

## **Human Capital Inequality and Income Inequality: Developing Countries**

**Suraya Mahmood<sup>1</sup> and Zaleha M. N.<sup>2\*</sup>**

*<sup>1</sup>School of Economics, Finance and Banking, College of Business, University Utara Malaysia, 06010 UUM Sintok, Kedah, Malaysia*

*<sup>2</sup>Faculty of Economics and Management, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia*

### **ABSTRACT**

This paper examines the effect of human capital inequality on income inequality in Developing Countries. Gini coefficient is used as a consistent measurement for both inequalities. This paper also adds a few control variables: Globalization Index, GDP per capita and total population. It uses dynamic panel data two-Step System Generalized Method of Moment (GMM) for 52 countries over the period of 1970-2010. The empirical results show that human capital inequality has a significance positive effect on income inequality. This result is similar with the theoretical framework, where the human capital inequality and income inequality are positively correlated. However, other control variables such as Global and total population are insignificant with income inequality except for GDP per capita at 5 and 10 percent level. Thus, in order to reduce income inequality and to give citizens equal opportunities, governments of developing countries and policymakers need to minimise human capital inequality.

*Keywords:* Human capital inequality, income inequality, Generalized Method of Moment (GMM), developing countries

### **INTRODUCTION**

The persistently increasing income inequalities in most developing countries have been producing negative effects on

the economies since 1980s until now. Some of these effects are political, social and economic in nature; such as, political instability, unhappy society, pressure for higher wealth redistribution, increasing crime rate, and low rate of growth<sup>1</sup>. The role

#### **ARTICLE INFO**

##### *Article history:*

Received: 21 May 2012

Accepted: 31 July 2013

##### *E-mail addresses:*

[ayarus81@yahoo.com](mailto:ayarus81@yahoo.com) (Suraya Mahmood),

[lehnoor@upm.edu.my](mailto:lehnoor@upm.edu.my) (Zaleha M. N.)

\* Corresponding author

<sup>1</sup>(Barro, 2000; Persson & Guido, 1994; Thorbecke & Charumilind, 2002; Kelly (2000); Brush, 2007)

of human capital is measured by the average years of education in order to reduce income inequality and its effects. It is one of the most important variables especially in 21<sup>st</sup> century as reported by World Bank (2009). However, the economic performance of a country should not solely depend on its average level of human capital in view of the fact that human capital is not freely traded in a market. The equal distribution of human capital all over the country is also vital in analyzing the country's economic performance as well as reducing income inequality. It is due to human capital functions as one of the determinants in influencing income inequality.

Theoretically, the human capital inequality and income inequality are positively correlated (Fields, 1980; Chakraborty & Das, 2005). If human capital inequality is high, income inequality can be expected to be high. However, previous studies have been using different measurements to estimate the effects of inequality in distribution of human capital on income inequality. They have shown contradictory or inconclusive results between these two variables. For example, Ram (1990) Park (1996) and Gregorio and Lee (2002) use a standard deviation of education as a measurement for human capital inequality and income share for income inequality in support of cross country data. They find that the existence of higher human capital inequality leads to higher income inequality. On the contrary, Ram (1984, 1989) and Digdowiseiso (2009) find that human capital inequality has no

significant effects on income inequality when using standard deviation for human capital inequality. In another study, Pose and Tselios (2009) discover that higher human capital inequality has led to higher income inequality in European Union (EU), the region where Theil Index is used to investigate these relationships. The studies reviewed earlier show inconclusive relationship between income inequality and human capital inequality. Hence it is difficult to clearly determine the direction of relationship. This problem might be attributed to the usage of inappropriate measurement for human capital inequality. Therefore, it is important to examine and use appropriate measurement to estimate both types of inequalities.

The objective of this paper is to examine the effects of human capital inequality on income inequality in developing countries. This paper applies the concept of Gini Coefficient as a consistent measurement for both inequalities: human capital Gini to measure human capital inequality; and Income Gini to measure income inequality. The human capital Gini seems to be an appropriate measurement. It is consistent, robust and a good measurement for the distribution of education compared to other measurements (Thomas *et al.* 2000, Castello & Domenech, 2002). Several studies have examined these relationships in cross country research. However, none has used Gini coefficient as a consistent measurement in developing countries. Hence this study specifically examines the relationship of both inequalities

covering data set for the years 1970 to 2010. The relationship between human capital inequality and income inequality is important for government of developing countries and policy makers. For instance, policy makers are keen to know the effects of human capital inequality on income distribution and how this relationship affects economic growth. Understanding this relationship will allow policy makers to assess whether human capital inequality will reduce income inequality.

The main contribution of this paper over previous empirical literature is in a number of important aspects. First, this study computes and extends data set of human capital inequality for two periods (2005-2010) using Human capital Gini for developing countries based on the latest data set from Barro and Lee (updated in 2010). Recently, Castello and Domenech (2002) computes the human capital Gini for the period of 1960 – 2000 by using Thomas *et al* model (2000) and Barro and Lee data set (2000). Thus, this paper produces the study results from larger sample and longer periods. Second, this paper considers the importance of human capital inequality in reducing income inequality. It is with a clear cut picture on the sign, direction and extent of the association between income inequality and human capital inequality for periods of 1970 to 2010 in developing countries. Both categories of inequalities use a consistent measurement. Finally, this paper employs the Generalized Method of Moments (GMM) using GMM two-step system as proposed by Arrelano and Bond (1991) for

broad panel data in developing countries. It differs from previous studies that have used OLS estimator, SUR Technique and other methods.

The rest of the paper is organized as follows: A Brief Theoretical and Empirical Review reviews the related literatures; Model, Econometric Method and Data explains the empirical model, method estimation and data used in the analysis; Empirical Result reports and discusses the econometric results; and the final section concludes and synthesizes the whole study.

#### **A BRIEF THEORETICAL AND EMPIRICAL REVIEW**

Theoretically, several literatures have explained the channel of effect of human capital inequality on income inequality. The first channel is through the rate of return on investment of human capital based on the ability and the distribution of earning theory. According to Becker (1962), the distribution of earning must be equal to the distribution of ability if everyone invests the same amount of effort in human capital. In view of ‘abler’ person tends to invest in human capital more than others, the earning leads to inequality. The other channel is based on the study by Shultz (1963). It states that the change of investment in human capital is the basic factor that reduces inequality in the personal distribution of income. However, the increase in human capital investment can be unequally distributed. It leads to greater income inequality. Moreover, Fields (1980) demonstrates a partial positive relationship between mean schooling level and earnings

inequality. That corroborates the positive relationship between human capital inequality and income inequality. This theory is further supported by Galor (2011) who emphasizes that income distribution has a significant impact on human capital formation and the development process.

Numerous empirical studies have examined the effect of human capital inequality on income inequality with mixed results. The studies use different measurements such as standard deviations of average years of education, Gini coefficient and Theil Index which measures educational inequality. For example, Becker and Chiswick (1966), Chiswick (1971), Tinbergen (1972), Pchachapoulos (1977), Lam and Levison (1990), Checci (2011), Gregoria and Lee (2002) and Mayer (2010) use standard deviations of average years of education to measure educational inequality. They conclude that there is a positive correlation between educational inequality and income inequality. On the contrary, Ram (1984), Park (1996) and Digdowniseiso(2009) find no significant effect of human capital inequality on the income distribution for cross-section data when they use the standard deviation of schooling as a measurement of human capital inequality. Study by Pose and Tselios (2009) use Theil index to measure income inequality and educational inequality in examining the effect of human capital inequality on income inequality for the regions of European Union. The result shows that higher human capital inequality leads to greater income inequality. Lin

(2007), Jun, Y. *et al* (2009) and Hisham (2012) examine the effect of human capital inequality on income inequality by using the Gini Coefficient for these variables. In their findings, they conclude that a lower education inequality causes a lower income inequality.

**MODEL, ECONOMETRIC METHOD AND DATA**

*Empirical model for the effect of human capital inequality on income inequality*

The theoretical research on how human capital influences income distribution originated from Schultz (1963), Becker and Chiswick (1966), Psacharopoulos (1977) and later trailed by Gregorio and Lee (2002). This paper adheres to Gregorio and Lee (2002) to estimate the relationship between human capital inequality and income inequality in developing countries However, it uses Gini coefficient of education to measure human capital inequality by reapplying standard deviation of education. The empirical model specification is illustrated below:

$$\begin{aligned} \ln \text{GiNi}_{j,t} &= \beta_1 \ln \text{GiNi}_{j,t-1} + \beta_2 \ln G^h_{j,t} + \beta_3 \ln \text{AYS}_{j,t} \\ &+ \beta_4 \ln \text{GDP}_{j,t} + \beta_5 \ln \text{GLOBAL}_{j,t} \\ &+ \beta_6 \ln \text{POP}_{j,t} + \varepsilon_{j,t} \end{aligned} \quad (1)$$

where GINI is Gini coefficient for income inequality;  $G^h$  is human capital inequality using Gini coefficient (human capital Gini); AYS is average years of education for the population aged 25 and above; control variables such as Globalization Index, population and GDP per capita; and  $\varepsilon$  is

Error term and  $j, i$  represents index countries and periods.

*Methods of Estimation*

This paper uses dynamic panel data procedure Generalized Method of Moments (GMM) to estimate the model specification for relationship between income inequality and human capital inequality in 52 developing countries with  $T=11$ . The reasons of using GMM: to allow the identification of country-specific effects; to control the unobserved effects by first-different data; to control the potential endogeneity of all the explanatory variables; and to control the simultaneity bias caused by the possibility that some of the explanatory variables may be endogenous. Some authors have found that Human capital Gini ( $G^H$ ), Human capital (average years of education), Global and POP are assumed to be endogenous.

Arellano and Bond (1991) propose transforming Equation (1) into first differences to eliminate country-specific effects as follows:

$$\begin{aligned} &Gini_{j,t} - Gini_{j,t-1} \\ &= \beta_1(\ln Gini_{j,t-1} - \ln Gini_{j,t-2}) \\ &+ \beta_2(\ln G^h_{j,t} - \ln G^h_{j,t-1}) \\ &+ \beta_3(\ln AYS_{j,t} - \ln AYS_{j,t-1}) \\ &+ \beta_4(\ln GDP_{j,t} - \ln GDP_{j,t-1}) \\ &+ \beta_5(\ln GLOBAL_{j,t} - \ln GLOBAL_{j,t-1}) \\ &+ \beta_6(\ln POP_{j,t} - \ln POP_{j,t-1}) \\ &+ (\varepsilon_{j,t} + \varepsilon_{j,t-1}) \end{aligned} \tag{2}$$

Arellano and Bond (1991) propose the lagged levels of the regressors to be used as instruments to address the possible simultaneity bias of explanatory

variables and the correlation between  $(\ln Gini_{j,t-1} - \ln Gini_{j,t-2})$  and  $(\varepsilon_{j,t} + \varepsilon_{j,t-1})$ . It is valid under the assumptions such as the error term is not serially correlated and the lag of the explanatory variables are weakly exogenous. This step is known as difference GMM estimation and the moment conditions are illustrated below:

$$\begin{aligned} &E[\ln Gini_{j,t-s}(\varepsilon_{j,t} + \varepsilon_{j,t-1})] \\ &= 0 \text{ for } s \geq 2; t = 3; \dots; T \end{aligned} \tag{3}$$

$$\begin{aligned} &E[\ln G^H_{j,t-s}(\varepsilon_{j,t} + \varepsilon_{j,t-1})] \\ &= 0 \text{ for } s \geq 2; t = 3; \dots; T \end{aligned} \tag{4}$$

$$\begin{aligned} &E[\ln AYS_{j,t-s}(\varepsilon_{j,t} + \varepsilon_{j,t-1})] \\ &= 0 \text{ for } s \geq 2; t = 3; \dots; T \end{aligned} \tag{5}$$

$$\begin{aligned} &E[\ln GDP_{j,t-s}(\varepsilon_{j,t} + \varepsilon_{j,t-1})] \\ &= 0 \text{ for } s \geq 2; t = 3; \dots; T \end{aligned} \tag{6}$$

$$\begin{aligned} &E[\ln GLOBAL_{j,t-s}(\varepsilon_{j,t} + \varepsilon_{j,t-1})] \\ &= 0 \text{ for } s \geq 2; t = 3; \dots; T \end{aligned} \tag{7}$$

$$\begin{aligned} &E[\ln POP_{j,t-s}(\varepsilon_{j,t} + \varepsilon_{j,t-1})] \\ &= 0 \text{ for } s \geq 2; t = 3; \dots; T \end{aligned} \tag{8}$$

It is known that the difference estimator is able to control country-specific effects and simultaneity bias. However, the difference estimator leads to biased parameter estimates in small samples and larger variance. This problem occurs when the explanatory variables are persistent and the lagged levels of the variables become weak instruments as reported by Alonso-Borrego and Arellano (1999) and Blundell and Bond (1998). To solve this problem, Arellano and Bover (1995) propose an alternative system; GMM combines the difference Equation (2) and the level Equation (1) with additional moment conditions for the second part of the system as illustrated below:

$$E [\ln\text{Gini}_{j,t-s} - \ln\text{Gini}_{j,t-s-1}) (\eta_i + \varepsilon_{j,t}) = 0 \text{ for } s = 1 \tag{9}$$

$$E [\ln\text{G}^h_{j,t-s} - \ln\text{G}^h_{j,t-s-1}) (\eta_i + \varepsilon_{j,t}) = 0 \text{ for } s = 1 \tag{10}$$

$$E [\ln\text{AYSgini}_{j,t-s} - \ln\text{AYS gini}_{j,t-s-1}) (\eta_i + \varepsilon_{j,t}) = 0 \text{ for } s = 1 \tag{11}$$

$$E [\ln\text{GDP}_{j,t-s} - \ln \text{GDP}_{j,t-s-1}) (\eta_i + \varepsilon_{j,t}) = 0 \text{ for } s = 1 \tag{12}$$

$$E [\ln\text{Global}_{j,t-s} - \ln \text{Global}_{j,t-s-1}) (\eta_i + \varepsilon_{j,t}) = 0 \text{ for } s = 1 \tag{13}$$

$$E [\ln\text{POP}_{j,t-s} - \ln \text{POP}_{j,t-s-1}) (\eta_i + \varepsilon_{j,t}) = 0 \text{ for } s = 1 \tag{14}$$

Basically, the GMM estimators are applied in one and two-step variants (Arellano and Bond, 1991). The one-step estimator is based on weighted matrices that are independent of estimated parameters. Whereas, the two-step GMM estimator uses the so-called optimal weighting matrices in which the moment conditions are weighted by a consistent estimate of their covariance matrix. Bowsher (2002) and Windmeijer (2005) find that the two-step GMM estimation with numerous instruments can lead to biased standard errors, parameter estimates and the numerous instruments may lead to a weakened identification test. This makes the two step system estimator asymptotically more efficient than the one-step estimator. Thus, the moment conditions presented in equation (3) to(14) are used and the two-step System GMM based on recommendation of Roodman (2009b) are employed.

To ensure the consistency of the GMM estimator, the validity of the

moment conditions is are tested using the conventional test of over identifying restrictions proposed by Sargan (1958) and Hansen (1982) and testing the null hypothesis that the error term is not second order serially correlated of the difference in equation (2). Besides that, AR (1) and AR (2) are tested to evaluate the validity of appropriate instrumentation (Arellano and Bond, 1991; Blundell and Bond, 1998). The purpose of testing AR is to determine the error term serial correlation, as far as the assumption of non-existence serial correlation of  $\varepsilon_{j,t}$ . The consistency of the estimators is important. If  $\varepsilon_{j,t}$  is not serially correlated, there should exist negative series correlation (AR (1)) for the first stage and there is no proof of serial correlation in the second stage (AR (2)).

*Data description and sources*

This paper uses several main variables and control variables to reduce the problem of omitted variables. The main variable used is Gini coefficient as a dependent variable. It is a most commonly used variable to measure income inequality. It is partly due to its conceptual clarity and easy calculation. Data for Gini Coefficient index is taken from Deininger and Squire World Income Inequality Data Set (2009) of consumption instead of combining income and consumption indices. Another main variable is human capital inequality. This paper uses human capital Gini from two sources to measure human capital inequality. We use Castello and Domenech data set (2002) for periods 1960 to 2000.

However, we extend and compute human capital Gini based on average years of education of the population aged between 25-64 years for periods 2005 and 2010. The average years of education is taken from Barro and Lee data set updated in 2010 and the model suggested by Thomas *et al.* (2001) is used. The Barro and Lee data set provides information on the average schooling years and educational attainment levels with four levels of education such as no education, primary, secondary and higher education. The human capital Gini ( $G^h$ ) can be computed as follows:

$$G^h = \frac{1}{2H} \sum_{i=0}^3 \sum_{j=0}^3 |\hat{x}_i - \hat{x}_j| n_i n_j \quad (15)$$

where  $H$  is the average schooling years of the population aged 25 years and above;  $i$  and  $j$  stand for the different levels of education;  $n_i$  and  $n_j$  are the shares of population with a given level of education; and  $\hat{x}_i$  and  $\hat{x}_j$  are the cumulative average schooling years of each educational level such as follows:

$$\begin{aligned} x_0 &= x_0 = 0 \\ x_1 &= x_1 \\ x_2 &= x_1 + x_2 \\ x_3 &= x_1 + x_2 + x_3 \end{aligned} \quad (16)$$

From equation (15) and (16) the human capital Gini coefficient can be rewritten as follows:

$$G^h = n_0 \frac{n_1 x_2 (n_2 + n_3) + n_3 x_3 (n_1 + n_2)}{n_1 x_1 + n_2 (x_1 + x_2) + n_3 (x_1 + x_2 + x_3)} \quad (18)$$

where  $x_0 = 0$ ,  $x_1$  is the average years of primary schooling of the total population divided by the percentage of the population with at least primary education;  $x_2$  is the

average years of secondary schooling of the total population divided by the percentage of the population with at least secondary education,  $x_3$  is average years of higher schooling of the total population divided by the percentage of the population with at least higher schooling;  $n_0$  is the percentage of population with no education;  $n_1$  is the percentage of the population with primary education;  $n_2$  measures the percentage of the population with secondary education; and  $n_3$  is the percentage of the population with higher education. As control variables, this paper includes a few variables for the econometric estimation such as Globalization Index, GDP per capita and total population to reduce omitted bias. The first control variable, Globalization Index is based on empirical evidence. It has a significant impact on income inequality (Jaumotte, *et al.*, 2008; Krugman, & Vanables, 1995; Ruffin, 2009). The Globalization Index used is extracted from Dreher (2007). It is comprised of three main dimensions of globalization: economics, social and political. Another control variable used in the analysis is Gross Domestic Production (GDP) per capita. Studies have shown that GDP per capita has positive and significant effect on income inequality and human capital inequality (Gregorio and Lee, 2002; Lin, 2007; Pose & Vassilis Tselios, 2009). The Gross Domestic Production per capita data is obtained from World Development Indicator (2009). The GDP covers 9 periods starting from 1970 to 2010. The final control variable used is the total population as a share of GDP. It also has

positive and significant effect on income inequality. The total population data is taken from Barro and Lee data set, updated in 2010, covering over 9 periods starting year from 1970 to 2010.

### EMPIRICAL RESULT

STATA 11.0 software is used to estimate the effect of human capital inequality on income inequality in developing countries for the period 1970-2010 using system Generalized Method of Moment (GMM) with two-steps. From the estimation coefficients, the income Gini with lagged one year (Incomegini (-1)) is positive and has significant effect on income inequality in developing countries. This implies that the income inequality in each developing country is very important in influencing the current income inequality. As expected, human capital inequality ( $G^h$ ) is significant with positive effect on income inequality at 5 percent level. The result is parallel with the theoretical prediction; human capital inequality and income inequality are positively correlated (Fields, 1980; Chakraborty and Das, 2005). In other words, reducing human capital inequality can lead to reduction in income inequality in developing countries. Furthermore, the average years of education (AYRS) also has a significant impact on income inequality with negative sign at 5 percent level. This finding is comparable with previous studies by Knight and Sabot (1983), Park (1996), Checchi (2001). The studies find that average years of education has a strong negative effect on income inequality. In addition, GDP per capita is also negatively

influencing income inequality at 5 percent significant level. It indicates that greater economic growth reduces income inequality, and vice versa.

However, the effect of globalization on income inequality as a control variable is not significant at 5 percent and 10 percent level. Similarly, Duncan (2000), reports that globalization should not be the contributing factor in reducing income inequality for developing countries except in the case of external shocks which occur as a result of greater openness in trade and investment. The insignificance of globalization found in this study is not reversing its positive impact. In fact, it raises the issue of how to manage risks as a result of greater openness in trade and investment. Moreover, the variable total population is also insignificant with income inequality at 5 percent and 10 percent level. Such results may be attributed to the measurement used. This problem can be mitigated by using data on population growth instead of total population.

Finally, based on the AR (2), the result finds no error term serial correlation in the second stage. While, Hansen Test proves that the instrument used in this model is a valid instrument. Both tests AR (2) and Hansen Test do not reject the null hypothesis.

### CONCLUSION

In this paper, we examine the role of human capital inequality and income inequality using Gini coefficient as a consistent measurement for both inequalities. It has not been precisely discussed altogether in previous research of 52 developing countries

TABLE 1  
The effect of human capital inequality on income inequality in Developing countries (1970-2010) based on Two Step System Generalized Method of Moment (GMM)

Dependent variable: Income inequality (incomegini)		
Explanatory Variable	Coefficient	t-value (p-value)
Incomegini(-1)	0.6855	8.24(0.000)*
Human capital inequality (G <sup>h</sup> )	0.4224	2.62(0.012)**
Average year of education (AYRS)	-0.0794	-2.01(0.043)**
GDP per capita (GDPC)	-0.05619	-1.78(0.032)**
Total of population (POP)	0.0117	1.06(0.295)
Global	-0.0524	-0.78(0.439)
Constant	1.7353	3.58(0.001)**
AR(1)	0.004**	
AR(2)	0.438	
Hansen Test	0.999	
Number of Observation	416	

\*Significant  $p < 0.01$  \*\*Significant  $p < 0.05$  AR(2) test and Hansen Test: Significant  $p > 0.05$

for periods 1970 to 2010. Importantly, this study confirms that higher equally distributed human capital opportunities can alleviate income inequality. Thus, this is a valid indication to the governments of developing countries, policy makers and politicians to pay attention to investment in human capital and distribution of human capital by accelerating the average years of education as it has a commanding potential in reducing income inequality. In the past, most policy decision makers have not considered education as a powerful tool of human capital and neglected in giving it the top priority. In addition, the government in many developing countries have allowed private sector to provide education in order to mitigate the problem of inequality in human capital. The privatization of education has indeed brought an increase in the share of private financing at the basic level but more commonly at the post basic

education level. Nowadays, the numbers of private schools and private universities have increased. This trend emerges largely owing to the incapability of the states in fulfilling the increasing demand at all levels. Thus, the policy makers should also pay more attention to distribution of private schools. Private schools are capable of delivering higher contributions: more resources for the education sector; more efficient use of these resources; and more flexibility in education deliverables. It is parallel with the Millennium Development Goal (MDG) in achieving the target education for all primary schools and generating equal distribution in human capital as well as reducing income inequality for all countries.

## REFERENCES

- Abdelbaki, H. H. (2012). An Analysis of Income Inequality and Education Inequality in Bahrain. *Modern Economy*, 3(5), 675-685.

- Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2), 288-297.
- Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1), 29-51.
- Barro, R. J. (2001). Human capital and growth. *The American Economic Review*, 91(2), 12-17.
- Barro, R. J., & Lee, J. W. (2000). *International data on educational attainment updates and National implications Bureau of Economic Research Cambridge, Mass., USA*. Bureau of Economic Research Cambridge, Mass., USA.
- Becker, G. S. (1962). Investment in human capital: A theoretical analysis. *The journal of political economy*, 70(5), 9-49
- Becker, G. S., & Chiswick, B.R.(1966). Education and the distribution of earnings. *American Economic Review*. 56, 358-369.
- Bergheim, S. (2005). Human capital is the key to growth: Success stories and policies for 2020. *Current Issues. Global Growth Centers*. Deutsche Bank Research.
- Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1), 115-143.
- Bond, S. R., Hoetler, A., & Temple, J. (2001). GMM Estimates of empirical Growth Models. Centre for economic policy Research. *Discuss Paper* No.3048.
- Bowsher, C. G. (2002). On testing overidentifying restrictions in dynamic panel data models. *Economics letters*, 77(2), 211-220.
- Brush, J. (2007). Does income inequality lead to more crime? A comparison of cross- and sectional time-series analyses of United States counties. *Economics Letters*, 96(2), 264-268.
- Castelló, A., & Doménech, R. (2002). Human capital inequality and economic growth: some new evidence. *The Economic Journal*, 112(478), C187-C200.
- Chakraborty, S., & Das. M. (2005). Mortality, human capital and persistent inequality. *Journal of Economic Growth*, 10(2), 159-192.
- Checchi, D. (2003). Inequality in Incomes and Access to Education: A Cross country Analysis (1960-95). *Labour*, 17(2), 153-201.
- Checchi, D. (2001). *Education, inequality and income inequality: Distributional Analyses Research Programme Papers 52*. Suntory and Toyota International Centres for Economics.
- Chiswick, B. R. (1971). Earnings inequality and economic development. *The Quarterly Journal of Economics*, 85(1), 21-39.
- Chiswick, B. R. (1974). *Income Inequality: Regional analyses within a human capital framework: National bureau of economics*. National bureau of economics.
- Chiswick, B. R., & Mincer, J. (1972). Time-series changes in personal income inequality in the United States from 1939, with projections to 1985. *The Journal of Political Economy*, 80(3), 34-66.
- De Gregorio, J., & Lee, J. W. (2002). Education and income inequality: New evidence from cross-country data. *Review of Income and wealth*, 48(3), 395-416.
- Digdowiseiso, K. (2009). Education inequality, economic growth, and income inequality: Evidence from Indonesia, 1996-2005. *MPRA Paper*.

- Dreher, A. (2007). Does Globalization Affect Growth? Evidence from a new Index of Globalization, *Applied Economics*, 38(10), 1091-1110.
- Fields, G. S. (1980). *Education and Income Distribution in Developing Countries: A Review of the Literature*. In *Education and Income*. World Bank Staff Working Paper No. 402. Washington, DC.
- Galor, O. (2011). *Inequality, human capital formation and the process of development*. National Bureau of Economic Research.
- Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica: Journal of the Econometric Society*, 1029-1054.
- Jun, Y., Xiao, H., & Xiaoyu, L. (2009). Educational inequality and income inequality. An empirical study on China. *Frontier Education China*, 4(3), 413-434.
- Kelly, M. (2000). Inequality and crime. *Review of Economics and Statistics*, 82(4), 530-539.
- Lin, C. H. A. (2007). Education Expansion, Educational Inequality, and Income Inequality: Evidence from Taiwan, 1976–2003. *Social indicators research*, 80(3), 601-615.
- Park, K.H (1996). Educational expansion and educational inequality on income distributions. *Economics of Education Review*, 15(1), 51-58.
- Pose & Vassilis Tselios. (2009). Education and Income Inequality In the regions of the European Union. *Journal of Regional Science*. 49(3), 411–437.
- Persson, T., & Guido, T. (1994). Is inequality harmful for growth?. *American Economic Review*, 84(3), 600–62.
- Psacharopoulos, G. (1977). Unequal access to education and income distribution. *De Economist*, 125(3), 383-392.
- Ram, R. (1984). Population increase, economic growth, educational inequality, and income distribution: Some recent evidence. *Journal of Development Economics*, 14(3), 419-428.
- Ram, R. (1989). Can educational expansion reduce income inequality in less-developed countries? *Economics of Education Review*, 8(2), 185-195.
- Ram, R. (1990). Educational expansion and schooling inequality: International evidence and some implications. *The Review of Economics and Statistics*, 72(2), 266-274.
- Roodman, D. (2006). How to do xtabond2: An introduction to "difference" and "system" GMM in Stata. *Center for global development*.
- Roodman, D. (2009). A note on the theme of too many instruments\*. *Oxford Bulletin of Economics and Statistics*, 71(1), 135-158.
- Ruffin, R.J. (2009). Globalization and income inequality. *Trade and Development Review*, 2(2), 56-59.
- Sargan, J. D. (1958). The estimation of economic relationships using instrumental variables. *Econometrica: Journal of the Econometric Society*, 393-415.
- Schultz, T. W., & William, T. (1963). *The economic value of education*: Columbia University Press.
- Thomas, V., Wang, Y., & Fan, X. (2001). *Measuring education inequality: Gini coefficients of education*. Policy Research Working Paper No. 2525, Washington, DC: The World Bank.
- Thomas, V., Wang, Y., & Fan, X. (2003). Measuring education inequality: Gini coefficients of education for 140 countries, 1960-2000. *Journal of Education Planning and Administration*, 17(1), 5-33.
- Thorbecke, E., & Charumilind, C. (2002). Economic Inequality and Its Socioeconomic Impact. *World Development*, 30(9), 1477–1495.

- Tinbergen, J. (1972). The impact of education on income distribution. *Review of Income and wealth*, 18(3), 255-265.
- World Bank, (2009). *World Development Report*. Washington, D.C.: World Bank.
- Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of econometrics*, 126(1), 25-51.