DOES EDUCATION BECOME A KEY TO EXPLAIN INCOME INEQUALITY

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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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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

2SLS	Two Stage Least Square
AR	Arellano-Bond
DC	Developed Countries
EDU	Education
FD	Financial Development
GDP	Gross Domestic Product
GINI	Gini coefficient
GMM	Generalized method of moments
LDC	Less developed Countries
LIS	Luxembourg Income Study
MFI	Microfinance Institution
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Square
SWIID	Standardized World Income Inequality Database
TECH	Technological Changes
TO	Trade Openness
WDI	World Development Indicators

LIST OF APPENDICES

ABSTRACT

Income inequality has always been an important issue all over the world. It is an unequal percentage of the income held by the populations, that there was a small group of people was taking over control on a large amount of the country's income. Developing countries and developed countries is studied in this paper, control variables such as financial development, economic growth, trade openness and technological changes were used to study the impact of education on income inequality in 34 developed countries from year 1971 to 2015 and 51 developing countries from year 2003 to 2015 respectively. Generalized Method of Moments (GMM) dynamic panel estimators is applied into this paper to conduct the research. There are two GMM dynamic panel estimators, which is "difference GMM" and "system GMM", and "system GMM" is found more liable then "difference GMM". This study will emphasize on the relationship between secondary education and income inequality in both developing and developed countries by using GMM estimator. In overall, the results show that education, financial development, economic growth, trade openness and technological changes are found affect income inequality. Variables that having positive relationship with income inequality are education, economic growth and trade openness, for developed countries. Whereas financial development and technological changes have a negative correlation with the income inequality. Under developing countries, education and income inequality are in a positive relationship. While financial development, economic growth, trade openness and technological changes have an adverse relationship on income inequality.

CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

This chapter will begin with a general introduction on the research background which includes income inequality in developed and developing countries followed by the research problem about the issues of income inequality. Besides, this study will discuss about the research objectives and research question. Lastly, the research significant will also be discussed in this section.

1.1 Research Background

Income inequality is defined as an unequal percentage of income held by the populations. Until today, income inequality remains an important issue because it concerns human welfare. Income inequality is happening in all countries around the world while the only difference is the severity of the gap between the poor and rich. It means that there is a small group of people taking over control on a large amount of the country's income (Strassbuger, 2018).

Most of the OECD countries have reached the largest gap between the rich and poor in the past 30 years. Nowadays, in the OECD regions, the 10 % richest population has earned 9.5 times of the 10% poorest income population; the ratio was 7:1 in the 1980s and has been rising throughout the period. However, the increase in overall income inequality was not only incur a rise in the share of income. Typically, the bottom-line incomes grew slowly in a period of prosperity and declined during recessions (Cingano, 2014). Besides, in advanced economies, emerging markets and developing countries (EMDCs) are having so-called a mixed of inequality trends. There were some countries had declined their inequality, but inequalities in access to education, health care, and finance were still remained. No doubt, the extent of inequality and the solutions have become the most popular debated issues for policymakers and researchers (Dabla-Norris, Kochhar, Suphaphiphat, Ricka & Tsounta, 2015).

Developing countries and emerging countries accounted for 70% and 59% of income inequality respectively. Income inequality of United States and China had absolutely increased for the past 20 years. Besides, there were some countries had remained their income inequality. They are Japan, Switzerland and Germany. In contrast, there are also some countries had a declined inequality such as Brazil. In addition, income inequality had increased dramatically in developing countries over the past two decades. Income inequality in developing countries increased by 11% during 1990 to 2010. However, until today there is more than 75% of the population that lives in the societies are facing unequal in income distribution compared to 1990s. In developing countries, income inequality was typically higher than advanced countries. Income inequality of China's had reached a dangerous level. Based on Li and Luo (2011), they showed that the income of the wealthiest 10% of the population was 32.8 times of the income of the poorest 10%, while the average income in the urban areas was 3.87 times of the average income in the rural areas. Furthermore, for developed country such as United States, the income inequality (the gap between the rich and poor) had been raising markedly. The shares of those wealthiest 1% have increased to almost a quarter of the wealth of all the countries, while the poorest left in haft have less than 5%.

Income inequality was often claimed clearly associated with education. Based on few researchers, income inequality could be influenced by education level, also called as skills deepening (Mincer, 1958; Schultz, 1961; Becker, 1962). Income distribution was related to the average of schooling of the population. Education had materialistic value which helped to increase income, stabilized employment and improved working condition of individual (Fields, 1980). The trend of education was kept on increasing for the population aged 15-64 in both developing and developed countries. In developing countries, primary school enrolment has risen about 80% to more than 90%. This representing that there is a close increase of 36 million in primary school children and there are now 90 million more students in secondary school compared to year 2000. The educated population continued to grow until year 2008 which income growth explains some of the reasons for this growth. Meanwhile in the developed countries, 70% of the graduates go on to higher education from kindergarten to high school in United States. Besides, education in France is compulsory from the ages of 6 to 16, although most students attend pre-school education and many begin higher education.

There was an issue found by Tilak (1989), the researcher found that the countries which have high returns to education are majority from developing countries. Those minority group benefited from the education caused the income distribution became more unequal and thus increased in income inequality. In Pakistan, the quality of education is a big problem because the individuals are lack of access to education from primary level. Even the enrollment rate of children access to primary school was 63%, however, half of the children have dropped out due to several reasons and inadequate education facilities. Furthermore, because of gender discrimination and inequality faced by women, female's education enrolment is only 43.6% of the total enrollment, which is lower than the education enrolment of male. There is also a restriction that do not have even a single high school for girls. There are many union councils that do not have high schools for girls. There are 31,740 units of primary schools in Pakistan. However, out of these, only 6,816 units of high schools are for girls. Hence, it is important for the females in Pakistan to be provided with an equal access to education compared to males. This caused the income distribution became unequal and increased the income inequality (Farhan, 2017).

According to the study from Bhagwati (1973), there was a paradigm stated that educated workforce has more competitive advantage than uneducated workforce. This indicated that the higher the level of education, the greater the chances to get a high-paying job. However, due to the concept of "fairness" and "education should be rewarded", it merely made the society to work because such paradigm was not fully attributed in reality. Therefore, this assembled those uneducated labor to receive an unfair reward and led to a higher income inequality.

In another viewpoint, highly educated employees might be hired below their educational level due to the scarcity of jobs. Thus, the income received by those educated employees would not tally with their education qualification (Bhagwati, 1973). Moreover, Bhagwati found that the productivity level of an employee was determined based on their education background, instead of spending resources in building human capital in the developing countries. However, sometimes it might occur a surplus in the supply of educated labor and it would led to the situation when a job that only required a high school or diploma qualification labor. Eventually, the job scope was not applicable to the education skills of the employees, so the resources spent on the education would be wasted. The inequality of income would increase.

For developed countries, most of the American were experiencing a rise in income but the higher income was most benefit during year 1988 to 1992. On the other hand, income of the lowest and middle group were mildly increased. Thus, this issue raises the income gap between the highest, middle and lowest income groups and led to a higher income inequality. This situation was due to the gap in educational attainment between these three groups (Lee, 1992). Furthermore, in early 1970s and 1980s, Japan was one of the countries that had most equal income distribution among the OECD countries. Japanese society has incurred the aggravation of income inequality due to “bubble economy” that happened in early 1990s. The aggravation of income inequality increased the numbers of unstable jobs, even the parental education level of individuals has continuously rises (Amano, 1990).

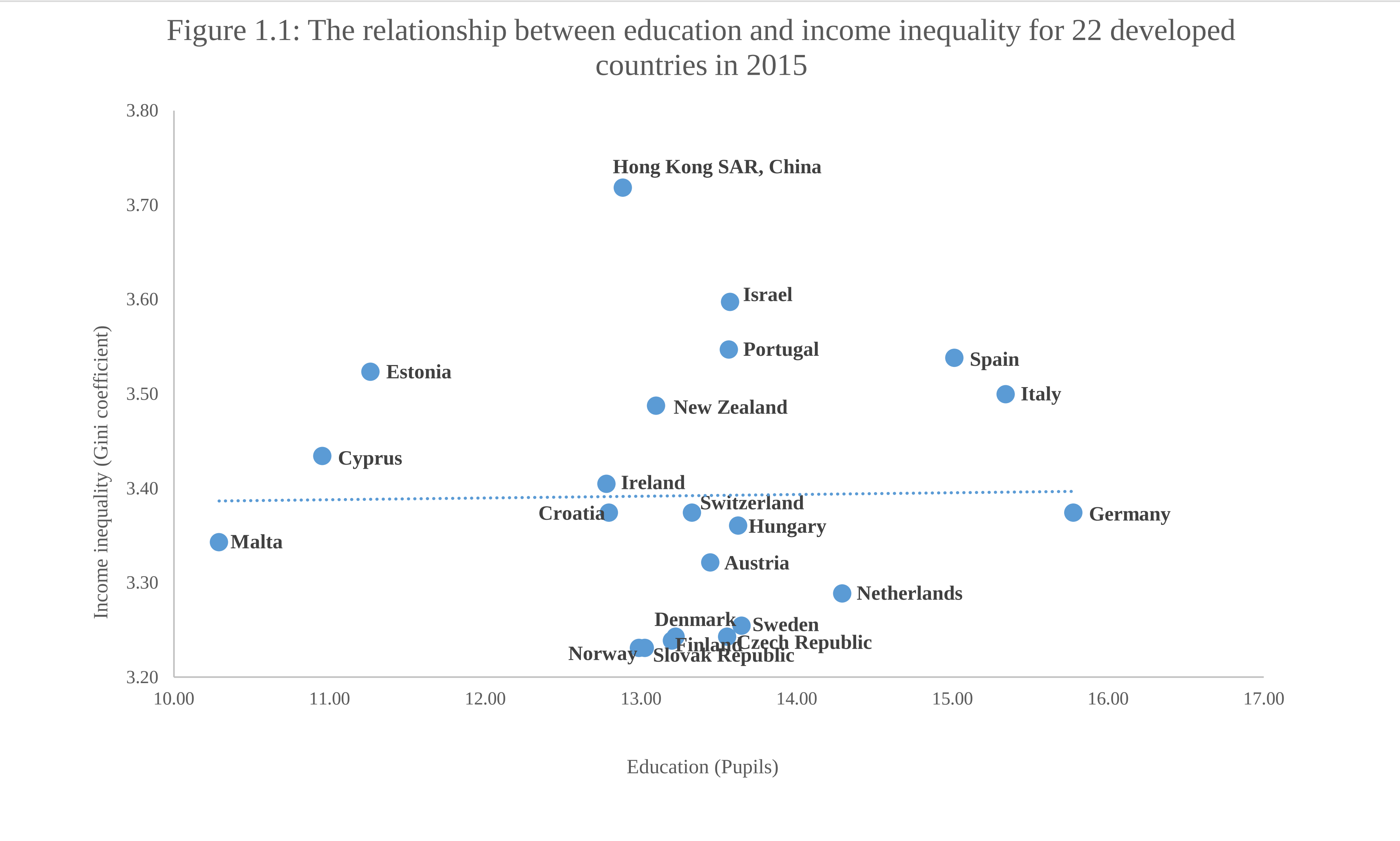
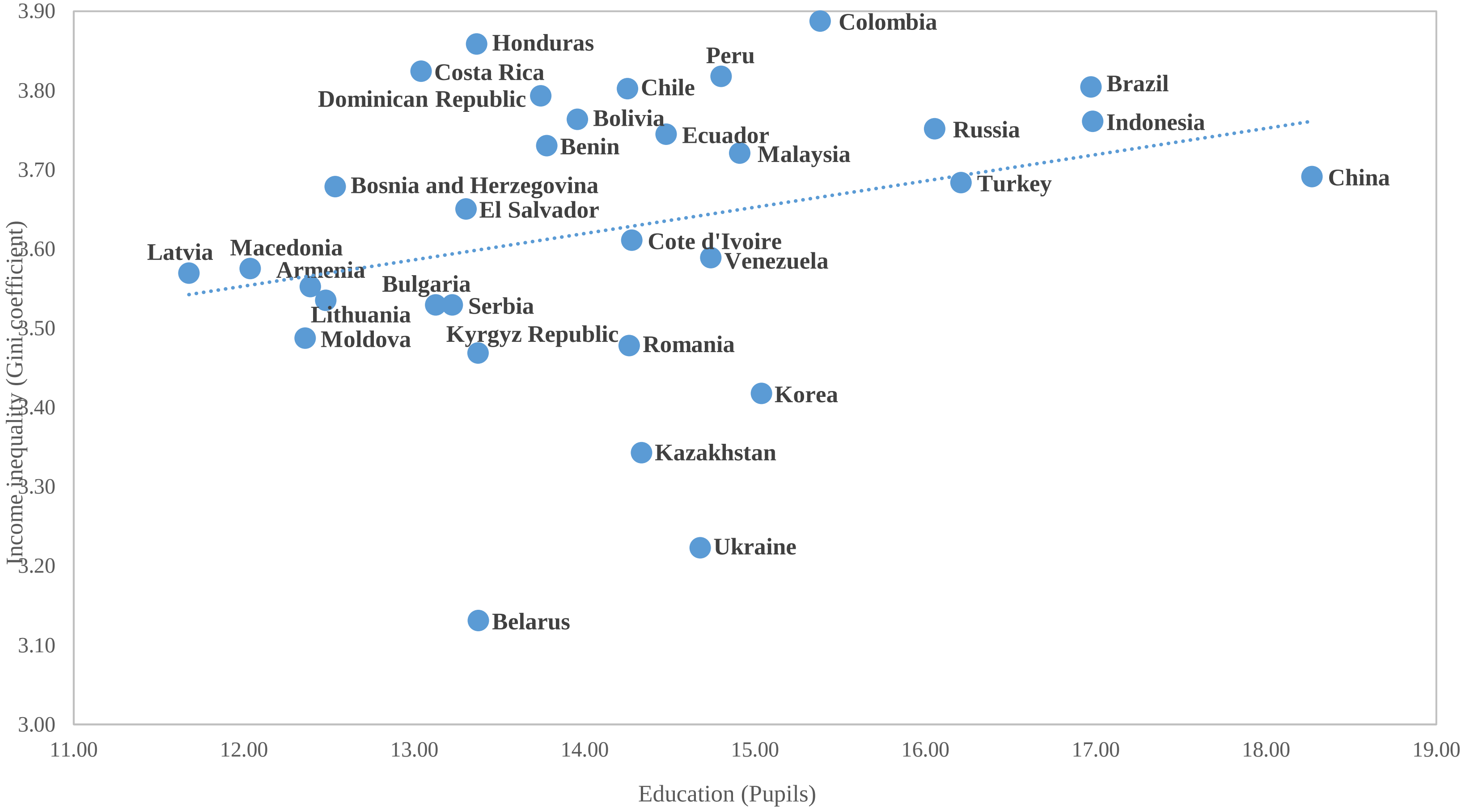


Figure 1.1: The relationship between education and income inequality for 22 developed countries in 2015
Income inequality (Gini coefficient)
3.80
3.70
3.60
3.50
3.40
3.30
3.20
10.00
11.00
12.00
13.00
14.00
15.00
16.00
17.00
Education (Pupils)
Hong Kong SAR, China
Israel
Portugal
Spain
Estonia
Italy
New Zealand
Cyprus
Ireland
Switzerland
Croatia
Germany
Hungary
Malta
Austria
Netherlands
Denmark
Sweden
Finland
Czech Republic
Norway
Slovak Republic

Figure 1.2: The relationship between education and income inequality for 32 developing countries in 2015



1.2 Research Problem

The trend of the income inequality is rising in the world and many researchers are trying to find out the reason behind. According to a report by OECD, it showed that there is an overall 1.7% of household income increased yearly. However, the bottom earners of the world only increased annually by 1.4% while the world top earners' income raised by 2%. Besides that, it was found that the top 10% of the Americans had the average of nine times income more than the rest of 90% in the U.S based on their household income in 2015 (Saez, 2018). As the result, it indicated that there was only minority are holding on most of the money and majority are holding on little amount of the money. The income inequality is becoming more serious in the world.

The countries that have been facing the problem of income inequality are not only the developing countries but also the developed countries. As the statistic result from OECD, Mexico had 48 out of 100 in GINI* among the developing countries while the U.S. had the first ranking among the developed countries which had 38 out of 100. As the result, income inequality happens in many countries, no matter how developed the country is, the income gap is still existing. Therefore, the issue of income inequality is how the country policy makers solve the problem as the policy makers play an important role in order to change the current condition.

According to the college-enrollment rate in U.S., it showed the gap between richer college students and poorer students is getting wider from 1970 to 2015. It means that most of the top-income group have obtained education more than the low-income people. The top-income group had 99% of people graduated from college while the low-income group only had 20% of people graduated from college in 2015. The reason was the low-income group often has competing issue such as job obligation or family issue which took them away from school and made them more likely to discontinue (White, 2015).

Based on the human capital theory, scholars believed that the optimal way to improve income inequality was to invest human capital. It implied that one of the methods towards evolution of income inequality was to provide education. Becker

GINI*: 0 – 100. 0 is perfect equality, 100 is perfect inequality.

and Chiswick (1966) suggested that education could balance the income distribution which mean the higher education could reduce the income inequality. However, Mincer (1974) proposed that there was a positive relationship between education and income inequality as educational expansion would widen the income gaps. Moreover, Mayer (2010) concluded that the reduction of education inequality would not promise to decrease inequality of income because income distribution might be influenced by other factors as well. Therefore, according to the results, the impact of education on income inequality is still ambiguous.

Based on the literature reviews, this study found out that most of the researchers did not combine and compare the impact of education on income inequality in both developing and developed countries. Moreover, researchers usually emphasized on all levels of education such as primary, secondary and tertiary education. (Shahabadi et al., 2018; Ismail, 2000; Mayer, 2010). The question is although many countries have a compulsory secondary education for the youngsters, but will it be an important issue to influence the income inequality? Therefore, this study will emphasize on the relationship between secondary education and income inequality in both developing and developed countries by using GMM estimator, so as to obtain a different result with the previous researchers.

1.3 Research Objectives

1.3.1 General Objectives

In this research, the main objective is to examine whether education will be the key variable to explain the income inequality in developing and developed countries. Following by other control variables such as financial development, economic growth, trade openness and technological changes, and so on.

1.3.2 Specific Objectives

1. To examine the impact of education on income inequality in developing countries.

2. To investigate the impact of education on income inequality in developed countries.

1.4 Research Questions

1. Does education affect income inequality?

2. Does different levels of education affect the result of income inequality?

3. Is it significant relationship between education and income inequality?

1.5 Research Significance

This section will roughly show the idea about how important education and its impact towards income inequality. The dependent variable of this study is income inequality while the independent variable is education. There are some empirical reviews conducted to provide the link between education and income inequality in this study. Generalized Method of Moments (GMM) also used to measure the relationship between education and income inequality in this study. The reason of this study using GMM model instead of other models is because Generalized Method of Moments (GMM) dynamic panel estimators are increasingly popular in many studies. Moreover, both "difference GMM" and "system GMM" estimators are designed for "small-T, large-N" panels analysis, and integrate with some assumptions on the data-generating procedure which will be discussed further in Chapter 3 Methodologies.

This study may bring out contributions to some parties. Firstly, by analyzing the relationship between education and income inequality, this might help those economics to solve the unemployment problems. According to Fields (1980), education can raise the chances of someone for working in a superior job. In developing countries, with the more education, economists might decrease the unemployment problem. When there is lower unemployment, indicates there is a higher employment and those lower income workers have more wages and this tend to decrease the different of income distribution and income inequality.

Government might also gain benefits from citizens towards this study. By understanding more on how education affect income inequality, this might reduce the crime rate, unemployment, illness, and social alienation. This is due to the quality of education may foster an individual to get a gainful employment, enhance the quality of life stable families, and become an active and productive citizens. When education has improved and solved those economic or political issue, this will gain the trust from the citizens to become a stronger country and society (Mitra, 2011).

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

In chapter 2, we will discuss further on income inequality by reviewing the past researcher's studies. It consists of three parts. The first part will present the theoretical review that applied the human capital theory where related with this study. Next is presenting the literature review of the relationship between income inequality and education, financial development, economic growth, trade openness and technological changes. Last part will be the gap of study which discusses about the differences between our study and previous researchers.

2.1 Theoretical Review

2.1.1 Human Capital Theory

A number of researchers (Becker & Chiswick, 1966; Fields, 1980; Gregorio & Lee, 2002; Mincer, 1974; Ram, 1989; Schultz, 1963) have examined the effects of education on income inequality can be explained by the traditional human capital theory.

The human capital theory indicated that the level of education among population ascertain the income inequality (Becker & Chiswick, 1966; Mincer, 1974). This theory suggests that the effectiveness of productive efforts mostly based on the labors' skills and knowledge, which came from the outcome of investment in human capital (Becker, 1962). Education becomes a key factor in examining the income distribution, because labor with skill and knowledge will be rewarded with a higher pay. Therefore, this theory predicts that the income inequality in a society was influenced by the labor demand and supply of educated people.

Whereas, this theory has found the relation among the educational level that was measured by the average years of schooling on income inequality can be either negative or positive, which depends on the expansion level of the education.

In previous research, Schultz (1963), stated "these changes in the investment in human capital are a basic factor reducing the inequality in the personal distribution of income". Schultz was referring to the situation in United States, which the human capital had a more rapid growth compared to non-human capital. Therefore, this viewpoint proclaims that as the human capital increases more than non-human capital, generally income inequality is expected to decline.

Partially in the spirit of human capital theory, Knight and Sabot (1983), claimed that whether the raise and decline in income inequality was affected by the changes in the educational expansion, depends on relative mean wages, wage dispersions and the size of different educational level. The main result has shown two types of effects on income inequality, which was the "composition" effect and "wage compression" effect. The first effect indicated the more education which rewarded with higher income tends to rise the income inequality. However, for the second effect follows by the "expansion of supply of educated labor relative to demand", will lead to an opposite direction effect (Ram, 1989).

In the study of human capital theory, Fields (1980), found a likely positive relationship between mean of education level and income inequality. Hence, this theory identifies if the educational level reduced will lead to a reduction in income inequality, while other variables held constant.

2.2 Review of the Literature

2.2.1 The Relationship between Income Inequality and Education

Based on few researchers (Mincer, 1974; Schultz, 1961; Becker, 1962), income inequality can be influenced by education level, also called as skills deepening (Williamson, 1991). According to Sianesi & Van Reenen (2003), the endowments at different levels of education such as primary, secondary, and tertiary education were depend on a country's development level. A higher level of educational attainment can be achieved through improvements in education such as lower tuition fees, better education financing and higher quality of education.

Due to the presence of wealth inequality, educational attainments and income inequality were positively correlated. Income inequality diminished the creation of new human capital. There was no good reason to support that it might lower the existing human capital which the 'stock' was referring to the average educational level of the population. In a past research, Li, Squire & Zou (1998) found that there was a positive significant relationship between secondary education on income inequality. When there was more political freedom, the society became more informed, the more difficult for those rich individual to appropriate extra resources. According to Mairesse (1990), he found that the coefficient of secondary education was higher than tertiary education, this proved that secondary had a greater sway on the variation in income inequality compared to tertiary education. In other words, the higher the secondary educational attainment, the higher the income inequality. Furthermore, the impact of secondary and tertiary educational achievement, as well as of educational inequality on income inequality was positively and significantly related due to imperfect competition for positions requiring advanced educational credentials. When the level of education (secondary and tertiary education) increased the highly educated people, it tend to raise the wages of those educated people compared to those who were less educated, thus, income inequality increased (Rodríguez-Pose, 2009). In contrast, the past result also showed that secondary education was negatively related to income inequality. The higher the education, the more the negative significant relationship related to income inequality (Barro, 1999).

There was a researcher proved that tertiary education and income inequality had a negative relationship. In other words, higher tertiary education lead to lower income inequality. More education had increased the upward mobility, thus, greater the income equality. Higher tertiary education also increased the earning opportunity, thus income inequality was decreased (Checchi, 2000). However, involved more in education allowed for a more informed participation in the market economy, thus the lobbying ability of rich drops. This raised the job and social opportunities for the poor individuals, thus, imply lower inequality (WorldBank, 2002).

According to Knight& Sabot (1983), the effect of education on income inequality was based on the balance of demand and supply. The balance between the “composition” and “wage compression” had impacted different types of educational attainment on income inequality. For the “composition” effect, when there was an increase in tertiary education, increased income inequality. While concerned with the “wage compression” effect, over time education leads to decreased income inequality. When the supply of highly educated workers raised, the increased of tertiary education will reduce the wages of highly educated workers, in opposite, when the supply dropped, simultaneously raised the wages of the less-educated workers. Tinbergen (1975) stated that, if there was a rise in the educated labor supply, it was likely to increase the competition for positions to require advanced educational credentials and hence reduce the income differential between the more and the less educated individuals. In addition, an increase on the proportion of the population attaining a higher level education leads to inflation in the value of educational credentials. In the long-run, decreased the wages for those highly educated workers. Thus, the effect of education on income inequality is based on the balance of supply and demand.

Refer to the research from Thorbecke & Charumilind (2002), for the supply side of skilled labor education, when there was a greater share of highly educated workers, the employer will indicate that those individuals with less education had a lower ability, and so the income of individual with less education might be reduced compared to those who have higher education. Hence, a greater wage inequality occur between individuals with high and low levels of education. From the demand side of skilled labor education, when the demand of unskilled labor were growing slower than the demand of skilled labor, the income inequality will rise.

According to some researchers on past studies, education was the most important indicator in human development. Education was not only to transform the quality of life, it was also a symbol as the source of economic growth, and expand the capacity of an individual in knowledge and professional skills. Based on past studies, many researchers had conducted the study to prove the positive relationship between education and income inequality (Coleman et al., 1975; Heckman & Vytlacil, 2001; Castelló & Doménech, 2002; Gregorio & Lee, 2002). There was a researcher (Mincer, 1974) found that there was a positive relationship between education and income inequality. He stated that educational expansion increased the income gaps. The reason was the rate of return on higher education was higher than the rate of return on the compulsory education. In addition, when there was more comparatively high position, educational expansion did not reduce income inequality.

In contrast, based on research conducted by Checchi, Ichino, & Rustichini (1999), they stated that family background was an important factor to affect the education. If a graduated high school student was able to attend college by obtaining loan, the employer will think that those who do not attend college had a lower ability on education level or they were came from poor families. High school graduates can afford went to college, but those individuals with low ability were not participate in higher education when budget constraints do not exist. Individuals who do not receive higher education do not indicate that they have high levels of abilities, employer will squeeze the wages of non-skilled workers and enlarge the gap of wages between those higher education individuals and lower education individuals (Hendel, Shapiro, & Willen, 2005). The research conducted by Sylwester (2002) also found that more educational expansion had reduced the income inequality in higher income level countries such as East Asia, Latin America and Africa represented by Gini coefficient. Moreover, from the empirical studies, researcher also found that a higher level of educational attainment among the labor force can equalize the effect on income distribution, hence, lower the income inequality (Becker & Chiswick, 1966; Park, 1996).

Sylwester (2002) stated that education had negative impact towards income inequality. Provided that individual have sufficient resources to forgo income and attend school, the public education can lower the level of income inequality. If individuals were too poor to attend school, the promoting of public education may skew the distribution of income. This was because they were taxed for revenue but do not enjoy the benefits of the public education system.

However, in the opposite view, Jimenez (1986) argued that many public education expenditures did not benefit the poor at all and, hence, income inequality did not drop but increased. One researcher also argued that the income inequality did not diminish even though many countries dedicated more resources to public education (Fields, 1980). From the empirical papers conducted by Ram (1989), he had concluded that it was ambiguous to determine whether public education expenditure can lower the income inequality. The researcher concluded that there was no strong evidence to support that the higher education can lower the income inequality.

2.2.2 The Relationship between Income Inequality and Financial Development

According to Abiad et al. (2008), financial development defined as a volume increase in financial activity. Based on the results from (De Haan & Sturm, 2017), proclaimed that income inequality increase due to high levels financial development, which was supported with the research of (Greenwood & Jovanovic, 1990) but it was in contrast with the prediction by (Bumann & Lensink, 2016). Besides, other recent researches have proved that increase in income inequality due to increase of financial development (Jauch & Watzka, 2012; Jaumotte et al., 2013, Li & Yu, 2014; Denk & Cournede, 2015; Dabla-Norris et al., 2015).

Extensive and intensive margin indicated different effects on finance. Extensive margin is the use of financial services by those individual that does not use it previously. For example, information and transaction costs, financial imperfections which lead to loosening of credit constraints have given advantages to the poorer individuals that lack of collateral and poor credit histories (Beck et al., 2007). Income inequality declined in this financial imperfection case which also supported by Galor & Moav (2004). In contrast, intensive margin gave a different effects of financial development on income inequality. The improvement in the quality of financial services does not widen the access of financial services to those poorer individuals; meanwhile was enjoyed by those richer level individuals who have already purchased financial services previously. In this intensive margin effects case gave benefits to those richer individuals, which lead to a larger gap in income inequality (Greenwood & Jovanovic, 1990).

Other than positive correlation among income inequality and financial development, some of the researchers argue that there is a negative correlation which the higher levels or quality institution of financial development, the lower the income inequality (Li et al. 1998; Clarke et al., 2006; Beck et al., 2007; Kappel, 2010; Hamori & Hashiguchi, 2012; Agnello & Sousa, 2012; Rajan & Zingales, 2003; Kunieda et al., 2014; Naceur & Zhang, 2016). The question of whether everyone in different social classes gains equal access to financial development was first considered and theoretical identified in the model by Greenwood & Jovanovic (1990), and showed that the relationship between income inequality and financial development were inverted U-shaped relationship.

Moreover, several studies concluded that some countries which have reached a particular threshold level of institutional quality or financial development only can lower the income inequality through financial development (Law et al., 2014; Bahmani-Oskooee & Zhang, 2015). For those poor income individuals who were excluded from getting loans previously, can access to it after financial sector developed well. In this case, financial development might be an effective tool to equalize the income distribution (Clarke et al., 2006). Various theoretical models proclaim that a better financial development will lower the income inequality, which is consistent with the idea financial development might benefit to those poorer individuals (Banerjee & Newman 1993; Galor & Zeira 1993).

2.2.3 The Relationship between Income Inequality and Economic Growth / Economic Development Growth

According to Rubin & Segal (2015), the volatility of income for the top 1% and 5% group is around twice compared to the lower 90% group as to the concurrent GDP per capita growth and next year’s GDP per capita growth. They found that, the top income group was highly sensitive to performance-based compensation schemes like bonuses, stocks and options during the post-war period from year 1953 to 2008. Moreover, with an increase in economic growth, the top income groups were able to gain more wealth income, therefore the income inequality gap became wider in this scenario. Generally, the results shown by the researchers proclaimed that higher economic growth tend to increase the income inequality in US, Japan and China (Yang & Greaney, 2017). On the other hand, other researchers who used the two-stage instrumental variables approach showed that, income share of the top 1% increased while the bottom 90% declined when the GDP per capita growth increased (Dollar & Kraay, 2002).

Based on recent studies, they showed economic growth is positively correlated with income inequality in Tunisia (Lundberg & Squire, 2003; Rubin & Segal, 2015; Wahiba & Weriemmi, 2014). Based on the semi parametric method that used by Chambers (2010), indicated the income inequality for all countries increased caused by economic growth over short or medium run.

In contrast, some researchers argued that there were negative relationship between income inequality and economic growth (Majumdar & Partridge, 2009; Nissim, 2007). Furthermore, Nissim (2007) revealed that when there was an economic boost condition, workers were paid in a higher income, which helped to lower income inequality. Besides, Rubin & Segal (2015), concluded that the lower income group was inversely correlated to the changes of GDP per capita growth. In developing countries, economic growth lowers the income inequality but has contrast effect in developed countries in long term effect (Chambers, 2010).

2.2.4 The Relationship between Income Inequality and Trade Openness (TO)

Trade openness is total imports and exports as a percentage of GDP. Edwards (1997), Lundberg & Squire (2003) found that trade openness measured as the sum of exports and imports as a share of the GDP was deemed for the potential trade and inequality relationship. Based on Heckscher-Ohlin Model in Jones (2008), it assumed that two types of countries had different results of the relationship between trade openness and income inequality which were developed country (DC) and less developed country (LDC). Developed countries usually had more skilled-labor thus they could export skill-intensive goods and indirectly relative income rate of skilled labor gap became wider which led to larger income inequality in the developed countries. In contrast, those developing countries would close up the income distribution because imports would harm their capital owner and skilled labor but exports would only bring advantages to unskilled workers. Hence, the trade openness resulted in an increased in income inequality in developed countries and reduced in less developed countries. However, there was an opponent argument by Rodrik (1998), he suggested that trade openness brought benefits to firms in developed countries because they were able to substitute unskilled workers with cheap imports, it weakened labor’s bargaining power and cut down their salary. Therefore, trade openness could be concluded that it brought most of the benefits to developed countries with less benefits to less developed countries. Besides, there were some empirical evidences showed that the impact of trade openness on income inequality were ambiguous (White & Anderson, 2001; Dollar & Kraay, 2002). In a nutshell, although some researchers argued that the relationship between trade openness and income inequality was uncertain, but most of the researchers found that it has positive impact in developed countries and negative impact in less developed countries. Therefore, it could be concluded that it was positive for developed countries and negative for less developed countries.

2.2.5 The Relationship between Income Inequality and Technological Changes

Ciriaci (2016) suggested that being innovative supports would help to maintain a firm’s organic employment growth pattern so the income distribution would be more tend to youngsters due to their fast adaption of innovation. Furthermore, there was another statement said that technological changes increased the inequality. Based on Frey and Osborne’s evidence, it showed that computerization usually influenced low-skilled jobs, and this would widen the income gap between skilled and unskilled labors. However, according to Schumpeterian hypothesis (Schumpeter, 1942), it indicated that technological change would lead to an increasing economic growth. Thus, the more rapid the rate of technological change was, the quicker the rate of economic growth was and it would give a drop on the income inequality level. The hypothesis also emphasized that technological changes and economic growth could not be separated. Besides, Kuznets (1963) suggested that faster rate of technological innovation were adopted, it would strengthen the negative nexus between economic growth and income inequalities. He also hypothesized that there was a rise in degree of inequality with increasing average household income at the beginning. Over time, public policy and labor market development would alleviate the effect, in the end the inequality would fall again but it needs to take time.

Higher labor productivity growth means that it only requests less labor to produce a particular level of output and is given a higher pay to them. Technological changes could rise labor productivity and lead to a positive impact on incomes. Income of individual would increase due to higher labor productivity, hence the savings of individual and capital supply would increase as well. Besides, the interest rate of bank would slowly decline. Therefore, this would result in an equal distribution of wages because of a weakening share of wages held by bondholders (Antonelli, 2017). In conclusion, most of the researchers proved that technological changes had more negative impact on the income inequality rather than positive impact.

2.3 Gap of study

Previous studies that related to this topic have used different explanatory variables on different individual country and different time period. Meanwhile in this study, the major focus is to identify the key impact of education and other control variables on income inequality in 34 developed countries from year 1971 to 2015 and 51 developing countries from year 2003 to 2015 respectively.

There were many previous researches applied various methods to investigate this related topic, nevertheless there were few researches merged those variables that applied in these studies by using Generalized Method of Moments (GMM) dynamic panel estimator. Most of the studies related to this topic were mostly estimated by applying *Ordinary Least Squares (*OLS), Panel Fixed Effects, Overlapping Generation Model, Probit, Fixed Effect and so forth, instead of using Generalized Method of Moments (GMM) estimator (Jakob & Sturmc, 2017; Nissim, 2007; Pose & Tselios, 2009; Checchi, 2000). There were also few researchers used Generalized Method of Moments (GMM) estimator, but using different explanatory variables (Mehic, 2018; Liu et al., 2017).

In this study, dynamic GMM model is applied instead of static model, because static model only able to capture the immediate effects of education on income inequality, where dynamic model is able to capture the time lag effects. A lag effect used to illustrate and capture the effects of the past or some essential effects on the variables (Roodman, 2006). Therefore, the estimations of this study can be more effective and efficient because the time lag effects have been captured on how those exogenous variables will influence the income inequality in various aspects.

CHAPTER 3: METHODOLOGY

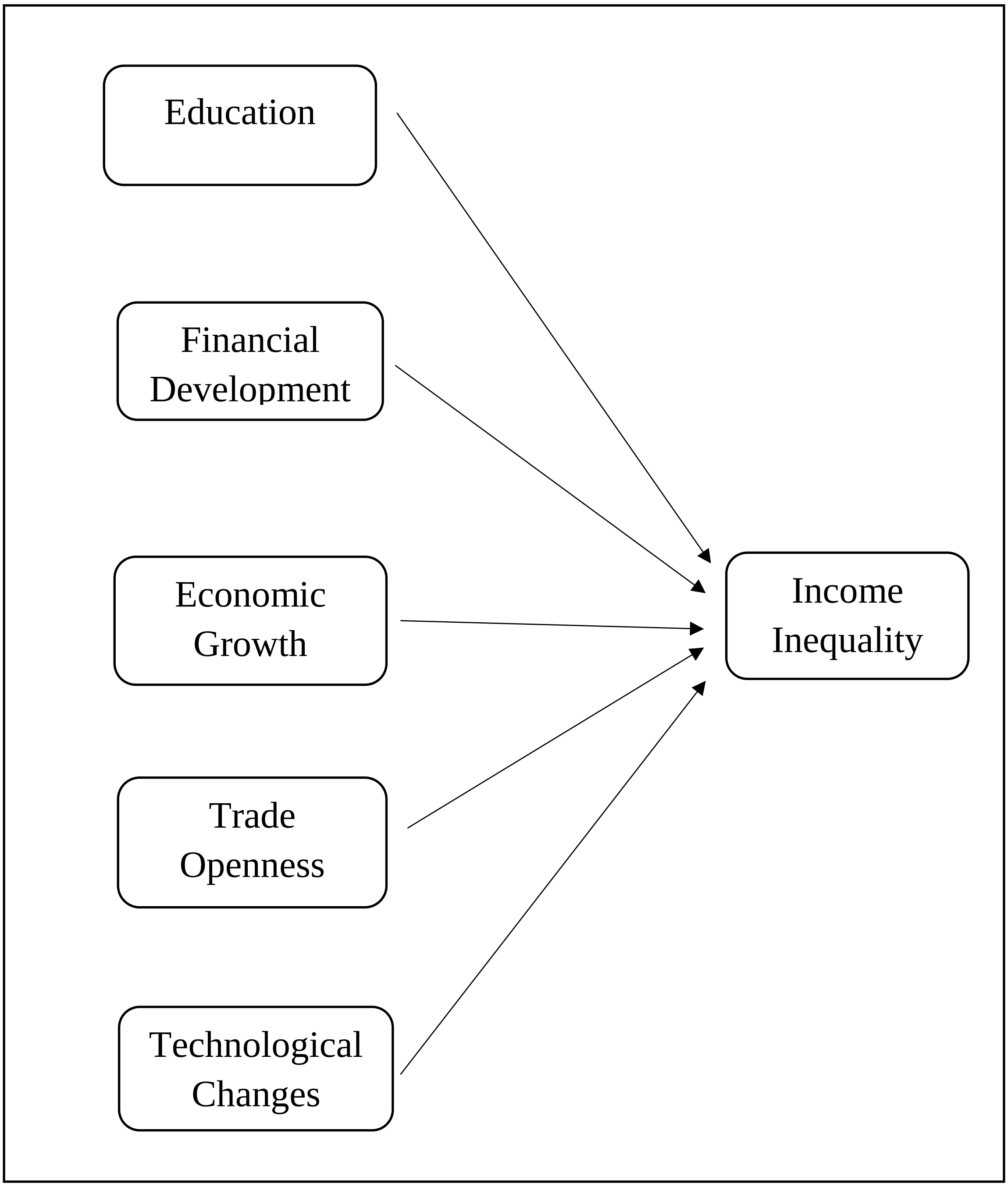
3.0 Introduction

This chapter is about research methodology, including research design, research framework, hypothesis development, data description and data analysis. Therefore, if the method used in the study is not appropriate, the result can be misleading so it is important to choose the right methodology. The methodologies discussed in this chapter will be further used in the following chapters. Besides, to ensure the accuracy of our results, this study will use several statistical tests to test our model.

3.1 Research Design

This study will use secondary data. Secondary data can be obtained from Standardized World Income Inequality Database (SWIID) and World Development Indicators (WDI), it contains official research data that completed by previous researchers, and it can be retrieved in a usable format easily (Hox & Boeijie, 2005). During the information and data collection process, journal articles are mostly used in this research paper because different supporting evidences are needed to find out whether education is affecting the income inequality levels of developing and developed countries.

3.2 Research Framework



Sources: Becker & Chiswick (1966), Greenwood & Jovanovic (1990), Lundberg & Squire (2003), Rodrikn(1998), Kuznets (1963).

3.2.1 Education and Income Inequality

Based on few researchers, income inequality could be influenced by education level (Mincer, 1958; Schultz, 1961; Becker, 1962), referred as skill deepening (Williamson, 1991). According to Sianesi & Van Reenen (2003), however, the endowments at different levels of education such as primary, secondary, and tertiary education were depended on a country's development level (Sianesi & Van Reenen, 2003). Due to imperfect competition for positions requiring advanced educational credentials, while the level of education increase highly educated people, this tend to raise the wages of those educated people compared to those who was less educated, thus, the income inequality increased. A higher level of education such as secondary and tertiary education gives more opportunity to those highly educated individual, because their income tend to be higher compared to less educated individuals. They also had more opportunities to engage in a higher paid jobs. This may enlarge the distance of the income distribution between highly educated and less educated individuals, thus, increase the income inequality (Rodríguez-Pose, 2009). In addition, more education would increase the upward mobility which led to greater income equality. Hence, the relationship between education and income inequality was expected to be positive in both developed and developing countries.

3.2.2 Financial Development and Income Inequality

Various theoretical models proclaimed that a better financial development would lower the income inequality, which was consistent with the idea of financial development might benefit to those poorer individuals (Banerjee & Newman 1993; Galor & Zeira 1993). For those poor income individuals who were excluded from getting loans previously, could access to it after financial sector developed well. In this case, financial development might be an effective tool to equalize the income distribution, thus, lower the income inequality (Clarke et al., 2006). Moreover, several researchers also concluded the negative relationship between education and income inequality was due to some countries that had reached a particular threshold level of institutional quality, so financial development only could lower the income inequality (Law et al., 2014; Bahmani-Oskooee & Zhang, 2015). Hence, there was an expected negative correlation between financial development and income inequality in both developed and developing countries.

3.2.3 Economic Growth and Income Inequality

In developed countries, according to recent studies (Lundberg & Squire, 2003; Rubin & Segal, 2015; Wahiba & Weriemmi, 2014) showed that economic growth was positively correlated with income inequality in Tunisia. Based on the semi parametric method that used by Chambers (2010), indicated the income inequality for all countries increased was caused by economic growth over short or medium run. With an increased in economic growth, the higher income group was able to gain more wealth income and the income inequality rose in this case. Generally, the results shown by the researchers proclaimed that higher economic growth tend to increase the income inequality in US and Japan. Hence, the expected relationship between economic growth and income inequality in long term effect are positive in developed countries.

In developing countries, the researchers stated that there was an inverse relationship between income inequality and economic growth (Majumdar & Partridge, 2009; Nissim, 2007). Furthermore, Nissim (2007), revealed that when there was an economic boost condition, workers were paid in a higher income, the wages of low income group increased, and so was able to minimize the income distribution gap and help to lower income inequality. Hence, the correlation between economic growth and income inequality was expected to be negative in developing countries.

3.2.4 Trade Openness and Income Inequality

Due to developed countries usually had more skilled-labor, thus they could export skill-intensive goods and income rate of skilled labor gap became wider which led to larger income inequality in the developed countries. There was a research conducted by Rodrik (1998), said that trade openness brought benefits to firms in developed countries because they were able to substitute unskilled workers with cheap imports, it weakened labor’s bargaining power and cut down their salaries. Therefore, the income inequality increased. Hence, trade openness was expected to have positive relationship with income inequality in developed countries.

In developing countries, those countries would close up the income distribution because imports would harm their capital owner and skilled labor but exports would only bring advantages to unskilled workers. Trade openness brought less benefits to developing countries. Many empirical evidences showed that the impact of trade openness on income inequality were ambiguous (White & Anderson, 2001; Dollar & Kraay, 2002; Higgins & Williamson, 1999; Edwards, 1997). Hence, trade openness was expected to reduce the income inequality in developing countries.

3.2.5 Technological Changes and Income Inequality

According to Schumpeterian hypothesis, technological change would lead economic growth to increase. When technological changes grow rapidly, it tends to increase economic growth too. Thus, it would give a drop on the income inequality level. Kuznets (1963) proposed that if there was short of demand on this compensation effect, it would have a downward pressure on the income overall. The premium shrinks and eventually disappears in the labor market, and the income inequality is also declined. Hence, technological changes had an expected negative correlation towards income inequality in developed countries.

Ciriaci (2016) suggested that being innovative supports would help to maintain a firm's organic employment growth pattern so the income distribution would be more tend to youngsters due to their fast adaption of innovation. Thus, the wages of the youngsters were more than those older employees. This might widen the gap of income between those youngsters and older employees. Based on Frey and Osborne's evidence, it showed that computerization usually influenced low-skilled jobs. This would widen the income gap between skilled and unskilled labors, thus indicates that income inequality increased when technological changes increased. Hence, there was an expected positive relationship between technological changes and income inequality in developing countries.

3.3 Hypothesis Development

Table 3.1

Hypothesis Development

Variable	Abbreviation	Definition	Expected Sign (Developed countries)	Expected Sign (Developing countries)	Data Source
Income Inequality	GINI	Estimation of Gini index of inequality in equivalised (square root scale) household disposable income that has deducted the post-tax and post-transfer, and using Luxembourg Income Study (LIS) data as the standard.	Positive	Positive	SWIID
Education	EDU	Education is one of the powerful tools used to reduce poverty and improve health, peace, gender equality and stability. Receiving education is also known as a human right.	Positive	Positive	World Bank
Financial Development	FD	Domestic credit provided by the financial sector which is used to measure the level of financial development. Financial	Negative	Negative	World Bank

		development occurs when financial market, instruments and intermediaries relieve the effects of transactions and information cost.			
Economic Growth	GDP	Economic growth normally measured by GDP annual percentage. GDP is calculated by summing up the gross value plus any product taxes and deducting the subsidies that are not contained in the products	Positive	Negative	World Bank
Trade Openness	TO	Trade is the total of imports and exports of goods and services, which is also measured as gross domestic product (GDP).	Positive	Negative	World Bank
Technological Changes	TECH	Patent applications is a type of measurement in technology, which gives new technical solutions or new ways to do something on a process or product.	Negative	Positive	World Bank

Notes. GINI is Income Inequality. EDU is Education. FD is Financial Development. GDP is Economic Growth. TO is Trade Openness. TECH is Technological Changes.

3.4 Data

This research identified the key impact of education and other control variables on income inequality in two categories of countries, which were developed countries and developing countries. For developed countries, it encompassed 405 observations, including 34 countries across 45 years from year 1971 to 2015. In developing countries, it encompassed 460 observations, including 51 countries across 13 years from the year 2003 to 2015. Meanwhile, this study applied unbalanced panel data. The mechanism is similar with the case in balanced data. However, individuals involved in unbalanced panel data were specified by the time dimension (Hurlin, 2018).

By gathering all the relevant data and methods, this research has taken the income inequality (GINI) into consideration of the endogenous variable. The data was derived from Standardized World Income Inequality Database (SWIID), measured in Gini coeficient (Zhang, 2010). For the exogenous variables, it included education (EDU), financial development (FD), economic growth (GDP), trade openness (TO) and technological changes (TECH). The data of all the exogenous variables were derived from World Development Indicator (WDI). All the obtained data was measured in percentage (%), except for the technological changes which used patent applications, non-residents.

Meanwhile, education (EDU) is the variable with the proxy of secondary education and pupils (Checchi, 2001). For financial development (FD), it applied domestic credit provided by financial sector as its proxy, measured in percentage of GDP (De Haan, & Sturm, 2017). Next, the economic growth (GDP) applied GDP growth as the proxy, and was measured in annual percentage (Rubin & Segal, 2015). Moreover, trade openness (TO) applied trade as the proxy and was measured in percentage of GDP (Edwards, 1997). Whereas, technological changes (TECH) applied patent applications, non-residents as the proxy (Jaffe, 1993).

3.5 Empirical model [1]

The researchers used Generalized Method of Moments (GMM) dynamic panel estimators in this study. There are two GMM dynamic panel estimators, which is “difference GMM” and “system GMM”. The first which is Arellano-Bond (1991) estimator, it reforming all the regressors by differencing, and named as “difference GMM”. Whereas system GMM is an augmented estimator version figured out by Arellano-Bover (1995) and fully developed by Blundell-Bond (1998).

The “system GMM” estimated that the fixed effects are uncorrelated to the instrument variables. Therefore, adding on more instruments can help to improve its efficiency.

Both “difference GMM” and “system GMM” estimators are designed for “small-T, large-N” panels analysis, and integrate with some assumptions on the data-generating procedure:

1. There may be accommodating a distributed fixed individual effect. An argument which fixed the following effect must be assumed away in cross-section regressions, and variation over time can be used to find out the parameters in favourable panel set-up.
2. This procedure may be dynamic as the past effects influenced the dependent variable.
3. Some explanatory variables are not rigidly exogenous.
4. The fixed effects-idiosyncratic errors may have specific-individual patterns of heteroscedasticity and autocorrelation.
5. The fixed effects-idiosyncratic errors are uncorrelated throughout individuals.
6. Some regressor may be fixed upon but not precisely exogenous; even if the independent errors influenced by the past. One of the examples is the lagged dependent variable.
7. “Small-T, large-N” means little time period and many individual units.

[1] Refer to research from Roodman (2006).

8. Internal instrumented variables that based on lags of are available; however, the estimator allows to add on external instruments.

The general model of the data-generating process:

$$\ln GINI_{it} = f(\ln GINI_{it-1}, \ln EDU_{it}, \ln FD_{it}, \ln GDP_{it}, \ln TO_{it}, \ln TECH_{it}) \quad (1)$$

$$\ln GINI_{it} = \alpha + \delta \ln GINI_{it-1} + \beta_1 \ln EDU_{it} + \beta_2 \ln FD_{it} + \beta_3 \ln GDP_{it} + \beta_4 \ln TO_{it} + \beta_5 \ln TECH_{it} + \varepsilon_{it} \quad (2)$$

where GINI is Income Inequality, EDU is education, FD is financial development, GDP is economic growth, TO is trade openness, and TECH is technological changes.

According to the dynamic GMM estimation, equation (1) is estimated by using the two-step GMM estimator that is proposed by Arellano and Bond (1991). They discussed that a dynamic panel data model can create additional instruments if one meets the orthogonality requirement that exist between lagged values of Y_{it} and the error term v_{it}. Under this method, the model can be rewritten as below:

$$GINI_{it} = \alpha\, GINI_{it-1} + X'_{it}\,\delta + \gamma_{it}\ ; \quad i = 1, 2, \ldots N \quad t = 1, 2, \ldots., T \quad (3)$$

$$E[\gamma_i] = E[\mu_{it}] = E[\gamma_{it}\,\mu_{it}] = 0$$

$GINI_{it}$ is the income inequality in logarithms, X'_{it} is the explanatory variable in logarithms. Where $\gamma_{it} = \gamma_i + \mu_{it}$, and the γ_i and μ_{it} are independent to each other or among themselves. γ_{it} is the country-specific effect that obtains the individual heterogeneity and *vit* is the error term.

Based on the previous researches, one-step results were frequently reported instead of two-step. It is because two-step estimation typically yields standard errors that downward biased. However, two-step estimation seemed to be more superior when Windmeijer (2005) made finite-sample correction and provided an accurate result. Furthermore, Windmeijer (2005) found that two-step GMM estimation performed better by providing lower standard errors and bias compared to one-step estimation.

In addition, system GMM is more accurate than difference GMM in certain circumstances. For example, when there is high variance of the fixed effect term across individual observation or the stochastic process is approximately being random walk, the difference GMM estimator might performs poorly in finite sample. However, system GMM estimator uses an additional set of moment condition in order to solve the problem that difference GMM estimator faced. Difference GMM estimator performs poorly in finite sample properties because the lagged levels of the series are only weakly correlated with subsequent first differences, so it leds to weak instruments for the first-differenced equations. On the other hand, system GMM permits lagged first difference to be used as in the levels equations and this make any bias that would arise be corrected by using the standard GMM estimator. According to Arrelano and Bond (1991), although system GMM was more accurate than difference GMM but researchers still have to pay attention on certain situations. For instance, it had to ensure that the model passes both the tests of instrument validity (Sargan/Hansen) and the second-order serial correlation (AR2). Moreover, Blundell et al. (2000) proved that system GMM estimator could overcome many of the disappointing characteristic of the difference GMM estimator as mentioned above. In practical, it is better to have more instruments to increase the accuracy of estimates and to construct the tests for the validity of over-identifying restrictions. Therefore, policymakers and scholars have to be careful of the methods or data used in the model so as to obtain the precise and reliable result.

3.6 Empirical Methodology

3.6.1 Arellano-Bond test for AR (1)

The Arellano-Bond test was introduced by Arellano and Bond in year 1991 in order to test the autocorrelation problems for the dynamic model or data. It was an appropriate test for autocorrelation in linear GMM regression on panels, which was especially important when the lags were used as an instrument. Arellano-Bond Test was also used by Roodman for the application to a single residual series (Roodman, 2006), and its estimation started by transforming all the regressors and using the GMM (Hansen 1982). There are few situations that fulfill the Arellano Bond estimator and its extension to the System GMM context.

The data should include individual units with little time period which is large N and small T. This is because the dynamic panel bias will become significant if T is large. Whereas if N is small, the Arellano-Bond autocorrelation test may become unreliable. Moreover, the model must be in a lineal functional relationship, the dependent variable that is dynamic and depends on its past realisations; while the independent variables are assumed to be endogenous. Therefore, they are correlated with past and possibly current realisations of the error. The data must also have a fixed individual effect and imply unobserved heterogeneity (Baum & Schaffer, 2013).

The Arellano-Bond test for autocorrelation is valid for any GMM regression on panel data, which also included ordinary least square (OLS) and two stage least square (2SLS) as well. When there are no regressors which is "post-determined", it was depends on the future disturbances. If the T is small, a fixed effect and within groups regression may violate this assumption. Arellano-Bond test for the autocorrelation problem has a null hypothesis which is no autocorrelation and can be applied to the different residuals. The first tests of Arellano-Bond for autocorrelation are the alternative of a first-order auto regressive AR (1) model. This alternative AR (1) model considered the possible departure from independence only. The test for AR (1) usually rejects the null hypothesis (Mileva, 2007).

H_0: There is no autocorrelation of order 1 in the model.

H_1: There is autocorrelation of order 1 in the model.

3.6.2 Arellano-Bond test for AR (2)

Arellano-Bond test was initially designed for the dynamic panel data models, which the AR (1) was present in the differenced errors by construction. The presence of AR (2) was to complement to the standard Sargan-Hansen test for the problem of over-identifying restriction. AR (2) is a significant diagnostic test to test whether the instruments are valid or invalid.

Furthermore, Mileva (2007) stated that this Arellano-Bond test for autocorrelation problem had a null hypothesis of no autocorrelation and it is applicable to the different residuals. Based on the efficient two-step GMM estimator, AR (2) was used to test the second order serial autocorrelation problem in the first-differenced residuals under the null hypothesis of no serial correlation. Due to the AR (2) test was used to detect the autocorrelation problem in levels, so the first differences are highly important.

According to Baum and Schaffer (2013), the residuals of the different equation should possess serial correlation. Different residual must not display significant AR (2) behavior if the assumption of serial independence in the original errors was warranted. These statistics could be found in the outputs of xtabond and xtabond2. The second lag of endogenous variables would become inappropriate instruments for their current value when the AR (2) statistic was significant. The null hypothesis is: "no autocorrelation of order 2".

H_0: There is no autocorrelation of order 2 in the model.

H_1: There is autocorrelation of order 2 in the model.

3.6.3 Sargan-Hansen Test

In Ordinary least Square (OLS) method, “Identification” can be defined as the assumption of the regressors that are statistically independent to the error terms or the moments of regressors with the error terms which are zero. “Moments” includes mean, variance, skew and kurtosis. General 2SLS framework is to distinguish the exogenous regressors and instrument in a model. However, the problem of 2SLS was that the moment status of the equation model cannot be held perfectly when the instruments were more than regressors, which was also known as overidentified specification (Roodman, 2006). Instruments indicate that the instrumental variables that fulfill the conditions such as orthogonal to error term and the dependent variable only affected indirectly (Baum, 2003). The equation that shows regressor is independent to the error term or the moments of regressor with the error terms are zero is stated below:

$$Y = \beta X + \varepsilon$$

$$E\,[W, \varepsilon] = 0$$

$$E\,[\varepsilon\,|W] = 0$$

where Y is dependent variable, β is a column of coefficients, X is a column of regressors, W is a column of instruments and ε is error term.

3.6.3.1 Sargan Test

Sargan test was proposed by John Denis Sargan in 1958 and this test is used to examine the overall validity of the instrument when there is overidentified statistical model. Sargan test refers to a minimized value of the one-step GMM criterion function and this test is a special case of Hansen test when there is homoscedasticity situation. This is because Sargan's statistic is not robust when there is autocorrelation and heteroscedasticity problem in the model (Baum, 2003). Although such problem happenesbut sargan test is still needed because Hansen test has its own problem which could weaken the robustness when there is large instruments (Roodman, 2006). Therefore, it must involve sargan test in the result when testing the overall validity of the instrument.

3.6.3.2 Hansen Test

Lars Peter Hansen extended the Sargan test to Hansen test in 1982. Hansen test has the same function with Sargan test, which is used to examine the overall validity of the instrument when there is overidentified statistical model. However, Hansen test is minimized value of the two step GMM criterion function. This test does not reply on the assumption of homoscedasticity and the absence of serial correlation in the error term. Besides that, as the problem mentioned above, Hansen test suffers due to the numerous used of instruments. Therefore, researchers must follow the rule of thumb which the number of instrument must not surplus the number of group and keep it below 76 in the model (Mileva, 2007). On the other hand, the difference between Sargan and Hansen tests is sphericity of error. Sargan test requires spherical errors but Hansen test requires non-spherical errors (e.g. heteroscedastic errors). The joint null hypothesis is that the instruments are valid. In other words, the instruments and the error terms are not correlated. The null hypothesis and rejection of null hypothesis are stated below:

H_0: The over identifying restrictions are valid / all instruments are valid

H_1: The instruments are either correlated with the errors or there are omitted variables in the model

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

The previous chapter have discussed the methodologies and stated out the sources of the chosen data in this study. Consequently, this chapter discusses how significant are the selected variables in the explanation of income inequality.

4.1 Descriptive Statistics

4.1.1 Descriptive Statistics for Developed countries

Table 4.1: Descriptive Statistics for developed countries

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
GINI	1674	3.407359	.2136398	2.912351	3.956996
EDU	1045	13.49625	1.656707	8.269501	17.02357
FD	665	4.440001	.5538715	-.3763553	5.726144
GDP	1245	2.884004	.2275394	-1.288821	3.717716
TO	1139	4.22744	.675685	2.189363	6.064695
TECH	963	7.681258	1.980038	0	12.32267

Notes. GINI is Income Inequality. EDU is Education. FD is Financial Development. GDP is Economic Growth. TO is Trade Openness. TECH is Technological Changes.

Table 4.1 indicates the descriptive statistics for the developed countries among the variables: GINI, EDU, FD, GDP, TO and TECH for 45 years. The means of the variables were 3.407359, 13.49625, 4.440001, 2.884004, 4.22744 and 7.681258 respectively. Besides that, the standard deviations of EDU and TECH were more than 1 which were 1.656707 and 1.980038. However, the standard deviations of GINI, FD, GDP, and TO were 0.2136398, 0.5538715, 0.2275394 and 0.675685 which were all below the value of 1. Based on the means and standard deviations, the variables of EDU and TECH had larger value among all of the variables. In addition, the maximum value among the variables was EDU (17.02357) whereas the minimum value was the FD (-0.3763553).

Table 4.2: Correlations relationship for developed countries

Variable	GINI	EDU	FD	GDP	TO	TECH
GINI	1.0000					
EDU	0.3137	1.0000				
FD	0.3486	0.3601	1.0000			
GDP	0.0372	0.0117	-0.0999	1.0000		
TO	-0.1565	-0.6883	-0.2307	-0.0609	1.0000	
TECH	0.1694	0.6716	0.2750	0.1261	-0.5204	1.0000

Notes. GINI is Income Inequality. EDU is Education. FD is Financial Development. GDP is Economic Growth. TO is Trade Openness. TECH is Technological Changes.

Table 4.2 indicates the correlation relationship between the variables: GINI, EDU, FD, GDP, TO and TECH in developed countries for the past 45 years. TO was the only variable which had negative relationship with GINI, EDU, FD, GDP and TECH. Furthermore, GDP had a negative relationship with FD which meant when the GDP increased by 1%, the FD would decrease by 0.0999%. Other than the correlations that were mentioned above, all of the variables had positive relationship with each other. Among the correlations, the relationship between TECH and EDU was the largest positive relationship. In contrast, the TO and EDU had the strongest negative relationship.

4.1.2 Descriptive Statistics for Developing countries

Table 4.3: Descriptive Statistics for developing countries

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
GINI	3,389	3.704913	0.1832132	3.091043	4.110874
EDU	1,472	0.0324823	0.059531	-0.3711271	0.583703
FD	1,639	-0.0011896	0.096256	-1.986199	0.6430717
GDP	2,669	3.99815	0.1441706	-0.2851067	4.458809
TO	2,811	4.070237	0.5900976	-1.742951	5.740934
TECH	1,297	0.0112501	0.540622	-3.401197	4.609328

Notes. GINI is Income Inequality. EDU is Education. FD is Financial Development. GDP is Economic Growth. TO is Trade Openness. TECH is Technological Changes.

Table 4.3 shows descriptive statistics for developing countries among the variables for 13 years. Based on the table above, the means of GINI, EDU, FD, GDP, TO and TECH were 3.704913, 0.0324823, -0.0011896, 3.99815, 4.070237 and 0.0112501 respectively. The minimum value and the maximum value of GINI were 3.091043 and 4.110874. Besides, the minimum value and the maximum value of EDU were -0.3711271 and 0.583703. For EDU standard deviation, 0.059531 was the lowest as compare to other variables. However, TO had the highest standard deviation which was 0.5900976.

Table 4.4: Correlations relationship for developing countries

Variable	GINI	EDU	FD	GDP	TO	TECH
GINI	1.0000					
EDU	0.3083	1.0000				
FD	0.0449	0.0299	1.0000			
GDP	-0.1522	0.1035	-0.0269	1.0000		
TO	-0.3913	-0.2575	0.0143	0.0422	1.0000	
TECH	0.0192	0.1063	0.0574	0.0920	-0.0688	1.0000

Notes. GINI is Income Inequality. EDU is Education. FD is Financial Development. GDP is Economic Growth. TO is Trade Openness. TECH is Technological Changes.

Table 4.4 shows the correlations relationship between all variables: GINI, EDU, FD, GDP, TO and TECH in developing countries for the past 13 years. Firstly, variable GDP had negative relationship with the variables GINI and FD. Then, variable TO had negative correlation with variables GINI and EDU. Furthermore, TECH had only one negative relationship with variables TO. Instead of those variables stated above with negative relationship, the other variables had shown positive relationships among each other. Moreover, GINI and EDU had shown the largest positive relationship. In contrast, GINI and TO had the strongest negative relationship.

4.2 Diagnostic checking

Before processing to the models results shown in Table 4.5 and Table 4.6, this study had run the Sargan-Hansen Test and Arellano-Bond Serial Correlation Test to ensure that the results from these two tests met the required significance level. After running the tests, the researchers proceed to the result of dynamic panel GMM estimation in 34 developed countries and 51 developing countries.

4.2.1 Sargan-Hansen Test

In this research, Sargan and Hansen tests were used to examine the overall validity of the instrument when there was overidentified statistical model. According to the table 4.5 and 4.6, the p-values of the Hansen test in developed and developing countries were 1 which were more than the significance level of 0.9. Therefore, the null hypothesis must not be rejected. It represented that the overidentifying restrictions were valid in the models of both developed and developing countries. In developed countries, the p-value of Sargan test was 1 which was same as the critical value of 1. It also indicated that the model in developed countries was significant and all instruments were valid.

4.2.2 Arellano-Bond Serial Correlation Test

Arellano-Bond Serial Correlation Test was applied to test the autocorrelation problem in a model. The test consists of null hypothesis which is no autocorrelation and applied to the different residuals. The first tests of Arellano-Bond for autocorrelation are the alternative of a first-order auto regressive AR (1) model. Based on the table 4.5 and 4.6, the p-values of AR (1) were 0.002 and 0.02 in developed and developing countries respectively. Both of the model rejected the null hypothesis because they were less than the critical value of 0.09. It also meant that there was autocorrelation of order 1 in the model of developed and developing countries. According to Mileva (2007), he suggested that the test for AR (1) process in first differences usually rejected the null hypothesis.

On the other hand, AR (2) was used to test for the second order serial autocorrelation problem in the first-differenced residuals under the null hypothesis of no serial correlation. The p-value of both model 5 had shown there was 0.181 in developed countries and 0.22 in developing countries. For both developed and developing countries, the p-values were larger than the critical value of 0.1 so it could be concluded that there was no autocorrelation of order 2 in the system model.

Table 4.5: Result of dynamic panel GMM estimation in 34 developed countries.

	(1) One-Step Difference GMM	(2) Two-Step Difference GMM	(3) Two-Step Robust Difference GMM	(4) One-Step System GMM	(5) Two-Step System GMM	(6) Two-Step Robust System GMM
GINI	0.189***	0.177***	0.177**	0.925***	0.965***	0.965***
	(4.30)	(17.78)	(2.42)	(10.40)	(26.89)	(6.59)
EDU	0.0244*	0.0270***	0.0270*	0.0815***	0.0776***	0.0776***
	(1.74)	(12.34)	(2.01)	(4.08)	(11.76)	(3.85)
FD	-0.00900	-0.00943***	-0.00943	-0.0734**	-0.0648***	-0.0648**
	(-0.56)	(-3.62)	(-0.69)	(-2.19)	(-16.53)	(-2.42)
GDP	0.00507	0.00459***	0.00459	0.0465**	0.0383***	0.0383**
	(0.99)	(3.47)	(1.06)	(2.07)	(8.78)	(2.05)
TO	0.0144	0.00767	0.00767	0.0781**	0.0729***	0.0729***
	(0.65)	(1.44)	(0.33)	(2.55)	(16.30)	(3.67)
TECH	-0.00897***	-0.00878***	-0.00878**	-0.0225***	-0.0191***	-0.0191**
	(-2.87)	(-12.56)	(-2.17)	(-3.04)	(-11.20)	(-2.65)
_CONS				-0.819	-0.922***	-0.922*
				(-1.59)	(-6.72)	(-1.89)
AR1	10.27(0)***	3.301(0.001)***	3.280(0.001)***	1.227(0.220)	3.209(0.001)***	3.119(0.002)***
AR2	4.254(0)***	2.060(0.039)**	1.926(0.054)*	-0.552(0.581)	-1.338(0.181)	-1.177(0.239)
Sargan Test	80.36(0)***	80.36(0)***	80.36(0)***	31.36(1.00)	31.36(1.00)	31.36(1.00)
Hansen Test		23.58(0.486)	23.58(0.486)		26.33(1.00)	26.33(1.00)
N	426	426	426	460	460	460

Notes. GINI is Income Inequality. EDU is Education. FD is Financial Development. GDP is Economic Growth. TO is Trade Openness. TECH is Technological Changes.
P-values are in parentheses. * Indicate statistical significance at the 10% level. ** Indicate statistical significance at the 5% level. *** Indicate statistical significance at the 1% level.

4.3 Difference and System GMM Approach

4.3.1 Difference and System GMM Approach Results for developed countries

Table 4.5 represents the dynamic panel GMM estimations for the income inequality in 34 developed countries. In the comparison, System GMM was better than Difference GMM which had discussed in Chapter 3 and the table above also showed all of the values were significant if compared to the results of the difference GMM. Therefore, the result of System GMM is more reliable. In two step system GMM analysis, the education was positively correlated with income inequality.

An increase 1% in EDU caused the GINI coefficient to increase 0.965%, and other variables remained constant, on average. Becker and Chiswick (1966) found that a higher level of educational attainment among the labor force could equalize the effect on income distribution, so the greater the income inequality. Besides, Mincer (1974) found that there was a positive relationship between education and income inequality. The reason was the rate of return on higher education was higher than the rate of return on the compulsory education. Therefore, when there was more comparatively high position, educational expansion did not reduce income inequality.

From the perspective of financial development, it was negatively correlated with income inequality in the developed countries which means that when 1% of FD increased, GINI coefficient would decrease by 0.0648%. According to Kappel (2010) and Hamori & Hashiguchi (2012), they implied that there was a negative correlation which the better the financial development the lower the income inequality.

Furthermore, the economic growth was positively correlated to income inequality as proven by Chambers (2010). The previous study concluded that economic growth had a positive effect to the income inequality in developed countries in long term. The results indicated that every 1% increase of GDP, the GINI coefficient would raise by 0.0383%, on average, keeping other variables unchanged. In addition, the result of this research was also consistent with the studies in US and Japan which proclaimed that higher economic growth tended to increase the income inequality in developed countries (Yang & Greaney, 2017).

Meanwhile, the result of two step system GMM showed that trade openness had a positive relationship with income inequality in developed countries. An increment of 1% in TO, the GINI coefficient would increase 0.0729%, on average, other variables remained constant. Based on the research done by Heckscher and Ohlin (1919), they proposed that there were two types of countries which held different results of the relationship between trade openness and income inequality. Developed countries usually had more skilled-labor thus they were able to export skill-intensive goods and indirectly relative income rate of skilled labor gap became wider. The wider gap was then causing the higher income inequality in the developed countries.

At the same time, technological changes in developed countries was negatively correlated with income inequality which denoted every 1% increase of TECH lead to a reduction of 0.0191% in GINI coefficient, on average, holding other variables constant. Kuznets (1963) suggested that the faster the technological innovations were adopted, the stronger the negative nexus between economic growth and income inequalities. On the other hand, previous study also supported the negative relationship by indicating that the more rapid the rate of technological change was, the quicker the rate of economic growth were and this situation would lessen the income inequality level (Schumpeter, 1942). Whereas, the 0.1261 positive correlation between TECH and GDP is shown in Table 4.2 correlations relationship for developed countries.

Table 4.6: Results of Difference GMM and System GMM Approach for 51 developing countries.

	(1) One-Step Difference GMM	(2) Two-Step Difference GMM	(3) Two-Step Robust Difference GMM	(4) One-Step System GMM	(5) Two-Step System GMM	(6) Two-Step Robust System GMM
GINI	0.936***	0.947***	0.947***	0.901***	0.903***	0.903***
	(82.31)	(49.50)	(20.56)	(124.09)	(108.24)	(20.74)
EDU	0.0246***	0.0227***	0.0227	0.0338***	0.0282***	0.0282**
	(3.69)	(3.15)	(1.40)	(5.14)	(6.06)	(2.07)
FD	-0.00779***	-0.00962***	-0.00962**	-0.0111***	-0.0123***	-0.0123*
	(-2.60)	(-4.84)	(-2.11)	(-3.72)	(-5.18)	(-1.92)
GDP	-0.0140***	-0.0133***	-0.0133*	-0.0148***	-0.0125***	-0.0125*
	(-5.11)	(-5.77)	(-1.84)	(-6.89)	(-6.53)	(-1.96)
TO	-0.0110***	-0.00784***	-0.00784*	-0.0100***	-0.0102***	-0.0102**
	(-5.43)	(-4.09)	(-1.72)	(-5.94)	(-6.98)	(-2.29)
TECH	0.00120***	0.00137***	0.00137	0.000914***	0.000880***	0.000880*
	(2.61)	(4.79)	(1.52)	(2.59)	(8.77)	(1.68)
_CONS				1.369***	1.182***	1.182*
				(8.25)	(6.68)	(1.75)
AR1	-2.790 (0.005)***	-2.550 (0.011)**	-2.289 (0.022)**	-3.048 (0.002)***	-2.520 (0.012)**	-2.324 (0.02)**
AR2	-1.353 (0.176)	-1.355 (0.176)	-1.290 (0.197)	-1.037 (0.30)	-1.227 (0.22)	-1.127 (0.26)
Sargan Test	540.0 (0)***	540.0 (0)***	540.0 (0)***	717.5 (0)***	717.5 (0)***	717.5 (0)***
Hansen Test		41.43 (1.00)	41.43 (1.00)		41.56 (1.00)	41.56 (1.00)
N	380	380	380	410	410	410

Notes. GINI is Income Inequality. EDU is Education. FD is Financial Development. GDP is Economic Growth. TO is Trade Openness. TECH is Technological Changes.
P-values are in parentheses. * Indicate statistical significance at the 10% level. ** Indicate statistical significance at the 5% level. *** Indicate statistical significance at the 1% level.

4.3.2 Difference and System GMM Approach Results for developing countries

Table 4.6 indicates the Difference GMM and System GMM estimations for income inequality in developing countries. In two-step system GMM model, GINI was statistically shown significance at 1% significance level. While, EDU and TO were statistically shown 5% significance level. On the other hand, the variables such as FD, GDP and TECH indicated a 10% significance level. Besides, both EDU and TECH showed positive coefficient, the other variables FD, GDP and TO indicated a negative coefficient.

Whenever there was an increase 1% in EDU, the GINI coefficient increased 0.0282%, on average, by holding other variables constant. According to past researchers, they found that there was a positive significant relationship between secondary educations on income inequality (Li, Squire& Zou, 1998; Mairesse, 1990; Rodríguez-Pose, 2009). According to Mairesse (1990), he found that the coefficient of secondary education was higher than tertiary education, this proved that secondary had a greater sway on the variation in income inequality compared to tertiary education.

Besides that, an increase 1% in FD, the GINI coefficient would decrease 0.0123%, on average, by holding other variables constant. For those poor income individuals who were excluded from getting loans previously, could get access to it after financial sector developed well (Clarke et al., 2006). Various theoretical models also proclaimed that a better financial development was able to lower the income inequality, which was consistent with the idea financial development might benefit those poorer individuals (Banerjee & Newman 1993; Galor & Zeira 1993). Therefore, a good financial development might be an effective tool to equalize and narrow the gap of income distribution.

By growing 1% in GDP, the GINI coefficient decreased 0.0125% in developing countries, on average, by holding other variables constant. According to Nissim (2007), when there was an economic boost condition, workers were paid in a higher income, which aided to lower income inequality. Economic growth was able to reduce the income inequality in developing countries but had contrast effect in developed countries in long term (Chambers, 2010). An increase 1% in TO might lead to a 0.0102% decrease in GINI coefficient, on average, by holding other variables constant. According to Heckscher and Ohlin (1919), developed and developing countries might have different relationship between income inequality and trade openness. Developing countries would close up the income distribution because imports would harm their capital owner and skilled labor but export would only bring advantages to unskilled workers. Hence, the trade openness increased income inequality in developing countries but reduced in developed countries.

An increase of 1% in TECH would increase 0.000880% of the GINI coefficient, on average, by holding other variables constant. In previous research, Ciriaci (2016) suggested that being innovative supports would help to maintain a firm’s organic employment growth pattern so the income distribution would be more tend to youngsters due to their fast adaption of innovation. Meanwhile, based on Frey and Osborne’s evidence, it showed that computerization usually influenced low-skilled or low-educated jobs, this would then widen the income gap between skilled and unskilled labors.

4.4 Developed countries versus Developing Countries

Based on the results of difference GMM and system GMM estimations for income inequality, there were moderately different among the results from 34 developed and 51 developing countries. For the developed countries, EDU and TO statistically showed significant at 1% significance level. However, FD, GDP and TECH had statistically shown significant at 5% significance level. In contrast, for developing countries, EDU and TO statistically showed significant at 5% significance level, while the variables such as FD, GDP and TECH indicated a 10% significance level.

Furthermore, the sign of variables for developed and developing countries were slightly unalike. For developed countries, FD and TECH showed negative correlation, which indicated these two variables had a negative effect on income inequality. Other variables such as EDU, GDP and TO had a positive effect on income inequality in developed countries. On the other hand, for developing countries, only EDU and TECH showed positive sign. This meant that these two variables had a positive effect on income inequality. However, the other variables which included FD, GDP and TO had shown a negative correlation, in which those variables had a significant negative effect on income inequality in developing countries. The only similar results between developed and developing countries were positive relationship among variable of EDU and income inequality (GINI) and negative relationship among variable of FD and income inequality (GINI).

CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATIONS

5.0 Introduction

In this chapter, this study summarizes the whole findings and discusses the results of the previous chapters. The findings have shown that the impact of education and others control variables such as financial development, economic growth, trade openness and technological changes on income inequality in 34 developed countries from year 1971 to 2015, as well as 51 developing countries from year 2003 to 2015 respectively. This chapter also includes the discussions of major findings, policy implications, limitations and recommendations for future researchers.

5.1 Discussions of Major Findings

Income inequality is defined as an unequal percentage of the income in populations. Income inequality has occurred worldwide, which has led to the serious gap between the poor and the rich. Therefore, income inequality remains an important issue till today as it involves human welfare. It is found that the scale of education, along with the impact of higher education has widen the income gap. In other words, higher education will cause the widening inequality gap.

Yet, there may be a lack of research conducted in both developed and developing countries in examining the relationship between income inequality and controlled variables. Thus, this research mainly discusses the impact of education and other controlled variables, such as financial development, economic growth, trade openness and technological changes on income inequality among 34 developed countries from year 1971 to 2015 and 51 developing countries from year 2003 to 2015 respectively.

This research uses the Generalized Method of Moments (GMM) dynamic panel estimator. This method is used as it is able to capture the lag effects and to ensure the efficiency and efficiency of the study. In comparison, the values of System GMM are significant and it is reliable compared to the results of the Difference GMM. In two step robust GMM analysis, education, economic growth and trade openness show a positive relationship with the income inequality, while financial development and technological changes are negatively associated with the income inequality in developed countries. For developing countries, education has a statistically significant and positive correlation with income inequality while financial development, economic growth, trade openness and technological changes have a negative relationship with the income inequality.

Overall, the result shows that education, financial development, economic growth, trade openness and technological changes are statistically significant in affecting income inequality. For developed countries, education, economic growth and trade openness have a positive effect on income inequality. However, financial development and technological changes have a negative correlation with income inequality. For developing countries, education is positively linked with income inequality. Nevertheless, financial development, economic growth, trade openness and technological changes have an adverse effect on income inequality.

5.2 Implications of the Study

Based on the empirical result and analysis of variables in Chapter 4, the study has found that education is the most important variable in influencing income inequality. Results show that education has brought a positive impact towards income inequality in both developed and developing countries. As the level of education increases, income inequality tends to increase as well. Secondary education has strong associations with income inequality.

There are some recommendations on policy implications that can be taken by related personnel to control and slow down income inequality. First, the government can consider in investing in a more accessible, affordable and quality education, especially for secondary education. According to the prediction by the executive director of Opportunity Nation, he stated that government should invest more in excessing to post-secondary school as 65% of the jobs in 2025 will be require more educated labor supply from post-secondary education (Divine, 2017). The government should improve the quality of education by lowering tuition fees, having a better education financing and improved the vocational training for trades and profession. Vocational training can change the mindsets of teachers. It can also help in encouraging them to actively participate in curriculum reform and development. A higher quality education means better services from teachers, administrators and librarians, this indicates a greater investment in physical capital for education.

Due to the disparities in the school expenditure, education cost and availability of private schools in different governorates, the poor have a lesser opportunity to pursuing secondary education compared to the rich. The increase in the distance of distribution tends to lead to the increase of income inequality. Policymakers should give more attention to the distribution of private schools in different governorates, as well as the cost and spending of school. The government, families, businesses, students, alumni and philanthropists should also take the responsibility in funding higher education such as secondary education. All relevant personnel may act as partnership in raising funds for better education such as secondary education. A stable funding base is also a key to raise the quality of education. The government can target some extra funds in order to help low income families in having the chance to provide secondary education for their children. Moreover, they can also reduce the reliance on local property taxes and pay attention to fund secondary education.

Gender discrimination in education ought to be improved as well. This issue is quite severe in certain countries. For instance, women are not allowed in receiving education in some countries. Thus, the lesser educated people, the higher income inequality. The government should either remain or increase the number of girls' school to give women a chance to access quality education, especially secondary school.

For the financial development factor, the study has found that it has a negative impact towards income inequality in developed and developing countries. The government should microfinance to reduce poverty and enhance the development strategies along with economic growth. The role of microfinance institution was to aid the poor in starting up business and to encourage the practice of saving. The government can develop a more detailed and effective regulatory to support the operation of microfinance institution (MFI). Besides that, the government can loosening control of the regulations in order to facilitate MFI to tap low cost funds either from domestic and foreign sources. Microfinance can also help to increase access to capital for low income people, as well as to reduce income inequality.

For the economic growth factor, the study has found that it has a negative impact towards the income inequality in developing countries. There are some suggestions for the government in enhancing economic growth in order to reduce income inequality. The government may create more job opportunities to reduce unemployment among low income workers. As job opportunities increase, unemployment decrease. When low income worker have wages, the income inequality tends to decrease. The government may also redistribute income through progressive tax such as extracting higher income tax from those of higher income. In addition, the government could use these extra income tax to fund the welfare benefits, education and health care. These are useful for government to reduce the income inequality through economic growth factor.

5.3 Limitations of the Study

Insufficient of data was found throughout the study. Both developed and developing countries are investigated in this research. Hence, it is difficult to gather complete data due to the wide range. Due to the limitation and restriction of the study, only secondary education was examined. This is because secondary education have more sources and data as compared to other levels of education such as tertiary education. The reason why tertiary education was not chosen for analysis was due to the extremely limited data in most countries. Thus, results will not be generated smoothly due to the lack of data.

On the other hand, there was sufficient data from secondary education to be generated. Throughout the process of data collection, huge numbers of data from numerous countries had to be filtered as it was not insufficient to generate results. There was also insignificant data between both developed and developing countries under different GMM.

5.4 Recommendations for Future Research

Future researchers are recommended to only focus in either developing or developed country in their study. The different countries and categories used by different researchers has made it difficult for aspiring researchers in examining the income inequality more in-depth. It is unsure if the income inequality is really affected by a particular country or region.

Furthermore, the study can be conducted in a more detailed and thorough approach. Researchers can focus on only one country in studying the relationship between education and income inequality. This will provide more specific information and clear ideas on the study rather than studying in a relatively wider range of samples. With this method, researchers will be able to get more accurate measures of the variables as well.

Last but not least, it is recommended to conduct a survey on the study to get more data sources. Survey questionnaires or forms can be distributed to gain further opinion and views. For example, since there is lack of data evidence of tertiary education, researchers can collect data themselves by conducting surveys in various places. Despite the time consuming process in visiting numerous colleges and universities, the data collected will serve as a significant material for the study.

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APPENDICES

Appendix 1.1: Developing countries

Algeria, Argentina, Armenia, Bangladesh, Belarus, Belize, Bosnia and Herzegovina, Brazil, Bulgaria, Chile, China, Colombia, Costa Rica, Georgia, Guatemala, Honduras, India, Indonesia, Iran, Jordan, Kazakhstan, Kenya, Korea, Kyrgyz Republic, Latvia, Lithuania, Macedonia, Madagascar, Malaysia, Mexico, Moldova, Montenegro, Morocco, Mozambique, Pakistan, Panama, Paraguay, Peru, Philippines, Romania, Russia, Serbia, South Africa, Sudan, Syrian Arab Republic, Tajikistan, Thailand, Tunisia, Turkey, Ukraine and Uruguay.

Appendix 1.2: Developed countries

Australia, Austria, Barbados, Belgium, Canada, Croatia, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong SAR, Hungary, Iceland, Ireland, Israel, Italy, Japan, Luxembourg, Malta, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom and United States.

Appendix 1.3: Result of developed countries

```
TWO STEP ROBUST SYSTEM GMM
Favoring space over speed. To switch, type or click on mata: mata set matafavor speed,
perm.
Warning: Number of instruments may be large relative to number of observations.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-step
estimation.
  Difference-in-Sargan/Hansen statistics may be negative.

Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
Group variable: timecode                        Number of obs      =       460
Time variable : time                            Number of groups   =        34
Number of instruments = 78                      Obs per group: min =         1
F(6, 33)      =     24.38                                      avg =     13.53
Prob > F      =     0.000                                      max =        42
------------------------------------------------------------------------------
             |              Corrected
        GINI |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
             |
        GINI |    .964933   .1464485     6.59   0.000     .6669812    1.262885
             |
             |
         EDU |   .0776125   .0201602     3.85   0.001     .0365963    .1186286
             |
             |
          FD |  -.0647507   .0267808    -2.42   0.021    -.1192367   -.0102646
             |
             |
         GDP |   .0383319   .0187209     2.05   0.049     .0002439    .0764199
             |
             |
          TO |   .0728529   .0198521     3.67   0.001     .0324634    .1132424
             |
             |
        TECH |   -.019131   .0072159    -2.65   0.012    -.0338118   -.0044502
             |
       _cons |  -.9217802   .4876278    -1.89   0.068    -1.913866    .0703061
------------------------------------------------------------------------------
Instruments for first differences equation
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(2/6).(ly1 lx21 lx45 lx51 lx123 lx197) collapsed
Instruments for levels equation
  Standard
    1960b.time 1961.time 1962.time 1963.time 1964.time 1965.time 1966.time
    1967.time 1968.time 1969.time 1970.time 1971.time 1972.time 1973.time
    1974.time 1975.time 1976.time 1977.time 1978.time 1979.time 1980.time
    1981.time 1982.time 1983.time 1984.time 1985.time 1986.time 1987.time
    1988.time 1989.time 1990.time 1991.time 1992.time 1993.time 1994.time
    1995.time 1996.time 1997.time 1998.time 1999.time 2000.time 2001.time
    2002.time 2003.time 2004.time 2005.time 2006.time 2007.time 2008.time
    2009.time 2010.time 2011.time 2012.time 2013.time 2014.time 2015.time
    2016.time
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    DL.(ly1 lx21 lx45 lx51 lx123 lx197) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =   3.12  Pr > z =  0.002
Arellano-Bond test for AR(2) in first differences: z =  -1.18  Pr > z =  0.239
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(71)   =  31.36  Prob > chi2 =  1.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(71)   =  26.33  Prob > chi2 =  1.000
  (Robust, but weakened by many instruments.)
```

TWO STEP SYSTEM GMM

```
Favoring space over speed. To switch, type or click on mata: mata set matafavor speed,
perm.

Warning: Number of instruments may be large relative to number of observations.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-step
estimation.
  Difference-in-Sargan/Hansen statistics may be negative.

Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
Group variable: timecode                        Number of obs      =       460
Time variable : time                            Number of groups   =        34
Number of instruments = 78                      Obs per group: min =         1
F(6, 33)      =   1166.57                                      avg =     13.53
Prob > F      =     0.000                                      max =        42
------------------------------------------------------------------------------
        GINI |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
             |
        GINI |    .964933   .0358804    26.89   0.000     .8919337    1.037932
             |
             |
         EDU |   .0776125   .0066022    11.76   0.000     .0641802    .0910447
             |
             |
          FD |  -.0647507   .0039167   -16.53   0.000    -.0727192   -.0567822
             |
             |
         GDP |   .0383319   .0043671     8.78   0.000     .0294471    .0472168
             |
             |
          TO |   .0728529   .0044691    16.30   0.000     .0637605    .0819453
             |
             |
        TECH |   -.019131   .0017077   -11.20   0.000    -.0226053   -.0156567
             |
       _cons |  -.9217802    .137185    -6.72   0.000    -1.200885   -.6426753
------------------------------------------------------------------------------
Warning: Uncorrected two-step standard errors are unreliable.

Instruments for first differences equation
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(2/6).(ly1 lx21 lx45 lx51 lx123 lx197) collapsed
Instruments for levels equation
  Standard
    1960b.time 1961.time 1962.time 1963.time 1964.time 1965.time 1966.time
    1967.time 1968.time 1969.time 1970.time 1971.time 1972.time 1973.time
    1974.time 1975.time 1976.time 1977.time 1978.time 1979.time 1980.time
    1981.time 1982.time 1983.time 1984.time 1985.time 1986.time 1987.time
    1988.time 1989.time 1990.time 1991.time 1992.time 1993.time 1994.time
    1995.time 1996.time 1997.time 1998.time 1999.time 2000.time 2001.time
    2002.time 2003.time 2004.time 2005.time 2006.time 2007.time 2008.time
    2009.time 2010.time 2011.time 2012.time 2013.time 2014.time 2015.time
    2016.time
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    DL.(ly1 lx21 lx45 lx51 lx123 lx197) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =   3.21  Pr > z =  0.001
Arellano-Bond test for AR(2) in first differences: z =  -1.34  Pr > z =  0.181
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(71)   =  31.36  Prob > chi2 =  1.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(71)   =  26.33  Prob > chi2 =  1.000
  (Robust, but weakened by many instruments.)
```

ONE STEP SYSTEM GMM

```
Favoring space over speed. To switch, type or click on mata: mata set matafavor speed,
perm.
Warning: Number of instruments may be large relative to number of observations.

Dynamic panel-data estimation, one-step system GMM
------------------------------------------------------------------------------
Group variable: timecode                        Number of obs      =       460
Time variable : time                            Number of groups   =        34
Number of instruments = 78                      Obs per group: min =         1
F(6, 453)     =     48.34                                      avg =     13.53
Prob > F      =     0.000                                      max =        42
------------------------------------------------------------------------------
        GINI |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
             |
        GINI |   .9251371   .0889184    10.40   0.000     .7503934    1.099881
             |
             |
         EDU |   .0815084   .0199666     4.08   0.000     .0422696    .1207471
             |
             |
          FD |  -.0733707   .0334382    -2.19   0.029    -.1390839   -.0076575
             |
             |
         GDP |   .0465227   .0224239     2.07   0.039     .0024549    .0905906
             |
             |
          TO |    .078055   .0305716     2.55   0.011     .0179752    .1381348
             |
             |
        TECH |  -.0225449   .0074076    -3.04   0.002    -.0371023   -.0079874
             |
       _cons |  -.8194513   .5168728    -1.59   0.114    -1.835217    .1963147
------------------------------------------------------------------------------
Instruments for first differences equation
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(2/6).(ly1 lx21 lx45 lx51 lx123 lx197) collapsed
Instruments for levels equation
  Standard
    1960b.time 1961.time 1962.time 1963.time 1964.time 1965.time 1966.time
    1967.time 1968.time 1969.time 1970.time 1971.time 1972.time 1973.time
    1974.time 1975.time 1976.time 1977.time 1978.time 1979.time 1980.time
    1981.time 1982.time 1983.time 1984.time 1985.time 1986.time 1987.time
    1988.time 1989.time 1990.time 1991.time 1992.time 1993.time 1994.time
    1995.time 1996.time 1997.time 1998.time 1999.time 2000.time 2001.time
    2002.time 2003.time 2004.time 2005.time 2006.time 2007.time 2008.time
    2009.time 2010.time 2011.time 2012.time 2013.time 2014.time 2015.time
    2016.time
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    DL.(ly1 lx21 lx45 lx51 lx123 lx197) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =   1.23  Pr > z =  0.220
Arellano-Bond test for AR(2) in first differences: z =  -0.55  Pr > z =  0.581
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(71)    =  31.36  Prob > chi2 =  1.000
  (Not robust, but not weakened by many instruments.)
```

TWO STEP ROBUST DIFFERENCE GMM

```
Favoring space over speed. To switch, type or click on mata: mata set matafavor speed,
perm.
Instruments for levels equations only ignored since noleveleq specified.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-step
estimation.
  Difference-in-Sargan/Hansen statistics may be negative.
```

```
Dynamic panel-data estimation, two-step difference GMM
------------------------------------------------------------------------------
Group variable: timecode                        Number of obs      =       426
Time variable : time                            Number of groups   =        33
Number of instruments = 30                      Obs per group: min =         0
F(6, 33)      =      6.14                                      avg =     12.91
Prob > F      =     0.000                                      max =        41
------------------------------------------------------------------------------
             |              Corrected
        GINI |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
             |
        GINI |   .1767217   .0730964     2.42   0.021     .0280061    .3254374
             |
             |
         EDU |   .0269758   .0133912     2.01   0.052    -.0002687    .0542204
             |
             |
          FD |  -.0094329   .0137505    -0.69   0.497    -.0374085    .0185426
             |
             |
         GDP |   .0045926   .0043227     1.06   0.296    -.0042021    .0133873
             |
             |
          TO |   .0076699   .0229343     0.33   0.740    -.0389903    .0543301
             |
             |
        TECH |  -.0087761   .0040428    -2.17   0.037    -.0170013   -.0005509
-----------------------------------------------------------------------------
Instruments for first differences equation
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(2/6).(ly1 lx21 lx45 lx51 lx123 lx197) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =   3.28  Pr > z =  0.001
Arellano-Bond test for AR(2) in first differences: z =   1.93  Pr > z =  0.054
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(24)    =  80.36  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(24)    =  23.58  Prob > chi2 =  0.486
  (Robust, but weakened by many instruments.)

TWO STEP DIFFERENCE GMM
Favoring space over speed. To switch, type or click on mata: mata set matafavor speed,
perm.
Instruments for levels equations only ignored since noleveleq specified.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-step
estimation.
  Difference-in-Sargan/Hansen statistics may be negative.

Dynamic panel-data estimation, two-step difference GMM
------------------------------------------------------------------------------
Group variable: timecode                        Number of obs      =       426
Time variable : time                            Number of groups   =        33
Number of instruments = 30                      Obs per group: min =         0
F(6, 33)      =   1229.05                                      avg =     12.91
Prob > F      =     0.000                                      max =        41
------------------------------------------------------------------------------
        GINI |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
             |
        GINI |   .1767217   .0099407    17.78   0.000     .1564972    .1969463
             |
             |
         EDU |   .0269758   .0021868    12.34   0.000     .0225268    .0314248
             |
             |
          FD |  -.0094329   .0026036    -3.62   0.001      -.01473   -.0041359
             |
             |
```

```
         GDP |   .0045926   .0013248     3.47   0.001     .0018973    .0072879
             |
             |
          TO |   .0076699   .0053117     1.44   0.158    -.0031369    .0184767
             |
             |
        TECH |  -.0087761    .000699   -12.56   0.000    -.0101982    -.007354
------------------------------------------------------------------------------
Warning: Uncorrected two-step standard errors are unreliable.

Instruments for first differences equation
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(2/6).(ly1 lx21 lx45 lx51 lx123 lx197) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =   3.30  Pr > z =  0.001
Arellano-Bond test for AR(2) in first differences: z =   2.06  Pr > z =  0.039
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(24)    =  80.36  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(24)    =  23.58  Prob > chi2 =  0.486
  (Robust, but weakened by many instruments.)

ONE STEP DIFFERENCE GMM
Favoring space over speed. To switch, type or click on mata: mata set matafavor speed,
perm.
Instruments for levels equations only ignored since noleveleq specified.

Dynamic panel-data estimation, one-step difference GMM
------------------------------------------------------------------------------
Group variable: timecode                        Number of obs      =       426
Time variable : time                            Number of groups   =        33
Number of instruments = 30                      Obs per group: min =         0
F(6, 420)     =      5.82                                      avg =     12.91
Prob > F      =     0.000                                      max =        41
------------------------------------------------------------------------------
        GINI |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
             |
        GINI |   .1893798   .0440904     4.30   0.000     .1027145     .276045
             |
             |
         EDU |   .0244156   .0140284     1.74   0.083     -.003159    .0519901
             |
             |
          FD |  -.0089956   .0159927    -0.56   0.574    -.0404312      .02244
             |
             |
         GDP |   .0050699   .0051186     0.99   0.323    -.0049913    .0151312
             |
             |
          TO |   .0144343   .0222684     0.65   0.517    -.0293371    .0582058
             |
             |
        TECH |  -.0089666   .0031222    -2.87   0.004    -.0151037   -.0028294
------------------------------------------------------------------------------
Instruments for first differences equation
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(2/6).(ly1 lx21 lx45 lx51 lx123 lx197) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  10.27  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =   4.25  Pr > z =  0.000
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(24)    =  80.36  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
```

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
GINI	1674	3.407359	.2136398	2.912351	3.956996
EDU	1045	13.49625	1.656707	8.269501	17.02357
FD	665	4.440001	.5538715	-.3763553	5.726144
GDP	1245	2.884004	.2275394	-1.288821	3.717716
TO	1139	4.22744	.675685	2.189363	6.064695
TECH	963	7.681258	1.980038	0	12.32267

Correlations

	GINI	EDU	FD	GDP	TO	TECH
GINI	1.0000					
EDU	0.3137	1.0000				
FD	0.3486	0.3601	1.0000			
GDP	0.0372	0.0117	-0.0999	1.0000		
TO	-0.1565	-0.6883	-0.2307	-0.0609	1.0000	
TECH	0.1694	0.6716	0.2750	0.1261	-0.5204	1.0000

Appendix 1.4: Result of developing countries

```
TWO STEP ROBUST SYSTEM GMM
Favoring space over speed. To switch, type or click on mata: mata set matafavor speed,
perm.
Warning: Number of instruments may be large relative to number of observations.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-step
estimation.
  Difference-in-Sargan/Hansen statistics may be negative.

Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
Group variable: timecode                        Number of obs      =       410
Time variable : time                            Number of groups   =        51
Number of instruments = 298                     Obs per group: min =         1
F(7, 50)      =    164.80                                      avg =      8.04
Prob > F      =     0.000                                      max =        14
------------------------------------------------------------------------------
             |              Corrected
        GINI |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
             |
        GINI |   .9027561   .0435189    20.74   0.000     .8153458    .9901665
             |
             |
         EDU |   .0281747   .0135791     2.07   0.043     .0009002    .0554491
             |
             |
          FD |   -.012321   .0064284    -1.92   0.061    -.0252328    .0005909
             |
             |
         GDP |  -.0124763    .006369    -1.96   0.056    -.0252688    .0003161
             |
             |
          TO |  -.0102314    .004467    -2.29   0.026    -.0192036   -.0012592
             |
             |
        TECH |   .0008801   .0005231     1.68   0.099    -.0001705    .0019307
             |
        time |  -.0003657    .000288    -1.27   0.210    -.0009441    .0002128
       _cons |   1.182338   .6763866     1.75   0.087    -.1762246      2.5409
-----------------------------------------------------------------------------
Instruments for first differences equation
  Standard
    D.(1960b.time 1961.time 1962.time 1963.time 1964.time 1965.time 1966.time
    1967.time 1968.time 1969.time 1970.time 1971.time 1972.time 1973.time
    1974.time 1975.time 1976.time 1977.time 1978.time 1979.time 1980.time
    1981.time 1982.time 1983.time 1984.time 1985.time 1986.time 1987.time
    1988.time 1989.time 1990.time 1991.time 1992.time 1993.time 1994.time
    1995.time 1996.time 1997.time 1998.time 1999.time 2000.time 2001.time
    2002.time 2003.time 2004.time 2005.time 2006.time 2007.time 2008.time
    2009.time 2010.time 2011.time 2012.time 2013.time 2014.time 2015.time
    2016.time 2017.time)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(6/57).(ly1 lx21g lx45g lx51 lx123 lx197g) collapsed
Instruments for levels equation
  Standard
    1960b.time 1961.time 1962.time 1963.time 1964.time 1965.time 1966.time
    1967.time 1968.time 1969.time 1970.time 1971.time 1972.time 1973.time
    1974.time 1975.time 1976.time 1977.time 1978.time 1979.time 1980.time
    1981.time 1982.time 1983.time 1984.time 1985.time 1986.time 1987.time
    1988.time 1989.time 1990.time 1991.time 1992.time 1993.time 1994.time
    1995.time 1996.time 1997.time 1998.time 1999.time 2000.time 2001.time
    2002.time 2003.time 2004.time 2005.time 2006.time 2007.time 2008.time
    2009.time 2010.time 2011.time 2012.time 2013.time 2014.time 2015.time
    2016.time 2017.time
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    DL5.(ly1 lx21g lx45g lx51 lx123 lx197g) collapsed
```

```
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -2.32  Pr > z =  0.020
Arellano-Bond test for AR(2) in first differences: z =  -1.13  Pr > z =  0.260
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(290)  = 717.53  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(290)  =  41.56  Prob > chi2 =  1.000
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(284)  =  38.73  Prob > chi2 =  1.000
    Difference (null H = exogenous): chi2(6)    =   2.83  Prob > chi2 =  0.830
  gmm(ly1 lx21g lx45g lx51 lx123 lx197g, collapse lag(6 .))
    Hansen test excluding group:     chi2(8)    =   5.38  Prob > chi2 =  0.717
    Difference (null H = exogenous): chi2(282)  =  36.18  Prob > chi2 =  1.000
  iv(1960b.time 1961.time 1962.time 1963.time 1964.time 1965.time 1966.time 1967.time
1968.time 1969.time 1970.time
>  1971.time 1972.time 1973.time 1974.time 1975.time 1976.time 1977.time 1978.time
1979.time 1980.time 1981.time 19
> 82.time 1983.time 1984.time 1985.time 1986.time 1987.time 1988.time 1989.time
1990.time 1991.time 1992.time 1993.
> time 1994.time 1995.time 1996.time 1997.time 1998.time 1999.time 2000.time 2001.time
2002.time 2003.time 2004.tim
> e 2005.time 2006.time 2007.time 2008.time 2009.time 2010.time 2011.time 2012.time
2013.time 2014.time 2015.time 2
> 016.time 2017.time)
    Hansen test excluding group:     chi2(275)  =  78.65  Prob > chi2 =  1.000
    Difference (null H = exogenous): chi2(15)   = -37.09  Prob > chi2 =  1.000
```

TWO STEP SYSTEM GMM

```
Favoring space over speed. To switch, type or click on mata: mata set matafavor speed,
perm.
Warning: Number of instruments may be large relative to number of observations.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-step
estimation.
  Difference-in-Sargan/Hansen statistics may be negative.

Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
Group variable: timecode                        Number of obs      =       410
Time variable : time                            Number of groups   =        51
Number of instruments = 298                     Obs per group: min =         1
F(7, 50)      =  15631.40                                      avg =      8.04
Prob > F      =     0.000                                      max =        14
------------------------------------------------------------------------------
        GINI |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
             |
        GINI |   .9027561     .00834   108.24   0.000     .8860048    .9195075
             |
             |
         EDU |   .0281747   .0046476     6.06   0.000     .0188397    .0375097
             |
             |
          FD |   -.012321   .0023781    -5.18   0.000    -.0170975   -.0075444
             |
             |
         GDP |  -.0124763   .0019112    -6.53   0.000    -.0163151   -.0086376
             |
             |
          TO |  -.0102314   .0014651    -6.98   0.000    -.0131741   -.0072887
             |
             |
        TECH |   .0008801   .0001004     8.77   0.000     .0006786    .0010817
             |
```

```
       time |  -.0003657   .0000801    -4.57   0.000    -.0005265   -.0002049
      _cons |   1.182338   .1768853     6.68   0.000     .8270533    1.537622
------------------------------------------------------------------------------
Warning: Uncorrected two-step standard errors are unreliable.

Instruments for first differences equation
  Standard
    D.(1960b.time 1961.time 1962.time 1963.time 1964.time 1965.time 1966.time
    1967.time 1968.time 1969.time 1970.time 1971.time 1972.time 1973.time
    1974.time 1975.time 1976.time 1977.time 1978.time 1979.time 1980.time
    1981.time 1982.time 1983.time 1984.time 1985.time 1986.time 1987.time
    1988.time 1989.time 1990.time 1991.time 1992.time 1993.time 1994.time
    1995.time 1996.time 1997.time 1998.time 1999.time 2000.time 2001.time
    2002.time 2003.time 2004.time 2005.time 2006.time 2007.time 2008.time
    2009.time 2010.time 2011.time 2012.time 2013.time 2014.time 2015.time
    2016.time 2017.time)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(6/57).(ly1 lx21g lx45g lx51 lx123 lx197g) collapsed
Instruments for levels equation
  Standard
    1960b.time 1961.time 1962.time 1963.time 1964.time 1965.time 1966.time
    1967.time 1968.time 1969.time 1970.time 1971.time 1972.time 1973.time
    1974.time 1975.time 1976.time 1977.time 1978.time 1979.time 1980.time
    1981.time 1982.time 1983.time 1984.time 1985.time 1986.time 1987.time
    1988.time 1989.time 1990.time 1991.time 1992.time 1993.time 1994.time
    1995.time 1996.time 1997.time 1998.time 1999.time 2000.time 2001.time
    2002.time 2003.time 2004.time 2005.time 2006.time 2007.time 2008.time
    2009.time 2010.time 2011.time 2012.time 2013.time 2014.time 2015.time
    2016.time 2017.time
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    DL5.(ly1 lx21g lx45g lx51 lx123 lx197g) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -2.52  Pr > z =  0.012
Arellano-Bond test for AR(2) in first differences: z =  -1.23  Pr > z =  0.220
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(290)   = 717.53  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(290)   =  41.56  Prob > chi2 =  1.000
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(284)   =  38.73  Prob > chi2 =  1.000
    Difference (null H = exogenous): chi2(6)     =   2.83  Prob > chi2 =  0.830
  gmm(ly1 lx21g lx45g lx51 lx123 lx197g, collapse lag(6 .))
    Hansen test excluding group:     chi2(8)     =   5.38  Prob > chi2 =  0.717
    Difference (null H = exogenous): chi2(282)   =  36.18  Prob > chi2 =  1.000
  iv(1960b.time 1961.time 1962.time 1963.time 1964.time 1965.time 1966.time 1967.time
1968.time 1969.time 1970.time
>  1971.time 1972.time 1973.time 1974.time 1975.time 1976.time 1977.time 1978.time
1979.time 1980.time 1981.time 19
> 82.time 1983.time 1984.time 1985.time 1986.time 1987.time 1988.time 1989.time
1990.time 1991.time 1992.time 1993.
> time 1994.time 1995.time 1996.time 1997.time 1998.time 1999.time 2000.time 2001.time
2002.time 2003.time 2004.tim
> e 2005.time 2006.time 2007.time 2008.time 2009.time 2010.time 2011.time 2012.time
2013.time 2014.time 2015.time 2
> 016.time 2017.time)
    Hansen test excluding group:     chi2(275)   =  78.65  Prob > chi2 =  1.000
    Difference (null H = exogenous): chi2(15)    = -37.09  Prob > chi2 =  1.000
```

ONE STEP SYSTEM GMM

```
Favoring space over speed. To switch, type or click on mata: mata set matafavor speed,
perm.
Warning: Number of instruments may be large relative to number of observations.

Dynamic panel-data estimation, one-step system GMM
------------------------------------------------------------------------------
```

```
Group variable: timecode                        Number of obs      =       410
Time variable : time                            Number of groups   =        51
Number of instruments = 298                     Obs per group: min =         1
F(7, 402)     =   6002.13                                      avg =      8.04
Prob > F      =     0.000                                      max =        14
------------------------------------------------------------------------------
        GINI |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
             |
        GINI |   .9005948   .0072576   124.09   0.000     .8863273    .9148623
             |
             |
         EDU |   .0337519   .0065614     5.14   0.000     .0208529    .0466509
             |
             |
          FD |  -.0110682   .0029765    -3.72   0.000    -.0169196   -.0052168
             |
             |
         GDP |  -.0147778   .0021456    -6.89   0.000    -.0189959   -.0105598
             |
             |
          TO |  -.0100094   .0016838    -5.94   0.000    -.0133195   -.0066993
             |
             |
        TECH |    .000914   .0003527     2.59   0.010     .0002207    .0016073
             |
        time |  -.0004508    .000075    -6.01   0.000    -.0005983   -.0003033
       _cons |   1.369295   .1659081     8.25   0.000     1.043139    1.695451
------------------------------------------------------------------------------
Instruments for first differences equation
  Standard
    D.(1960b.time 1961.time 1962.time 1963.time 1964.time 1965.time 1966.time
    1967.time 1968.time 1969.time 1970.time 1971.time 1972.time 1973.time
    1974.time 1975.time 1976.time 1977.time 1978.time 1979.time 1980.time
    1981.time 1982.time 1983.time 1984.time 1985.time 1986.time 1987.time
    1988.time 1989.time 1990.time 1991.time 1992.time 1993.time 1994.time
    1995.time 1996.time 1997.time 1998.time 1999.time 2000.time 2001.time
    2002.time 2003.time 2004.time 2005.time 2006.time 2007.time 2008.time
    2009.time 2010.time 2011.time 2012.time 2013.time 2014.time 2015.time
    2016.time 2017.time)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(6/57).(ly1 lx21g lx45g lx51 lx123 lx197g) collapsed
Instruments for levels equation
  Standard
    1960b.time 1961.time 1962.time 1963.time 1964.time 1965.time 1966.time
    1967.time 1968.time 1969.time 1970.time 1971.time 1972.time 1973.time
    1974.time 1975.time 1976.time 1977.time 1978.time 1979.time 1980.time
    1981.time 1982.time 1983.time 1984.time 1985.time 1986.time 1987.time
    1988.time 1989.time 1990.time 1991.time 1992.time 1993.time 1994.time
    1995.time 1996.time 1997.time 1998.time 1999.time 2000.time 2001.time
    2002.time 2003.time 2004.time 2005.time 2006.time 2007.time 2008.time
    2009.time 2010.time 2011.time 2012.time 2013.time 2014.time 2015.time
    2016.time 2017.time
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    DL5.(ly1 lx21g lx45g lx51 lx123 lx197g) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -3.05  Pr > z =  0.002
Arellano-Bond test for AR(2) in first differences: z =  -1.04  Pr > z =  0.300
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(290)  = 717.53  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)

Difference-in-Sargan tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Sargan test excluding group:     chi2(284)  = 562.03  Prob > chi2 =  0.000
    Difference (null H = exogenous): chi2(6)    = 155.50  Prob > chi2 =  0.000
  gmm(ly1 lx21g lx45g lx51 lx123 lx197g, collapse lag(6 .))
    Sargan test excluding group:     chi2(8)    =  16.30  Prob > chi2 =  0.038
    Difference (null H = exogenous): chi2(282)  = 701.23  Prob > chi2 =  0.000
```

```
  iv(1960b.time 1961.time 1962.time 1963.time 1964.time 1965.time 1966.time 1967.time
1968.time 1969.time 1970.time
>  1971.time 1972.time 1973.time 1974.time 1975.time 1976.time 1977.time 1978.time
1979.time 1980.time 1981.time 19
> 82.time 1983.time 1984.time 1985.time 1986.time 1987.time 1988.time 1989.time
1990.time 1991.time 1992.time 1993.
> time 1994.time 1995.time 1996.time 1997.time 1998.time 1999.time 2000.time 2001.time
2002.time 2003.time 2004.tim
> e 2005.time 2006.time 2007.time 2008.time 2009.time 2010.time 2011.time 2012.time
2013.time 2014.time 2015.time 2
> 016.time 2017.time)
    Sargan test excluding group:     chi2(275)  = 645.36  Prob > chi2 =  0.000
    Difference (null H = exogenous): chi2(15)   =  72.17  Prob > chi2 =  0.000
```

TWO STEP ROBUST DIFFERENCE GMM

```
Favoring space over speed. To switch, type or click on mata: mata set matafavor speed,
perm.
Warning: Number of instruments may be large relative to number of observations.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-step
estimation.
  Difference-in-Sargan/Hansen statistics may be negative.

Dynamic panel-data estimation, two-step difference GMM
------------------------------------------------------------------------------
Group variable: timecode                        Number of obs      =       380
Time variable : time                            Number of groups   =        47
Number of instruments = 290                     Obs per group: min =         0
F(7, 47)      =    151.94                                      avg =      8.09
Prob > F      =     0.000                                      max =        14
------------------------------------------------------------------------------
             |              Corrected
        GINI |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
             |
        GINI |   .9468772   .0460561    20.56   0.000     .8542242     1.03953
             |
             |
         EDU |   .0226697   .0161795     1.40   0.168    -.0098793    .0552187
             |
             |
          FD |  -.0096183   .0045568    -2.11   0.040    -.0187855   -.0004512
             |
             |
         GDP |  -.0132601   .0071876    -1.84   0.071    -.0277197    .0011995
             |
             |
          TO |  -.0078443   .0045659    -1.72   0.092    -.0170296    .0013411
             |
             |
        TECH |    .001371   .0009049     1.52   0.136    -.0004494    .0031913
             |
        time |  -.0002498   .0002437    -1.03   0.310      -.00074    .0002403
------------------------------------------------------------------------------
Instruments for first differences equation
  Standard
    D.(1960b.time 1961.time 1962.time 1963.time 1964.time 1965.time 1966.time
    1967.time 1968.time 1969.time 1970.time 1971.time 1972.time 1973.time
    1974.time 1975.time 1976.time 1977.time 1978.time 1979.time 1980.time
    1981.time 1982.time 1983.time 1984.time 1985.time 1986.time 1987.time
    1988.time 1989.time 1990.time 1991.time 1992.time 1993.time 1994.time
    1995.time 1996.time 1997.time 1998.time 1999.time 2000.time 2001.time
    2002.time 2003.time 2004.time 2005.time 2006.time 2007.time 2008.time
    2009.time 2010.time 2011.time 2012.time 2013.time 2014.time 2015.time
    2016.time 2017.time)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(6/57).(ly1 lx21g lx45g lx51 lx123 lx197g) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -2.29  Pr > z =  0.022
Arellano-Bond test for AR(2) in first differences: z =  -1.29  Pr > z =  0.197
```

```
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(283)  = 540.04  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(283)  =  41.43  Prob > chi2 =  1.000
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  gmm(ly1 lx21g lx45g lx51 lx123 lx197g, collapse lag(6 .))
    Hansen test excluding group:     chi2(7)    =   9.20  Prob > chi2 =  0.239
    Difference (null H = exogenous): chi2(276)  =  32.23  Prob > chi2 =  1.000
  iv(1960b.time 1961.time 1962.time 1963.time 1964.time 1965.time 1966.time 1967.time
1968.time 1969.time 1970.time
>  1971.time 1972.time 1973.time 1974.time 1975.time 1976.time 1977.time 1978.time
1979.time 1980.time 1981.time 19
> 82.time 1983.time 1984.time 1985.time 1986.time 1987.time 1988.time 1989.time
1990.time 1991.time 1992.time 1993.
> time 1994.time 1995.time 1996.time 1997.time 1998.time 1999.time 2000.time 2001.time
2002.time 2003.time 2004.tim
> e 2005.time 2006.time 2007.time 2008.time 2009.time 2010.time 2011.time 2012.time
2013.time 2014.time 2015.time 2
> 016.time 2017.time)
    Hansen test excluding group:     chi2(269)  =  41.07  Prob > chi2 =  1.000
    Difference (null H = exogenous): chi2(14)   =   0.36  Prob > chi2 =  1.000
```

TWO STEP DIFFERENCE GMM

```
Favoring space over speed. To switch, type or click on mata: mata set matafavor speed,
perm.
Warning: Number of instruments may be large relative to number of observations.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-step
estimation.
  Difference-in-Sargan/Hansen statistics may be negative.

Dynamic panel-data estimation, two-step difference GMM
------------------------------------------------------------------------------
Group variable: timecode                        Number of obs      =       380
Time variable : time                            Number of groups   =        47
Number of instruments = 290                     Obs per group: min =         0
F(7, 47)      =   2253.17                                      avg =      8.09
Prob > F      =     0.000                                      max =        14
------------------------------------------------------------------------------
        GINI |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
             |
        GINI |   .9468772    .019128    49.50   0.000     .9083966    .9853578
             |
             |
         EDU |   .0226697   .0071965     3.15   0.003     .0081922    .0371472
             |
             |
          FD |  -.0096183   .0019862    -4.84   0.000    -.0136141   -.0056226
             |
             |
         GDP |  -.0132601   .0022999    -5.77   0.000    -.0178869   -.0086333
             |
             |
          TO |  -.0078443   .0019192    -4.09   0.000    -.0117053   -.0039833
             |
             |
        TECH |    .001371    .000286     4.79   0.000     .0007956    .0019463
             |
        time |  -.0002498   .0001049    -2.38   0.021    -.0004608   -.0000389
------------------------------------------------------------------------------
Warning: Uncorrected two-step standard errors are unreliable.

Instruments for first differences equation
  Standard
    D.(1960b.time 1961.time 1962.time 1963.time 1964.time 1965.time 1966.time
```

```
    1967.time 1968.time 1969.time 1970.time 1971.time 1972.time 1973.time
    1974.time 1975.time 1976.time 1977.time 1978.time 1979.time 1980.time
    1981.time 1982.time 1983.time 1984.time 1985.time 1986.time 1987.time
    1988.time 1989.time 1990.time 1991.time 1992.time 1993.time 1994.time
    1995.time 1996.time 1997.time 1998.time 1999.time 2000.time 2001.time
    2002.time 2003.time 2004.time 2005.time 2006.time 2007.time 2008.time
    2009.time 2010.time 2011.time 2012.time 2013.time 2014.time 2015.time
    2016.time 2017.time)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(6/57).(ly1 lx21g lx45g lx51 lx123 lx197g) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -2.55  Pr > z =  0.011
Arellano-Bond test for AR(2) in first differences: z =  -1.35  Pr > z =  0.176
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(283)  = 540.04  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(283)  =  41.43  Prob > chi2 =  1.000
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  gmm(ly1 lx21g lx45g lx51 lx123 lx197g, collapse lag(6 .))
    Hansen test excluding group:     chi2(7)    =   9.20  Prob > chi2 =  0.239
    Difference (null H = exogenous): chi2(276)  =  32.23  Prob > chi2 =  1.000
  iv(1960b.time 1961.time 1962.time 1963.time 1964.time 1965.time 1966.time 1967.time
1968.time 1969.time 1970.time
>  1971.time 1972.time 1973.time 1974.time 1975.time 1976.time 1977.time 1978.time
1979.time 1980.time 1981.time 19
> 82.time 1983.time 1984.time 1985.time 1986.time 1987.time 1988.time 1989.time
1990.time 1991.time 1992.time 1993.
> time 1994.time 1995.time 1996.time 1997.time 1998.time 1999.time 2000.time 2001.time
2002.time 2003.time 2004.tim
> e 2005.time 2006.time 2007.time 2008.time 2009.time 2010.time 2011.time 2012.time
2013.time 2014.time 2015.time 2
> 016.time 2017.time)
    Hansen test excluding group:     chi2(269)  =  41.07  Prob > chi2 =  1.000
    Difference (null H = exogenous): chi2(14)   =   0.36  Prob > chi2 =  1.000
```

```
ONE STEP DIFFERENCE GMM
Favoring space over speed. To switch, type or click on mata: mata set matafavor speed,
perm.
Warning: Number of instruments may be large relative to number of observations.

Dynamic panel-data estimation, one-step difference GMM
------------------------------------------------------------------------------
Group variable: timecode                        Number of obs      =       380
Time variable : time                            Number of groups   =        47
Number of instruments = 290                     Obs per group: min =         0
F(7, 373)     =   1645.02                                      avg =      8.09
Prob > F      =     0.000                                      max =        14
------------------------------------------------------------------------------
        GINI |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
             |
        GINI |   .9363865   .0113769    82.31   0.000     .9140155    .9587575
             |
             |
         EDU |   .0246073   .0066599     3.69   0.000     .0115116    .0377029
             |
             |
          FD |  -.0077898   .0029909    -2.60   0.010     -.013671   -.0019086
             |
             |
         GDP |   -.014018   .0027437    -5.11   0.000     -.019413    -.008623
             |
             |
          TO |  -.0109562   .0020163    -5.43   0.000     -.014921   -.0069914
             |
```

```
             |
        TECH |   .0012004   .0004598     2.61   0.009     .0002962    .0021046
             |
        time |  -.0003538   .0000881    -4.01   0.000    -.0005271   -.0001805
------------------------------------------------------------------------------
Instruments for first differences equation
  Standard
    D.(1960b.time 1961.time 1962.time 1963.time 1964.time 1965.time 1966.time
    1967.time 1968.time 1969.time 1970.time 1971.time 1972.time 1973.time
    1974.time 1975.time 1976.time 1977.time 1978.time 1979.time 1980.time
    1981.time 1982.time 1983.time 1984.time 1985.time 1986.time 1987.time
    1988.time 1989.time 1990.time 1991.time 1992.time 1993.time 1994.time
    1995.time 1996.time 1997.time 1998.time 1999.time 2000.time 2001.time
    2002.time 2003.time 2004.time 2005.time 2006.time 2007.time 2008.time
    2009.time 2010.time 2011.time 2012.time 2013.time 2014.time 2015.time
    2016.time 2017.time)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(6/57).(ly1 lx21g lx45g lx51 lx123 lx197g) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -2.79  Pr > z =  0.005
Arellano-Bond test for AR(2) in first differences: z =  -1.35  Pr > z =  0.176
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(283)  = 540.04  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)

Difference-in-Sargan tests of exogeneity of instrument subsets:
  gmm(ly1 lx21g lx45g lx51 lx123 lx197g, collapse lag(6 .))
    Sargan test excluding group:     chi2(7)    =   7.53  Prob > chi2 =  0.376
    Difference (null H = exogenous): chi2(276)  = 532.50  Prob > chi2 =  0.000
  iv(1960b.time 1961.time 1962.time 1963.time 1964.time 1965.time 1966.time 1967.time
1968.time 1969.time 1970.time
>  1971.time 1972.time 1973.time 1974.time 1975.time 1976.time 1977.time 1978.time
1979.time 1980.time 1981.time 19
> 82.time 1983.time 1984.time 1985.time 1986.time 1987.time 1988.time 1989.time
1990.time 1991.time 1992.time 1993.
> time 1994.time 1995.time 1996.time 1997.time 1998.time 1999.time 2000.time 2001.time
2002.time 2003.time 2004.tim
> e 2005.time 2006.time 2007.time 2008.time 2009.time 2010.time 2011.time 2012.time
2013.time 2014.time 2015.time 2
> 016.time 2017.time)
    Sargan test excluding group:     chi2(269)  = 514.48  Prob > chi2 =  0.000
    Difference (null H = exogenous): chi2(14)   =  25.56  Prob > chi2 =  0.029
```

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
GINI	3389	3.704913	.1832132	3.091043	4.110874
EDU	1472	.0324823	.059531	-.3711271	.583703
FD	1639	-.0011896	.096256	-1.986199	.6430717
GDP	2669	3.99815	.1441706	-.2851067	4.458809
TO	2811	4.070237	.5900976	-1.742951	5.740934
TECH	1297	.0112501	.540622	-3.401197	4.609328

Correlations

	GINI	EDU	FD	GDP	TO	TECH
GINI	1.0000					
EDU	0.3083	1.0000				
FD	0.0449	0.0299	1.0000			
GDP	-0.1522	0.1035	-0.0269	1.0000		
TO	-0.3913	-0.2575	0.0143	0.0422	1.0000	
TECH	0.0192	0.1063	0.0574	0.0920	-0.0688	1.0000