 which is not more than the significance level of 0.01, 0.05, and 0.1 shows that FEM is more preferable for this study as compared to REM.

4.4.2 Chow Test

Table 4.12

Result of Chow Test

Test	F Statistic	P-value
Chow Test	166.26	0.0000 ***

Chow test and Likelihood Ratio test are used to choose between POLS or REM. In this study, the Chow test approach is chosen and it has a null hypothesis of POLS is more preferable while alternative hypothesis of FEM is more favorable. The decision rule is to reject null hypothesis if p-value is not more than the significance level. The p-value (0.0000) in Table 4.12 which is not more than the significance level of 0.01, 0.05, and 0.1 implies that we should reject null hypothesis. Therefore, the FEM is more favourable in this study.

4.4.3 Breusch-Pagan Lagrange Multiplier Test (LM Test)

Table 4.13

Result of LM Test

Test	Chi-square Statistic	P-value
LM Test	0.0000	1.0000

LM test enables us to choose the best model among POLS and REM. The null hypothesis is that POLS is preferable while the alternative hypothesis is that REM is preferable. The decision rule is reject null hypothesis if the p-value is less than the significance level. Based on Table 4.13, the p-value (1.0000) which is more than the significance level implies that POLS is more preferable when comparing to the REM in this study.

4.5 Conclusion

In this chapter, various type of diagnostic checking tests has been conducted to check if the model faces problems like multicollinearity or heteroscedasticity. The results show that the series is heteroscedasticity and has an autocorrelation problem. Therefore, the researchers used robust standard error to regress the panel data models to solve these problems. Furthermore, Hausman test, Chow test, and LM test are being conducted and the result indicates that FEM is the best model. In effect, the discussion finding in the next chapter is mainly depend on the FEM.

Chapter 5 Discussion, Conclusion, and Implication

5.0 Introduction

The overall research outcome is discuses and analyses in this last chapter. Throughout this part, major findings of the research are reported in the form of a summary of statistical analyses and discussions followed by implications, limitations, recommendations, and conclusions.

5.1 Summary of Statistic Analyses

Table 5.1

Summary of Statistical Analyses Result

Diagnostic Checking	Analysis	Result
Unit Root Test	Im-Pesaran-Shin Test	All variables are stationary at first difference except for population growth
	Fisher Type Test	All variables are stationary at first difference
Multicollinearity	Variance Inflation Factor and Tolerance Factor	There is no multicollinearity problem
Heteroscedasticity	Breusch-Pagan/ Cook-Weisberg test	There is heteroscedasticity problem but solved with robust standard error

Autocorrelation	Wooldridge test	There is an autocorrelation problem but solved with robust standard error
REM and FEM	Hausman test	FEM is more preferable
POLS and FEM	F-test	FEM is more preferable
POLS and REM	Breusch-Pagan Lagrange Multiplier test	POLS is more preferable

Variables	POLS	FEM	REM
LGDPG	Negative insignificant	Negative significant	Negative significant
LFDI	Positive significant	Negative significant	Positive insignificant
LPOP	Positive significant	Positive significant	Positive significant
LAUTO	Positive significant	Negative insignificant	Positive insignificant

Note. FEM is preferable as compared to POLS and REM

5.2 Discussions of Major Findings

5.2.1 Gross Domestic Product Growth (GDPG)

According to our result in the previous chapter, a statistically significant and negative correlation is determined between Gross Domestic Product growth and the unemployment rate in Asia at a 1% significance level which is consistent with our proposed hypothesis. This indicates an increase in GDPG by one percent, the unemployment rate reduces by 0.0158. It is because a high GDPG will result in an increase in overall production and investment, which will encourage job creation. Eventually, rapid production growth will result in more people being employed in a country while simultaneously lowering the unemployment rate. Besides, a high GDPG increases a country's economic certainty, which encourages greater investment and business development, causing a reduction in unemployment rates owing to increased job and value creation. Moreover, the result is consistent with Chand et al., (2017), Bhownik (2016), Chowdhury and Hossain (2014), as well as Li and Liu (2012) since their findings also suggest a negative correlation between the two variables. Additionally, it is per Okun's law with 1 percent of GDPG, the unemployment rate declined by 0.0158 percent.

5.2.2 Foreign Direct Investment Net Inflow (FDI)

Besides, the result showed that Foreign Direct Investment (FDI) inflow is significant to the unemployment rate and indicates an inverse relationship between these two variables at a 1% significance level. When there is a one percent increase in FDI, the unemployment rate will decrease by 0.0250. This is because FDI inflow has positive spillover effects which diffuse more useful techniques all through an economy by access to high technology, skills, management, training, and the systems, which can increase total factor productivity of a firm. Moreover, as the level of productivity increases, this will lead to an increase in competition among international firms, a rise in exports, the balance of payments will improve and the demand for labor will increase. Other than that, inward Greenfield FDI will increase job opportunities as new firms are being established. For example, unemployment in Korea decreases as greenfield FDI inflows and spillover effects cause new employment to be created in domestic firms. (Lee, 2020). This result is similar to Palat (2011), Chen (2017), Sjoholm (2008), and Mucuk and Demirsel (2013) where this researcher agrees that Foreign Direct Investment and the unemployment rate are negatively correlated.

5.2.3 Population Growth (POP)

Additionally, the empirical findings show that there is a strong and positive relationship between population growth and the unemployment rate at a 1% significance level. Every one percent rise in population growth will lead to a 0.0306 percent increase in the unemployment rate. This is because when population growth increases rapidly in the long run, more young people will enter the labor market. Hence, it creates a higher labor force participation rate to occupy limited employment opportunities, eventually contributes to a rise in the unemployment rate. This pattern can view in densely populated nations like China and India, where rising population growth adds to a greater labor force participation rate that surpasses the available work opportunities to cover the entire population, resulting in high unemployment. Meanwhile, countries like Japan always had a lower population rate, which has resulted in a lower labor force participation which leads to a fall in the unemployment rate. The positively correlated outcome is aligned with the proposed hypothesis that implies when the population grows in an economy consequently the unemployment rate will rise. Empirical results show that a 1% growth rate of population has a substantial influence on rising unemployment levels due to abundant supply of labor in contrast to employment growth. Besides, this finding is correspondent with previous studies as Singh and Sandeep (2014), Aurangzeb and Khola (2013), and Heliati (2019) discovered a positively correlated relationship between the two variables.

5.2.4 Automation Level (AUTO)

For the automation level, we have enough evidence in our empirical results to state that the relationship between automation level and unemployment is insignificant at a 1% significance level. The relationship between automation level and unemployment rate shows negative which implies that when there is an expansion in automation level by one percent, the unemployment rate will likewise decrease by 0.0557. This is due to an increase in automation level which will increase the productivity of the firm and it stimulates the consumer demand for goods and services because of lower prices and improved quality which likewise increases employment. Moreover, technological innovation will reduce the cost of production, generate new markets and varieties of products thus it will create more job opportunities in the economy consequently unemployment will diminish. The outcome is not precise with what we expected in the hypothesis of study which is positively correlated. Moreover, these results are parallel with Mutascu (2021) and Adachi et al. (2020) their outcome likewise shows joblessness rate and automation level have a negative relationship. Nonetheless, the Solow Swan Model theory does not hold in this case.

5.3 Implications of the Study

This study focuses on how GDP growth, FDI net inflow, population growth, and automation level impact the unemployment rate in China, India, Japan, South Korea, and Thailand. The results of this study allow the readers and relevant authorities to recognize several important implications.

5.3.1 Gross Domestic Product Growth (GDPG)

The government plays a crucial role in reducing unemployment by making use of the expansionary fiscal and monetary policy. When there is a high unemployment rate, the policymakers may use expansionary fiscal policy by reducing the taxes or increase government spending. A lower tax is able to increase the private and public sector's production, which then creates more job opportunities and leading to a lower unemployment rate (Battaglini, 2011). Increase public spending may influence the economy by boosting the market aggregate demand and indirectly lower the unemployment rate. Moreover, in the presence of unemployment, the policymakers may also use expansionary monetary policy to reduce the interest rate. A lower borrowing cost may incentivize firms to invest in expanding their operations, hence reduce the unemployment rate in the country. Besides, an increase in money supply in terms of raising the financial institution's total lending also helps to lower the unemployment rate (Essien et al., 2016). According to a case study in

Indonesia, the author suggests that coordination between fiscal and monetary policy has a significant impact on archive a lower unemployment rate in short term (Sumando, 2015).

5.3.2 Foreign Direct Investment Net Inflow (FDI)

To attract more FDI inflow to lower down unemployment, the government should control the exchange rate to a desirable level that is in the investor's best interest as the exchange rate is one of the major factors affecting the FDI inflow in a country. When the exchange rate fluctuates to an unfavorable level, it will negatively impact the FDI inflow and lead to a higher unemployment rate in the country. Hence, the government can intervene in the foreign exchange market by using the foreign or home currency reserve to stabilize its currency value (Humpage, 2003). Besides, the government should also develop infrastructure in order to attract more FDI inflow. According to a case study in Malaysia, the author claims that good infrastructure such as transportation, communication, and public utilities are the important determinant in attracting FDI inflow to the country (Fazidah, 2013). Furthermore, from the evidence of China, establishing special economic zones (SEZs) could help to attract more FDI inflow (Cheng, 2008). SEZs are devoted to preserving market order, safeguarding property rights, and effectively simplifying processes in order to enhance the business environment. SEZs are dedicated to supporting ongoing infrastructure development in areas such as utilities, communications, logistics, and transportation (Song et al., 2020). Hence, countries with high unemployment rates can implement these policies to tackle the unemployment issue.

5.3.3 Population Growth (POP)

Overpopulation causes a higher unemployment rate may seriously lead to higher poverty and a negative impact on economic growth. Lack of natural resources and environmental issues are also challenges that might arise. Therefore, the government should keep track of population growth and ensure there are sufficient resources available to serve its citizens to solve the unemployment issue. Creating a birth control policy such as one child legislation is a crucial action to solve the overpopulation issue in the country. The Chinese government had altered its stance on birth control and promote contraception and other birth control measures like abortion had effective results in population reduction (Gavin & Jin, 1994). India as the world's largest populous country should implement the birth control policy to prevent overpopulation. Moreover, the policymakers should promote family planning by providing adequate education for the citizens. Successful evidence was found from the case of Iran that launched a nationwide family planning project in 1989, and it resulted in a significant reduction in the fertility rate. Therefore, countries experiencing a growing population should implement such policies to reduce the impact of population growth on the unemployment rate.

5.3.4 Automation Level (AUTO)

According to the International Federation of Robotics (IFR), automation does impact low-skilled and low-income employment, but it does create greater job opportunities for the high-skilled, high-income employees. A study shows that the dynamic economy influenced by automation can generate millions of jobs by 2030 (McKinsey Global Institute, 2017). To better equip future employees, the government should modify the education systems to focus more on critical thinking, analytical, and social skills, rather than technical skills that are easily being takeover by automation. Suitable government intervention is needed such as government-enforced welfare legislation may mandate certain occupations to be performed solely by human labor, therefore externally restricting automation (Kim et al., 2017). Besides, the provision of income and transition support for workers by the government is a way to smooth the workforce transition (McKinsey Global Institute, 2017). For example, policies like flexible benefits that follow employees regardless of jobs and unemployment insurance will help displaced employees being employed successfully.

5.4 Limitations of the Study

Throughout our study, we have encountered some limitations exists which could obturate us to get the perfect results. First, one of the major problems that we faced is a constraint of resources and limitation to access the data where we were only able to obtain the data from one source which is 'World Bank Database' for all the variables except automation level but this sources itself does not give us a complete data set that needed for our research. Moreover, the absence of reliable and accessible data will limit the extent of our sample size and analysis, and it is very time-consuming for us.

Other than that, there is a limited study examining the effect of population growth and automation level on the unemployment rate compared to the other two variables. Finally, to run the regression model, we do not have an enormous sample size since in our research we only generated 75 observations due to the lack of data available for many Asia countries. Thus, this causes heteroscedasticity problems to occur in our results as the number of countries selected for our study is only five countries considered less. However, we managed to solve this heteroscedasticity problem even though our sample size is small. Normally, large sample size is needed for panel data analysis to have a more reliable and accurate outcome in other words, the larger the number of observations, the accuracy in final results will increases.

5.5 Recommendations for Future Research

To further enhance the studies regarding determinants of unemployment in Asia, future researchers should consider more detailed oriented analysis to improve the precision of the findings. As Asia consists of 48 countries on continent, it is best for future research to increase sample sizes. According to Hertwig et al. (2008) and Noordzij et al. (2010), since any significant existing impact may not be detectable if the sample size is too small as larger samples. This is because when samples in larger size will result in better and precise estimation of population means than smaller samples and help to enhance the accuracy of future estimation.

Additionally, researchers in the future are advised to use data and information from various online sources not limited to one source to avoid incomplete data set. Instead of focusing on 'World Bank Database' and the International Federation of Robotics (IFR), future researchers can choose to obtain data from other reputable sources such as Census Economic Information Center (CEIC), International Monetary Fund (IMF), and many others.

Lastly, they can also consider including more factors like the rate inflation, exchange rate, interest rate, labor force, as well as export since these variables indirectly and directly impact a country's unemployment rate. Hence, by considering these variables for future research, the absence of reliable and accessible data is able to be avoided. This also increases the availability of broad studies to examine the determinants of unemployment in Asia that help in proper analysis.

5.6 Conclusion

This study is conducted to objectify the investigation of factors that affect the unemployment rate in five selected Asia countries which are China, India, Japan, South Korea, and Thailand within a sample period from 2005 to 2019. This study has identified four factors that might play a vital role in determining the unemployment rate in a country are GDP growth, FDI net inflow, population growth, and automation level. According to our results, FEM is the model that best describes the data collected as compared to POLS and REM. Throughout the study, population growth has a positive relationship with the unemployment rate whereas GDP growth, FDI net inflow, and automation level have a negative relationship with the unemployment rate. Therefore, the research provided limitations and recommendations that aim to help future researchers who are interested in studying this area. Policymakers play a vital role in tackling unemployment issues by developing permanent policies related to employment. Overall, this study may serve as a reference for policymakers, businesspeople, and individuals to understand the unemployment situation well.

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Appendices

Appendix 1: Result of Descriptive Statistics

```
. univar LUR LFDI LGDPG LPOP LAUTO
                                        -------------- Quantiles --------------
Variable       n     Mean      S.D.       Min       .25       Mdn       .75       Max
-------------------------------------------------------------------------------
     LUR      75     1.10      0.75     -1.56      1.13      1.39      1.53      1.74
    LFDI      75    23.86      1.59     14.94     23.15     23.63     24.55     26.40
   LGDPG      75     2.04      2.07    -15.41      2.01      2.26      2.55      2.98
    LPOP      75    -0.82      2.20    -17.42     -0.65     -0.35     -0.18      0.58
   LAUTO      75     9.14      1.48      6.11      7.88      9.28     10.46     11.94
-------------------------------------------------------------------------------
```

Appendix 2: Panel unit root test

Appendix 2.1: IPS Test at level form

Appendix 2.1.1: Unemployment Rate (UR)

```
. xtunitroot ips LUR

Im-Pesaran-Shin unit-root test for LUR
--------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: Some panels are stationary              Number of periods =     15

AR parameter: Panel-specific                Asymptotics: T,N -> Infinity
Panel means:  Included                                       sequentially
Time trend:   Not included

ADF regressions: No lags included
------------------------------------------------------------------------------
                                                Fixed-N exact critical values
                    Statistic      p-value          1%       5%       10%
------------------------------------------------------------------------------
 t-bar               -1.4017                      -2.540   -2.210   -2.060
 t-tilde-bar         -1.2342
 Z-t-tilde-bar        0.3415        0.6337
------------------------------------------------------------------------------
```

Appendix 2.1.2: Gross Domestic Products Growth (GDPG)

```
. xtunitroot ips LGDPG

Im-Pesaran-Shin unit-root test for LGDPG
----------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: Some panels are stationary              Number of periods =     15

AR parameter: Panel-specific                Asymptotics: T,N -> Infinity
Panel means:  Included                                       sequentially
Time trend:   Not included

ADF regressions: No lags included
------------------------------------------------------------------------------
                                                Fixed-N exact critical values
                    Statistic      p-value          1%       5%       10%
------------------------------------------------------------------------------
 t-bar               -3.2525                      -2.540   -2.210   -2.060
 t-tilde-bar         -2.2872
 Z-t-tilde-bar       -2.7911        0.0026
------------------------------------------------------------------------------
```

Appendix 2.1.3: Foreign Direct Investment Net Inflow (FDI)

```
. xtunitroot ips LFDI

Im-Pesaran-Shin unit-root test for LFDI
---------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: Some panels are stationary              Number of periods =     15

AR parameter: Panel-specific                Asymptotics: T,N -> Infinity
Panel means:  Included                                       sequentially
Time trend:   Not included

ADF regressions: No lags included
------------------------------------------------------------------------------
                                              Fixed-N exact critical values
                    Statistic      p-value          1%       5%      10%
------------------------------------------------------------------------------
 t-bar               -3.8635                     -2.540   -2.210   -2.060
 t-tilde-bar         -2.6030
 Z-t-tilde-bar       -3.7304        0.0001
------------------------------------------------------------------------------
```

Appendix 2.1.4: Population Growth (POP)

```
. xtunitroot ips LPOP

Im-Pesaran-Shin unit-root test for LPOP
---------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: Some panels are stationary              Number of periods =     15

AR parameter: Panel-specific                Asymptotics: T,N -> Infinity
Panel means:  Included                                       sequentially
Time trend:   Not included

ADF regressions: No lags included
------------------------------------------------------------------------------
                                              Fixed-N exact critical values
                    Statistic      p-value          1%       5%      10%
------------------------------------------------------------------------------
 t-bar               -0.0565                     -2.540   -2.210   -2.060
 t-tilde-bar         -0.0634
 Z-t-tilde-bar        3.8245        0.9999
------------------------------------------------------------------------------
```

Appendix 2.1.5: Automation Level (AUTO)

```
. xtunitroot ips LAUTO

Im-Pesaran-Shin unit-root test for LAUTO
----------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: Some panels are stationary              Number of periods =     15

AR parameter: Panel-specific                Asymptotics: T,N -> Infinity
Panel means:  Included                                       sequentially
Time trend:   Not included

ADF regressions: No lags included
------------------------------------------------------------------------------
                                              Fixed-N exact critical values
                    Statistic      p-value          1%       5%      10%
------------------------------------------------------------------------------
 t-bar               -1.1407                     -2.540   -2.210   -2.060
 t-tilde-bar         -1.1176
 Z-t-tilde-bar        0.6884        0.7544
------------------------------------------------------------------------------
```

Appendix 2.2 IPS Test at first difference

Appendix 2.2.1: UR

```
. xtunitroot ips D.LUR

Im-Pesaran-Shin unit-root test for D.LUR
----------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: Some panels are stationary              Number of periods =     14

AR parameter: Panel-specific                Asymptotics: T,N -> Infinity
Panel means:  Included                                       sequentially
Time trend:   Not included

ADF regressions: No lags included
------------------------------------------------------------------------------
                                              Fixed-N exact critical values
                    Statistic      p-value        1%       5%      10%
------------------------------------------------------------------------------
 t-bar               -3.1170                   -2.540   -2.210   -2.060
 t-tilde-bar         -2.3166
 Z-t-tilde-bar       -2.9461        0.0016
------------------------------------------------------------------------------
```

Appendix 2.2.2: GDPG

```
. xtunitroot ips D.LGDPG

Im-Pesaran-Shin unit-root test for D.LGDPG
------------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: Some panels are stationary              Number of periods =     14

AR parameter: Panel-specific                Asymptotics: T,N -> Infinity
Panel means:  Included                                       sequentially
Time trend:   Not included

ADF regressions: No lags included
------------------------------------------------------------------------------
                                              Fixed-N exact critical values
                    Statistic      p-value        1%       5%      10%
------------------------------------------------------------------------------
 t-bar               -5.2895                   -2.540   -2.210   -2.060
 t-tilde-bar         -2.9016
 Z-t-tilde-bar       -4.7002        0.0000
------------------------------------------------------------------------------
```

Appendix 2.2.3: FDI

```
. xtunitroot ips D.LFDI

Im-Pesaran-Shin unit-root test for D.LFDI
-----------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: Some panels are stationary              Number of periods =     14

AR parameter: Panel-specific                Asymptotics: T,N -> Infinity
Panel means:  Included                                       sequentially
Time trend:   Not included

ADF regressions: No lags included
------------------------------------------------------------------------------
                                              Fixed-N exact critical values
                    Statistic      p-value        1%       5%      10%
------------------------------------------------------------------------------
 t-bar               -5.5022                   -2.540   -2.210   -2.060
 t-tilde-bar         -2.8841
 Z-t-tilde-bar       -4.6476        0.0000
------------------------------------------------------------------------------
```

Appendix 2.2.4: POP

```
. xtunitroot ips D.LPOP

Im-Pesaran-Shin unit-root test for D.LPOP
─────────────────────────────────────────
Ho: All panels contain unit roots          Number of panels  =      5
Ha: Some panels are stationary             Number of periods =     14

AR parameter: Panel-specific               Asymptotics: T,N -> Infinity
Panel means:  Included                                     sequentially
Time trend:   Not included

ADF regressions: No lags included
──────────────────────────────────────────────────────────────────────────────
                                             Fixed-N exact critical values
                    Statistic      p-value          1%       5%       10%
──────────────────────────────────────────────────────────────────────────────
 t-bar               -1.2735                    -2.540   -2.210   -2.060
 t-tilde-bar         -0.7827
 Z-t-tilde-bar        1.6529        0.9508
──────────────────────────────────────────────────────────────────────────────
```

Appendix 2.2.5: AUTO

```
. xtunitroot ips D.LAUTO

Im-Pesaran-Shin unit-root test for D.LAUTO
──────────────────────────────────────────
Ho: All panels contain unit roots          Number of panels  =      5
Ha: Some panels are stationary             Number of periods =     14

AR parameter: Panel-specific               Asymptotics: T,N -> Infinity
Panel means:  Included                                     sequentially
Time trend:   Not included

ADF regressions: No lags included
──────────────────────────────────────────────────────────────────────────────
                                             Fixed-N exact critical values
                    Statistic      p-value          1%       5%       10%
──────────────────────────────────────────────────────────────────────────────
 t-bar               -3.5923                    -2.540   -2.210   -2.060
 t-tilde-bar         -2.5344
 Z-t-tilde-bar       -3.5992        0.0002
──────────────────────────────────────────────────────────────────────────────
```

Appendix 2.3: IPS Test at second difference

Appendix 2.3.1: UR

```
. xtunitroot ips D2.LUR

Im-Pesaran-Shin unit-root test for D2.LUR
─────────────────────────────────────────
Ho: All panels contain unit roots          Number of panels  =      5
Ha: Some panels are stationary             Number of periods =     13

AR parameter: Panel-specific               Asymptotics: T,N -> Infinity
Panel means:  Included                                     sequentially
Time trend:   Not included

ADF regressions: No lags included
──────────────────────────────────────────────────────────────────────────────
                                             Fixed-N exact critical values
                    Statistic      p-value          1%       5%       10%
──────────────────────────────────────────────────────────────────────────────
 t-bar               -4.2018                    -2.540   -2.210   -2.060
 t-tilde-bar         -2.5917
 Z-t-tilde-bar       -3.8463        0.0001
──────────────────────────────────────────────────────────────────────────────
```

Appendix 2.3.2: GDPG

```
.  xtunitroot ips D2.LGDPG

Im-Pesaran-Shin unit-root test for D2.LGDPG
-------------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: Some panels are stationary              Number of periods =     13

AR parameter: Panel-specific                Asymptotics: T,N -> Infinity
Panel means:  Included                                       sequentially
Time trend:   Not included

ADF regressions: No lags included
------------------------------------------------------------------------------
                                            Fixed-N exact critical values
                    Statistic      p-value          1%       5%       10%
------------------------------------------------------------------------------
 t-bar               -6.2042                     -2.540  -2.210  -2.060
 t-tilde-bar         -2.9179
 Z-t-tilde-bar       -4.8323        0.0000
------------------------------------------------------------------------------
```

Appendix 2.3.3: FDI

```
. xtunitroot ips D2.LFDI

Im-Pesaran-Shin unit-root test for D2.LFDI
------------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: Some panels are stationary              Number of periods =     13

AR parameter: Panel-specific                Asymptotics: T,N -> Infinity
Panel means:  Included                                       sequentially
Time trend:   Not included

ADF regressions: No lags included
------------------------------------------------------------------------------
                                            Fixed-N exact critical values
                    Statistic      p-value          1%       5%       10%
------------------------------------------------------------------------------
 t-bar               -7.3018                     -2.540  -2.210  -2.060
 t-tilde-bar         -2.9449
 Z-t-tilde-bar       -4.9139        0.0000
------------------------------------------------------------------------------
```

Appendix 2.3.4: POP

```
. xtunitroot ips D2.LGDP

Im-Pesaran-Shin unit-root test for D2.LGDP
------------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: Some panels are stationary              Number of periods =     13

AR parameter: Panel-specific                Asymptotics: T,N -> Infinity
Panel means:  Included                                       sequentially
Time trend:   Not included

ADF regressions: No lags included
------------------------------------------------------------------------------
                                            Fixed-N exact critical values
                    Statistic      p-value          1%       5%       10%
------------------------------------------------------------------------------
 t-bar               -4.5895                     -2.540  -2.210  -2.060
 t-tilde-bar         -2.7118
 Z-t-tilde-bar       -4.2095        0.0000
------------------------------------------------------------------------------
```

Appendix 2.3.5: AUTO

```
. xtunitroot ips D2.LAUTO

Im-Pesaran-Shin unit-root test for D2.LAUTO
-------------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: Some panels are stationary              Number of periods =     13

AR parameter: Panel-specific                Asymptotics: T,N -> Infinity
Panel means:  Included                                      sequentially
Time trend:   Not included

ADF regressions: No lags included
------------------------------------------------------------------------------
                                                Fixed-N exact critical values
                    Statistic      p-value          1%       5%       10%
------------------------------------------------------------------------------
 t-bar               -4.7903                      -2.540  -2.210  -2.060
 t-tilde-bar         -2.7566
 Z-t-tilde-bar       -4.3449        0.0000
------------------------------------------------------------------------------
```

Appendix 2.4: Fisher's Type Test at level form

Appendix 2.4.1: UR

```
. xtunitroot fisher LUR, dfuller lags(0)

Fisher-type unit-root test for LUR
Based on augmented Dickey-Fuller tests
--------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: At least one panel is stationary        Number of periods =     15

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 0 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(10)   P        10.2267       0.4208
 Inverse normal            Z         0.2491       0.5984
 Inverse logit t(29)       L*        0.3386       0.6313
 Modified inv. chi-squared Pm        0.0507       0.4798
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Appendix 2.4.2: GDPG

```
. xtunitroot fisher LGDPG, dfuller lags(0)

Fisher-type unit-root test for LGDPG
Based on augmented Dickey-Fuller tests
--------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: At least one panel is stationary        Number of periods =     15

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 0 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(10)   P        50.7862       0.0000
 Inverse normal            Z        -4.6260       0.0000
 Inverse logit t(29)       L*       -5.9431       0.0000
 Modified inv. chi-squared Pm        9.1201       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Appendix 2.4.3: FDI

```
.  xtunitroot fisher LFDI , dfuller lags(0)

Fisher-type unit-root test for LFDI
Based on augmented Dickey-Fuller tests
--------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: At least one panel is stationary        Number of periods =     15

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 0 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(10)   P        66.5949       0.0000
 Inverse normal            Z        -6.2217       0.0000
 Inverse logit t(29)       L*       -8.3149       0.0000
 Modified inv. chi-squared Pm       12.6550       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Appendix 2.4.4: POP

```
.  xtunitroot fisher LPOP, dfuller lags(0)

Fisher-type unit-root test for LPOP
Based on augmented Dickey-Fuller tests
--------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: At least one panel is stationary        Number of periods =     15

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 0 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(10)   P         6.9456       0.7306
 Inverse normal            Z         1.4477       0.9261
 Inverse logit t(24)       L*        1.6120       0.9400
 Modified inv. chi-squared Pm       -0.6830       0.7527
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Appendix 2.4.5: AUTO

```
.  xtunitroot fisher LAUTO, dfuller lags(0)

Fisher-type unit-root test for LAUTO
Based on augmented Dickey-Fuller tests
--------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: At least one panel is stationary        Number of periods =     15

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 0 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(10)   P         3.9292       0.9505
 Inverse normal            Z         1.1436       0.8736
 Inverse logit t(29)       L*        1.0579       0.8506
 Modified inv. chi-squared Pm       -1.3575       0.9127
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Appendix 2.5: Fisher's Type Test at first difference

Appendix 2.5.1: UR

```
. xtunitroot fisher D.LUR, dfuller lags(0)
(5 missing values generated)

Fisher-type unit-root test for D.LUR
Based on augmented Dickey-Fuller tests
--------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: At least one panel is stationary        Number of periods =     14

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 0 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(10)   P        40.4071       0.0000
 Inverse normal            Z        -4.3102       0.0000
 Inverse logit t(29)       L*       -4.9860       0.0000
 Modified inv. chi-squared Pm        6.7992       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Appendix 2.5.2: GDPG

```
. xtunitroot fisher D.LGDPG, dfuller lags(0)
(5 missing values generated)

Fisher-type unit-root test for D.LGDPG
Based on augmented Dickey-Fuller tests
--------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: At least one panel is stationary        Number of periods =     14

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 0 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(10)   P       124.1777       0.0000
 Inverse normal            Z        -9.7132       0.0000
 Inverse logit t(29)       L*      -15.5894       0.0000
 Modified inv. chi-squared Pm       25.5309       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Appendix 2.5.3: FDI

```
. xtunitroot fisher D.LFDI, dfuller lags(0)
(5 missing values generated)

Fisher-type unit-root test for D.LFDI
Based on augmented Dickey-Fuller tests
--------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: At least one panel is stationary        Number of periods =     14

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 0 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(10)   P       139.7042       0.0000
 Inverse normal            Z       -10.0257       0.0000
 Inverse logit t(29)       L*      -17.5380       0.0000
 Modified inv. chi-squared Pm       29.0027       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Appendix 2.5.4: POP

```
. xtunitroot fisher D.LPOP, dfuller lags(0)
(5 missing values generated)

Fisher-type unit-root test for D.LPOP
Based on augmented Dickey-Fuller tests
--------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: At least one panel is stationary        Number of periods =     14

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 0 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(10)   P        26.7930       0.0028
 Inverse normal            Z         0.5372       0.7044
 Inverse logit t(29)       L*       -0.5629       0.2889
 Modified inv. chi-squared Pm        3.7550       0.0001
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Appendix 2.5.5: AUTO

```
. xtunitroot fisher D.LAUTO, dfuller lags(0)
(5 missing values generated)

Fisher-type unit-root test for D.LAUTO
Based on augmented Dickey-Fuller tests
--------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: At least one panel is stationary        Number of periods =     14

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 0 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(10)   P        52.0542       0.0000
 Inverse normal            Z        -5.6169       0.0000
 Inverse logit t(29)       L*       -6.5211       0.0000
 Modified inv. chi-squared Pm        9.4036       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Appendix 2.6: Fisher's Type Test at second difference

Appendix 2.6.1: UR

```
.  xtunitroot fisher D2.LUR, dfuller lags(0)
(10 missing values generated)

Fisher-type unit-root test for D2.LUR
Based on augmented Dickey-Fuller tests
--------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: At least one panel is stationary        Number of periods =     13

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 0 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(10)   P        78.8317       0.0000
 Inverse normal            Z        -7.0690       0.0000
 Inverse logit t(29)       L*       -9.8888       0.0000
 Modified inv. chi-squared Pm       15.3912       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Appendix 2.6.2: GDPG

```
. xtunitroot fisher D2.LGDPG, dfuller lags(0)
(10 missing values generated)

Fisher-type unit-root test for D2.LGDPG
Based on augmented Dickey-Fuller tests
---------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: At least one panel is stationary        Number of periods =     13

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 0 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(10)   P       171.2966       0.0000
 Inverse normal            Z       -11.6823       0.0000
 Inverse logit t(29)       L*      -21.5051       0.0000
 Modified inv. chi-squared Pm       36.0670       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Appendix 2.6.3: FDI

```
.  xtunitroot fisher D2.LFDI, dfuller lags(0)
(10 missing values generated)

Fisher-type unit-root test for D2.LFDI
Based on augmented Dickey-Fuller tests
--------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: At least one panel is stationary        Number of periods =     13

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 0 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(10)   P       188.5977       0.0000
 Inverse normal            Z       -12.1949       0.0000
 Inverse logit t(29)       L*      -23.6770       0.0000
 Modified inv. chi-squared Pm       39.9357       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Appendix 2.6.4: POP

```
.  xtunitroot fisher D2.LPOP, dfuller lags(0)
(10 missing values generated)

Fisher-type unit-root test for D2.LPOP
Based on augmented Dickey-Fuller tests
--------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: At least one panel is stationary        Number of periods =     13

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 0 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(10)   P        50.5711       0.0000
 Inverse normal            Z        -2.7595       0.0029
 Inverse logit t(29)       L*       -5.4348       0.0000
 Modified inv. chi-squared Pm        9.0720       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Appendix 2.6.5: AUTO

```
.  xtunitroot fisher D2.LAUTO, dfuller lags(0)
(10 missing values generated)

Fisher-type unit-root test for D2.LAUTO
Based on augmented Dickey-Fuller tests
---------------------------------------
Ho: All panels contain unit roots           Number of panels  =      5
Ha: At least one panel is stationary        Number of periods =     13

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 0 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(10)   P        98.8554       0.0000
 Inverse normal            Z        -8.6077       0.0000
 Inverse logit t(29)       L*      -12.4099       0.0000
 Modified inv. chi-squared Pm       19.8687       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Appendix 3: Multicollinearity Test

```
. vif
```

Variable	VIF	1/VIF
LAUTO	1.19	0.843696
LPOP	1.18	0.851048
LFDI	1.05	0.955820
LGDPG	1.03	0.966997
Mean VIF	1.11	

Appendix 4: Wooldridge Test

```
. xtserial LUR LFDI LGDPG LPOP LAUTO

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,       4) =     13.800
           Prob > F =      0.0206
```

Appendix 5: Pooled Ordinary Least Square Model

```
. reg LUR LFDI LGDPG LPOP LAUTO, robust

Linear regression                               Number of obs     =         75
                                                F(4, 70)          =       4.99
                                                Prob > F          =     0.0014
                                                R-squared         =     0.1508
                                                Root MSE          =     .71468
```

LUR	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
LFDI	.1168818	.0676998	1.73	0.089	-.0181412	.2519048
LGDPG	-.0168316	.0145266	-1.16	0.251	-.0458039	.0121408
LPOP	.0485522	.0184096	2.64	0.010	.0118354	.0852691
LAUTO	.1422524	.0599721	2.37	0.020	.0226419	.2618629
_cons	-2.918843	1.580235	-1.85	0.069	-6.070522	.2328362

Appendix 6: Fixed Effect Model

```
. xtreg LUR LFDI LGDPG LPOP LAUTO, fe cluster(Country)

Fixed-effects (within) regression               Number of obs      =        75
Group variable: c_id                            Number of groups   =         5

R-sq:  within  = 0.1526                         Obs per group: min =        15
       between = 0.1657                                        avg =      15.0
       overall = 0.0434                                        max =        15

                                                F(4,4)             =   4985.23
corr(u_i, Xb)  = -0.3781                        Prob > F           =    0.0000

                                (Std. Err. adjusted for 5 clusters in Country)
------------------------------------------------------------------------------
             |               Robust
         LUR |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        LFDI |  -.0250216   .0046015    -5.44   0.006    -.0377974   -.0122457
       LGDPG |   -.015832   .0015886    -9.97   0.001    -.0202425   -.0114215
        LPOP |   .0306069   .0015813    19.36   0.000     .0262165    .0349973
       LAUTO |  -.0556483   .0673558    -0.83   0.455     -.242658    .1313613
       _cons |   2.259548   .6780451     3.33   0.029     .3769933    4.142103
-------------+----------------------------------------------------------------
     sigma_u |  .84882528
     sigma_e |  .22115064
         rho |  .93643509   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Appendix 7: Random Effect Model

```
. xtreg LUR LFDI LGDPG LPOP LAUTO, re cluster (Country)

Random-effects GLS regression                   Number of obs     =         75
Group variable: c_id                            Number of groups  =          5

R-sq:                                           Obs per group:
     within  = 0.0068                                         min =         15
     between = 0.2843                                         avg =       15.0
     overall = 0.1508                                         max =         15

                                                Wald chi2(4)      =     226.75
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000

                                (Std. Err. adjusted for 5 clusters in Country)
------------------------------------------------------------------------------
             |               Robust
         LUR |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        LFDI |   .1168818   .1180983     0.99   0.322    -.1145867    .3483503
       LGDPG |  -.0168316   .0050707    -3.32   0.001      -.02677   -.0068931
        LPOP |   .0485522   .0185554     2.62   0.009     .0121843    .0849202
       LAUTO |   .1422524   .2154453     0.66   0.509    -.2800127    .5645175
       _cons |  -2.918843   3.720621    -0.78   0.433    -10.21113    4.373441
-------------+----------------------------------------------------------------
     sigma_u |          0
     sigma_e |  .22115064
         rho |          0   (fraction of variance due to u_i)
------------------------------------------------------------------------------

.
```

Appendix 8: Hausman Test

```
. hausman FEM REM, sigmamore

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |      FEM          REM         Difference          S.E.
-------------+----------------------------------------------------------------
        LFDI |   -.0250216     .1168818       -.1419034        .0604567
       LGDPG |    -.015832    -.0168316        .0009996        .0139353
        LPOP |    .0306069     .0485522       -.0179453        .0271174
       LAUTO |   -.0556483     .1422524       -.1979007        .0992831
------------------------------------------------------------------------------
                          b = consistent under Ho and Ha; obtained from xtreg
           B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(4) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       63.68
                Prob>chi2 =      0.0000
```

Appendix 9: Chow Test

```
. xtreg LUR LFDI LGDPG LPOP LAUTO,fe

Fixed-effects (within) regression               Number of obs     =         75
Group variable: c_id                            Number of groups  =          5

R-sq:                                           Obs per group:
     within  = 0.1526                                         min =         15
     between = 0.1657                                         avg =       15.0
     overall = 0.0434                                         max =         15

                                                F(4,66)           =       2.97
corr(u_i, Xb)  = -0.3781                        Prob > F          =     0.0255

------------------------------------------------------------------------------
         LUR |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        LFDI |  -.0250216   .0249767    -1.00   0.320    -.0748891    .0248459
       LGDPG |   -.015832   .0133565    -1.19   0.240    -.0424991    .0108351
        LPOP |   .0306069    .015201     2.01   0.048     .0002572    .0609567
       LAUTO |  -.0556483    .036095    -1.54   0.128    -.1277143    .0164176
       _cons |   2.259548   .6514951     3.47   0.001     .9587962      3.5603
-------------+----------------------------------------------------------------
     sigma_u |  .84882528
     sigma_e |  .22115064
         rho |  .93643509   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(4, 66) = 166.26                     Prob > F = 0.0000
```

Appendix 10: Bresuch-Pagan Lagrange Multiplier Test

```
. xttest0

Breusch and Pagan Lagrangian multiplier test for random effects

        LUR[c_id,t] = Xb + u[c_id] + e[c_id,t]

        Estimated results:
                         |       Var     sd = sqrt(Var)
                ---------+-----------------------------
                     LUR |   .5689922       .7543157
                       e |   .0489076       .2211506
                       u |          0              0

        Test:   Var(u) = 0
                             chibar2(01) =     0.00
                          Prob > chibar2 =   1.0000
```