HUMAN CAPITAL, INEQUALITY AND ECONOMIC GROWTH IN THAILAND

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ABSTRACT

Title of Dissertation	HUMAN CAPITAL, INEQUALITY AND ECONOMIC GROWTH IN THAILAND
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This dissertation contains three papers concentrating on human capital, inequality and economic growth in Thailand. All three papers use the Labor Force Survey (LFS), conducted by National Statistical Office (NSO) in Thailand. First paper (Chapter two of this dissertation) aims to find intergenerational rate of transmission of human capital. As one of the major limitations of finding intergenerational rate of transmission is endogeneity problem, this paper contributes by proposing an alternative instrument to find rate of transmission of human capital. In addition to methodological contribution, this paper finds new evidence of rate of transmission from Thailand. Moreover, it also finds that the children from lower income families are getting less education than their counterparts. Second paper (Chapter three of this dissertation) analyses on the rural-urban differences and inequality trend of human capital in Thailand. Using the rural-urban dummy, this paper found that on an average, rural children are getting about 0.67 years less schooling than urban children. This paper also concludes that intergenerational transmission is higher in lower educated families than that in higher educated families. One of the major contributions of this paper is to control nature or nurture effects from the parents to find rural-urban gap in education. Third paper (Chapter four of this dissertation) aims to find the long run effects of human capital inequality on economic growth. It generates the provincial panel data of human capital inequality from the year 1995 to 2012. Second generation panel econometric techniques are applied to find the long run effects of human capital inequality on aggregate economy. It concludes that inequality of human capital has significant and negative effect on overall economy. There are several contributions of this paper, among them using the sub-national annual data, controlling cross sectional dependence, and finding long-run effects of human capital on economic growth are important.

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CHAPTER 1
INTRODUCTION

Human capital is one of the main factors in the production function. Thus, human capital accumulation is the major concern in every country. To build better human capital, most of the countries are engaged in various educational policies, such as compulsory primary and secondary education, education loan program, and female education stipend program. Educational policies are very closely connected with intergenerational transmission. For instance, if the rate of transmission is high then the policies may target to educate only one generation and the next generation will be educated through intergenerational transmission. Another implication of intergenerational transmission could be in the policy of female stipend program. If rate of transmission of human capital is higher from father than mother, only female stipend might not benefit to the next generation more than gender unbiased stipend program (J. R. Behrman & Rosenzweig, 2005). Hence, this dissertation first concentrated on intergenerational transmission of human capital. Second, we extended our concentration on the distribution and distributional effects of human capital on aggregate economy. Inequality is debatable issue in last few decades in economic literature. Most of the arguments regarding inequality are provided with the evidence with income inequality data (Aghion, Caroli, & García-Peñalosa, 1999), which actually used as a proxy of wealth inequality. In addition, land or asset inequality is also focused in the transition of economic growth in some literature (Adamopoulos, 2008). However, the issue of human capital inequality came into the concentration in later era of inequality research due to availability of data (Castelló & Doménech, 2002). It got popularity especially after publishing cross county human capital dataset by Barro (2001); and using this dataset Castelló & Doménech (2002) first provided the comparative evidence between human capital inequality and income inequality in growth regression. They suggest first human capital inequality is more robust than income inequality in growth regression. Thus, human capital inequality came into focus in growth regression in last decade. This dissertation uses sub-national data from Thailand to estimate human capital inequality and growth relationship. The next paragraph will discuss about the data issues in this dissertation.

There are three main chapters in this dissertation. First and fifth chapter is about introduction and conclusion respectively. Chapter two studied intergenerational transmission of human capital as well as the efficiency of student loan scheme in Thailand. Chapter three is about the trend and dimension of human capital inequality in Thailand. Chapter four analyzes the cointegrating relationship between human capital inequality and economic growth in Thailand. Both intergenerational study and human capital inequality study faced data challenges. Thai Labor Force Survey (LFS) data has been used in all chapters in this dissertation. For the intergenerational study, the data challenges arise because of multigenerational data is needed as well as endogeneity problem in the model. The multigenerational data is generated with the question of "What is the relationship with the household head?" in LFS questionnaire. The endogeneity problem has been solved by using instrumental variable. We used parents' cohorts mean schooling in their respective provinces as an instrument for parents' education, which is also generated from LFS by data programing. Data issue in the chapter three is similar to chapter two as it uses the intergenerational framework to analyze the trend and dimension of human capital inequality. One of the major contributions in chapter four is finding cointegrating relationship between human capital inequality and economic growth using sub-national data from Thailand. We generated provincial series of human capital inequality data from individual year of schooling data, which is distributed from 0 to 21 years of schooling. Thus the measurement of inequality in human capital might be more robust than human capital inequality measurement previous studies, in which educational attainment dummy has been used instead of exact year of schooling (Castelló & Doménech, 2002). The advantage of subnational data compare to cross country data in finding the effects of human capital inequality in economic growth mostly lies in heterogeneity issue. However, there are several contributions of each chapter in this dissertation, which will be discussed in the following paragraphs.

Chapter two will focus on the intergenerational transmission of human capital. It measures rate of intergenerational transmission of human capital for both father and mother in Thailand. The rate of transmission of human capital might indicate the future human capital accumulation in the economy. Moreover, from the policy perspective rate of transmission plays an important role. For instance, in the case of higher rate of transmission, if one generation is educated, next generations will also be educated through intergenerational transmission. Thus, policymakers may concentrate only on one generation to boost aggregate human capital in the long run and it will be transferred to next generation automatically. Using the intergenerational transmission model, chapter two also conducted a policy based research to analyze the policy of Student Loan Scheme (SLS) in Thailand. This chapter has several contributions to the existing intergenerational study. First, it uses an alternative instrument to find rate of intergenerational transmission. Second, this paper claims to be the first to find rate of intergenerational transmission in Thailand as well as in Asia. Moreover, the findings of this chapter contribute in policy making to increase aggregate level of human capital. However, the distribution of human capital should be observed as it has negative effects on aggregate economy (Castelló & Doménech, 2002). Hence, we concentrate to the distribution of human capital in chapter three.

Chapter three aims to find the trend and dimensions of the human capital inequality. For the trend and dimensions, we added two dummy variables in the intergenerational transmission model developed in chapter two. Because of the completely different aims of the chapter, we separated this chapter from chapter two. For the trend of the human capital inequality, parents' education dummy has been used. Parents' education dummy has been generated based on the mean education of the parents in the respective provinces. For instance, parents' education in household i will be equal to one if average year of schooling of father and mother is lower than the provincial average year of schooling of parents' generation, otherwise it will be zero. The coefficient of parents' education dummy implies the trend in human capital inequality. For instance, if the coefficient of parental education dummy is positive, implies that children from lower educated parents are getting higher level of schooling than the children from higher educated parents. In other words, rate of intergenerational transmission is higher in comparatively lower educated households than higher educated households. On the dimensions of human capital inequality, we added a rural-urban dummy in our model. The rural-urban dummy is equal to one if the household stays in rural area, otherwise the value is zero. The coefficient of the rural-urban dummy explains the educational difference between rural children and urban children. This chapter found that there is decreasing trend in human capital inequality and there exists rural-urban inequality in human capital. However, as discussed earlier, the effects of human capital inequality on aggregate economy need to be observed due to its robustness in growth regression. We extend our concentration on the long-run relationship between human capital inequality and economic growth in the chapter four.

Chapter four aims to identify whether the human capital inequality affects in economic growth in the long-run. Most of the previous literature focused on the relationship between income inequality and economic growth. A very few literature studied the causal relationship of human capital inequality and economic growth. Using the sub-national data from Thailand, this chapter applied advance panel cointegration techniques to find long-run association between economic growth and human capital inequality. This chapter contributes to the existing literature in four ways. First, it claims to be the first used cointegration test or long run association between human capital inequality and economic growth in Thailand. Second, this paper uses annual sub-national data for the first time in analyzing human capital inequality and economic growth relationship. Third, we consider cross sectional dependence (CSD) in panel model. Lastly, we employed new data set and exact year of schooling has been used to generate inequality, which is distributed from 0 to 21. We applied second generation panel unit root test, panel cointegration test and recently developed cointegration estimation techniques to estimate the parameters. Subnational data might face the problem of cross sectional dependence. For the cross sectional dependence in the model the estimated parameters could be inconsistent in the model. Thus, first generation econometric techniques for unit root test, cointegration test and cointegration estimation techniques might not be appropriate as these techniques assume the there is no cross sectional dependence in the model. Hence this paper checked cross sectional dependence in the model and found that there is cross sectional dependence in the model. Based on the findings of cross sectional dependence, this paper employs second generation econometric techniques to find long run association between human capital inequality and economic growth. This chapter found that human capital inequality has significantly negative effects on economic growth, which supports the existing findings using cross country data. Although, we found that the effects of average level of human capital to economic growth is not significant.

Lastly, chapter 5 is about the conclusion, which includes concluding remarks from each chapter. In short, this dissertation concludes the following- (1) the intergenerational transmission of human capital in Thailand is higher than the developed countries, as well as the rate of transmission from father is higher than the mother. (2) there is decreasing trend in human capital inequality but there exists rural-urban human capital inequality in Thailand. (3) there are significantly negative effects of human capital inequality in economic growth in Thailand. The details will be found in the next consecutive chapters.

CHAPTER 2
INTERGENERATIONAL TRANSMISSION OF HUMAN CAPITAL: EVIDENCE WITH AN ALTERNATIVE INSTRUMENT FROM THAILAND

Abstract

This paper aims to find the rate of intergenerational transmission of human capital, and comparative schooling attainment between lower and higher income families using the Labor Force Survey (LFS) in Thailand. Instrumental Variable (IV) approach has been used in this paper. We proposed an alternative instrument for parental education to identify rate of transmission, which is the parents' cohorts' mean schooling in their respective provinces. This paper found that rate of transmission of human capital from father and mother is quite similar in Thailand. For both, rate of transmission in Thailand is higher than the developed countries. In addition, it is found that children from lower income families are getting lesser education than higher income families in Thailand. This paper used an alternative instrument which could solve the endogeneity problem in the literature of intergenerational transmission of human capital. The results of rate of transmission can help to make educational policies in countries like Thailand. It also could help the policymakers to redesign the student loan scheme (SLS) in Thailand. This study used an alternative instrument for parental education to identify rate of transmission in instrumental variable approach. This paper is the first to identify the intergenerational transmission rate in Thailand. In addition, it analyzes Thai SLS in intergenerational framework.

Keywords Intergenerational Transmission; Human Capital; Inequality; Instrumental Variable

2.1 Introduction

Does parents' education boost the child education? This paper focuses on the intergenerational linkage or transmission of human capital from parents' education to child education. The education might be transmitted either through the nature (genetically transmitted) or nurturing of the child or both. The nature effects need to be controlled to find the nurture effect of intergenerational linkage, which is the challenging issue in estimating the intergenerational model. However, different identification strategies have been used in existing literature to estimate the nurturing effect (see Section 2). Because the intergenerational study of human capital is important in policy design, especially in educational reform policies. Thus, it has been widely discussed for the past few decades. For instance, policy regarding enrichment of only female education might not be beneficiary in the long run if rate of transmission from mother is lower than father.[1]

This paper contributes to existing literature in four ways. First, we introduced an alternative instrument for parental education to estimate the model, which is parents' provincial cohorts' mean education. According to our best knowledge, this paper used this instrument for the first time to find rate of transmission of human capital. Second, this paper claims to be the first to find causal estimates of intergenerational transmission of human capital in Thailand as well as in Asia. Although, a very few of existing literature found this causal relationship from the perspective of developing countries.[2] Most of the evidences are provided in existing literature from developed countries perspective. Third, this paper engaged in policy evaluation whether the Student Loan Scheme (SLS) policy in Thailand is effective. In addition, based on our results, this paper engaged in policy recommendations such as higher educational reform policy, student loan program, and compulsory education policy.

Thailand might be an interesting country to find intergenerational rate of transmission because it may help in future educational reform. The first educational reform was implemented in 1999 (Lounkaew, 2013). There were many important

[1] See the page 1746 in Behrman & Rosenzweig (2005).
[2] Celhay & Gallegos (2015) found intergenerational transmission of human capital in Chile is 0.46, which is quite high compare to Nordic countries' transmission.

features in that reform. Two of the key features were 12 years of free education and 9 years of compulsory education. The second educational reform was implemented in 2012. Between the two educational reforms, government continuously increased the educational budget, which is nearly doubled in a decade (Ministry of Education, 2011; Siamwalla et al., 2011). This study might help the policymakers to implement further educational reforms in Thailand. Moreover, nurturing child or investment in kids might vary with different socio-economic context of parents. In developing countries like Thailand, extended families are very common where multigenerational people live together.[3] In many cases, parents are taking care of the whole family or both children and grandparents with the parents' financial constraint. So investment in kids to income ratio might be lesser than developed countries and rate of transmission might be different from developed countries. Moreover, this paper tries to find whether children from lower income families are getting less education than from higher income families. We put our interest on this issue to analyze the effectiveness of student loan scheme (SLS) in Thailand. The SLS was started from the year 1996 to support the tuition fees and living expenses for the students from lower income families.

This study is organized into six sections. In section two, we discussed about the previous literature related to our topic. Section three is focused on the empirical model and methodology. Data used in this paper are discussed in section four. Empirical results are provided in section five and section six is about conclusion.

2.2 Literature Review

This section tries to cover existing literature on intergenerational transmission of human capital. Hence, we divided this section into few subsections. First, it includes the existing identification strategies to find intergenerational transmission rate. Second, it includes the existing evidences of intergenerational transmission of human capital from different country perspective. Last part concentrates on the

[3] According to the Survey of Older Person in Thailand 95.4% of older people live with their children and 48.3% of them have co-residence with their grandchildren. For details please see Knodel & Chayovan, (2012).

comparative studies of child education from different income group families as well as SLS in Thailand.

The existing studies of intergenerational transmission of human capital mostly used three identification strategies (Identical Twin, Adoptees, and Instrumental Variable (IV) approach) to deal with endogeneity problem of parental education.[4] In this part, we mostly concentrate on the existing literature using IV to estimate the rate of transmission. Black, Devereux, & Salvanes (2005) used Norwegians minimum school leaving age reform as an instrument for parental education and found that intergenerational transmission from father is not significant and from mother is very low (0.12). However, their OLS estimates are significantly different from zero and transmission rate from father and mother is similar, from 0.21 to 0.24. Chevalier (2004) used same instrument for UK and found the coefficient for mother is 0.11 and negative for father. Using grade repetition instead of year of schooling, and education reform policies as an instrument, negative transmission rate for both father and mother have been found in some existing literature (Maurin & McNally, 2008; Oreopoulos, Page, & Stevens, 2006). Holmlund, Lindahl, & Plug (2011) used compulsory schooling reform as an instrument for parental education in Sweden, found very low transmission rate using IV compare to OLS and most of the cases are insignificant. Carneiro et al. (2007) used an alternative instrument for parental education, like local tuition fees, unemployment rates and wages but the instruments are highly varied with time and less convincing. Lindahl, Palme, Sandgren-Massih, & Sjögren (2014) used great grandparents' education as an instrument for parental education and found IV coefficient not statistically significant. Grandfathers' twin brothers' education also used as an instrument for father's education in J. Behrman & Taubman (1985). Most of the existing studies used educational reform policies as an instrument for parental education. Unlike education reform policies in US or Norway, educational reform policies in UK are less convincing as an instrument due to less variability in data. Instead of IV, identical twins and adoptees approach are used in some papers. In identical twins, the differenced educational data of twins are used to

[4] For Twin studies, please see Antonovics & Goldberger, 2005; J. R. Behrman & Rosenzweig, 2005; Holmlund et al., 2011; Pronzato, 2012. And for Adoptees studies, please see Björklund, Lindahl, & Plug, 2006; Holmlund et al., 2011; Sacerdote, 2007.

avoid endogeneity problem but sample size of identical twins are small. In the adoptees strategy, one of the criticisms is that parents do not select their adopted children randomly. However, it is difficult to find a suitable instrument and most of the instruments are less convincing because of statistically weakness or less variation in data.[5] Therefore, this paper proposed to use an alternative instrument to identify the intergenerational transmission rate of human capital, which is found as valid instrument in statistical testing.

Parents face wealth constraint in maximizing their consumption and investment in their kids (Becker & Tomes, 1986). Credit constraint or absence of public education might make the children from lower earnings family worse off. There are several studies, tried to analyze the relationship between parents' income and child education. Shea (2000) found that parents' income indirectly affects to their child education and direct effects found in some studies (Blanden, 2004; Oreopoulos et al., 2006). Using the Norwegian oil shock as an instrument of parental income, Løken (2010) found there is no such causal relationship between family income and child education. However, Thailand introduced the SLS from 1996 to support students from lower income family. SLS in Thailand has been criticized in the existing studies. For instance, the criticisms are poor administration (Ziderman, 2003), misallocation and misuse of money (Tangkijvanich, and Manusbunpeampun, 2006), do not target the poor students (Ziderman, 2002). Using the family income dummy in intergenerational framework, this paper engaged in comparative study of schooling attainment between children from lower and higher income families. The results in this study also analyze the effectiveness of SLS, which might be helpful for policymakers to rethink about the SLS in Thailand.

2.3 Empirical Specification & Methodology

2.3.1 Empirical Specification

Empirical model is based on the theory of intergenerational mobility of human capital from Becker & Tomes (1986). According to their model, parents optimize

[5] See Holmlund, H., Lindahl, M., & Plug, E. (2011). The causal effect of parents' schooling on children's schooling: A comparison of estimation methods. Journal of Economic Literature, 49(3), 615-651. (Page 525)

their own consumption and investment on child's human capital with respect to their wealth constraint. The outcome of this model is the generational linkage of earnings, for instance, earnings of children is affected by earnings of parents and earnings of grandparents. Later on this model is modified and education has been used instead of earnings to find rate of intergenerational transmission of human capital (Holmlund et al., 2011; Plug & Vijverberg, 2005; Solon, 2014). Following Black, Devereux, & Salvanes (2005) and Holmlund, Lindahl, & Plug (2011), we specified the reduced form empirical model as follows

$$h_{it} = \beta_0 + \beta_1 h_{it-1} + \beta_2 age_{it-1} + \gamma d_i^w + \varepsilon_{it} \qquad 1$$

Equation (1) is AR(1) model, in which h_{it} and h_{it-1} be the child human capital and parents' human capital respectively. The estimated β_1 measures the intergenerational transmission rate of human capital, which is expected to be positive because return on investment in children is positive. age_{it-1} be the age of parents in household i, which controls for the age specific characteristics of parents. Although Black, Devereux, & Salvanes (2005) argued that age of child should be included if all children in the sample did not finish their study or some are currently studying. We exclude child age in the model, because we excluded the children who are currently studying or did not finish their study during the survey.[6] ε_{it} be the error term captured unobservable effects such as genetic effects, luck.

In addition to finding rate of transmission of human capital, we are interested to find whether children from lower income families are getting less schooling than children from higher income families. Theoretically, parents face the income constraint in investing their child's education and child education in lower income families should be lower. Hence, we included the dummy of family income, which helps to analyze credit market as well as coverage of public education. Here in equation (1), d_i^w be the family income dummy, which is equal to 1 if average income of family i is less than the provincial mean income and 0 otherwise. γ be the corresponding parameter for family income dummy. We expect that the sign of

[6] Black et al. (2005) suggested that if all children did not finish their schooling in the sample, should include child age in the model. They also suggested that child age might be endogenous because timing of birth is the parents' decision. So it is better to exclude child age from the model.

estimated γ is negative because capital market is not perfect, which is interpreted as controlling the effects of parental education, children from lower income families are getting less education than their counterparts. The magnitude of estimated γ explains the perfection in capital market in terms of education loan as well as the coverage of public education. It also could help the policymakers to rethink about the existing SLS in Thailand.

2.3.2 Methodology

Finding rate of intergenerational transmission with the sample of children and biological parents is challenging due to endogeneity problem. Because parental education is not exogenously determined, which might be affected by gene, luck of parents and other unobservable factors (Black et al., 2005; Holmlund et al., 2011; Lindahl et al., 2014). Ordinary Least Square (OLS) is unable to give us consistent parameter because $Cov(h_{it-1}, \varepsilon_{it}) \neq 0$. Most common solution of the endogeneity problem is to use IV approach or Two Stage Least Square (2SLS) method. The two basic conditions of using IV are- strong correlation between instrumental variable and endogenous regressor, and the correlation between instrumental variable and error term (ε_{it}) should be zero.[7] Existing literature mostly used education reform policy as an instrument for parental education. Holmlund, Lindahl, & Plug (2011) argued that most of instruments are less convincing due to statistical weakness (tuition fees, college location) or less variation (exam quality, UK education reform policy). They also argued that education reform policies in US or Norway are more convincing because of more variability and statistical strength.

This paper used an alternative instrument to deal with the endogeneity problem from parental education. The instrument is basically cohort's mean schooling of each parents in each province. We took average year of schooling by age, sex and province for all parents as instrument for parents' schooling. Let $mean\_ysch_{asp}$ be our instrumental variable, which is mean year of schooling by age, sex and province. a, s and p represent age, sex and province respectively. s=male and s=female indicates instrument for father and mother's education respectively. It is reasonable to

[7] For details please see Wooldridge, Jeffrey M. Introductory econometrics: A modern approach. Nelson Education, 2015. Page 507-516

argue that parents' education is correlated with their cohort's education in their provinces as parents' share the common shocks with their cohorts in their respective provinces. We expect that our instrument is statistically valid as it is uncorrelated with unobservable abilities and has no direct effects on child education. Moreover, there are enough variability in instruments because it varies with age of father/mother in different provinces. We argue that our instrument is more convincing due to overcome the limitations of less variation and statistical weakness discussed above. The descriptive statistics and statistical validity of our instruments are shown in Data and Results section respectively. In 2SLS, our first stage and second stage regression equations are in equation (2) and (3) respectively

$$h_{it-1} = \alpha_0 + \alpha_1 mean\_ysch_{asp} + \alpha_2 age_{it-1} + \gamma d_i^w + v_{it} \quad 2$$

$$h_{it} = \beta_0 + \beta_1 h_{it-1} + \beta_2 age_{it-1} + \gamma d_i^w + \varepsilon_{it} \quad 3$$

where $mean\_ysch_{asp}$ be the instrument for parents' education.

2.4 Data

This paper used the data from Thai Labor Force Survey (LFS) conducted by the National Statistical Office (NSO), Thailand. Thai LFS is quarterly collected, the first quarter started from February, which is dry season or non-agricultural season. The third quarter normally started from August, which is rainy season or agricultural season.[8] In this paper, we selected the sample of all quarters for the year 2012.[9] Thai LFS covered the whole kingdom and sample size is relatively large.

We generated the individual year of schooling for all respondents then separated into two generations. The sample is divided into parents' and children by the question of "What is the relation to the household head?" in the LFS questionnaire. We transformed years of schooling from schooling attainment data in LFS. Educational attainment data has been collected in Thai LFS with the question "What is your highest education level?" Based on this question, if highest education is

[8] See Leckcivilize (2015)

[9] Quarter 2, 2013 was the last available managed data but last available year for all quarters was 2012.

primary school, we put six years of schooling. Similarly, for secondary and upper secondary, we put 9 and 12 years of schooling respectively. For the university education, years of schooling has been transformed as follow- 16 years of schooling for bachelor degree, 18 years of schooling for master degree and 21 years of schooling for PhD degree.

The descriptions and summary statistics of all the variables including instrument are shown in Table 1 and Table 2 respectively.

Table 2.1 Description of Variables

Variables	Description
Children's Education ($\boldsymbol{h_{it}}$)	Average year of schooling of children in a household i
Parents' Education ($\boldsymbol{h_{it-1}}$)	Parents' year of schooling (Father or mother)
Family Income Dummy ($\boldsymbol{d_i^w}$)	$d_i^w = 1$ if average wage earnings of family i is less than provincial average wage, 0 otherwise
Instrument ($\boldsymbol{mean\_ysch_{asp}}$)	Average year of schooling of cohorts for mother and father in each province.

Table 2.2 Summary Statistics

Variables	Observations	Mean	Standard Deviation
Children			
Age	48155	34.77	9.41
Year of Schooling	48110	9.65	3.85
Father			
Age	31262	61.96	11.20
Year of Schooling	31197	4.99	3.18
Mother			
Age	43798	60.88	11.59
Year of Schooling	43746	4.25	2.77
Instrument ($\boldsymbol{mean\_ysch_{asp}}$)	31262	5.79	1.59
Family Income Dummy	31262	0.43	0.50

From the data (see Table 2), it is found that average year of schooling of child generation is much higher than the parents' generation, which implies faster growth in aggregate human capital over generations in Thailand. Provincial level average year of schooling of both parents and children are shown in Figure 1.

Figure 2.1 Provincial Average Year of Schooling of Parents and Children

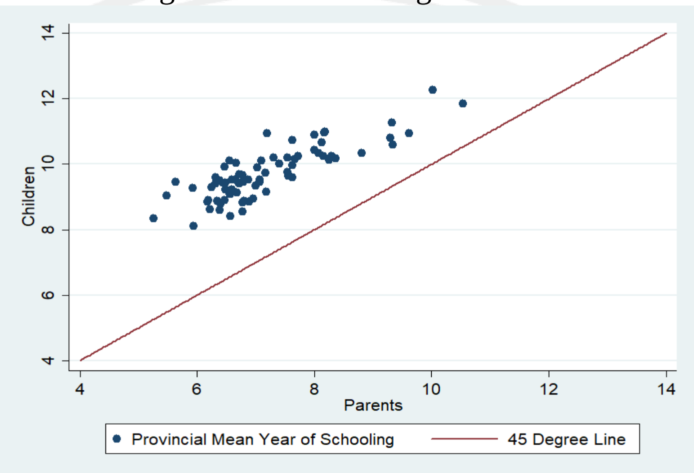


Figure 1 represents provincial average year of schooling for the year 2012.
Source: Labor Force Survey (2012), National Statistical Office, Thailand.

2.5 Results & Discussion

This section provides the estimated results in several subsections. First, it provides the results of intergenerational transmission rate of human capital for both father and mother in Thailand. Second section concentrates on child education of lower wage earning families and policy evaluation. Lastly, post estimation diagnosis or the validity of IV estimators are discussed.

2.5.1 Intergenerational Transmission

We found that both OLS and IV estimators are significantly different from zero. Our IV estimators show that rate of transmission from father is similar to that from mother or rate of transmission from father and mother are significantly high. It is found that the rate of intergenerational transmission from father is 0.54. It could be interpreted as- if father's schooling is increased by one year, on an average child education will be increased by 0.54 years of schooling. Similarly, the rate of transmission from the mother could be interpreted as- if mother's year of schooling increases by one year, on an average child education will be increased by 0.49 years of schooling. We got higher rate of transmission than existing studies for both father and mother, because we included children who already completed their study in the sample. The transmission rate in this paper is close to developing countries like Chile and much higher than Nordic countries.[10] It is found that IV estimates are larger than OLS estimates, typically what it should be. Although, Black, Devereux, & Salvanes (2005) found that the IV estimates are smaller than OLS estimates, it might be because of using different instrument. The details results are shown in Table 3.

Table 2.3 Regression Results

Dependent Variable: Children's Education ($\boldsymbol{h_{it}}$)	**Father**		**Mother**	
	OLS	**IV**	**OLS**	**IV**
Constant	10.03***	9.07***	11.08***	10.45***
	(80.00)	(42.76)	(102.22)	(44.17)
Parents' Education ($\boldsymbol{h_{it-1}}$)	0.43***	0.54***	0.41***	0.49***
	(68.60)	(25.45)	(64.92)	(18.45)
Parents' Age ($\boldsymbol{age_{it-1}}$)	-0.03***	-0.03***	-0.04***	-0.04***
	(-18.50)	(-13.10)	(-30.05)	(-18.95)
Family Wage Dummy ($\boldsymbol{d^h_{it-1}}$)	-0.40***	-0.34***	-0.63***	-0.59***
	(-10.10)	(-8.26)	(-18.01)	(-15.92)
	N=31179	N=31179	N=43715	N=43715
	Adjusted R-squared: 0.16	Adjusted R-squared: 0.15	Adjusted R-squared: 0.13	Adjusted R-squared: 0.13
	First Stage Regression (IV)		*First Stage Regression (IV)*	
	Adjusted R-squared: 0.12		Adjusted R-squared: 0.12	
	Partial R-squared: 0.09		Partial R-squared: 0.06	
	F statistic: 2954		F statistic: 2664	
	Sargan statistic: 0.00		Sargan statistic: 0.00	

[10] Celhay & Gallegos (2015) found that intergenerational transmission rate from parental education is about 0.46 for Chile. For Sweden, it is 0.21 to 0.25 (see Lindahl, Palme, Sandgren-Massih, & Sjögren, 2014).

Note: ***, **, * indicates the significant level at 1%, 5% and 10% respectively. $\boldsymbol{N}$ be the number of observations in the regression. $\boldsymbol{t}$ and $\boldsymbol{z}$ statistics are in the parentheses for OLS and IV respectively.

We pointed out two issues from the results. First, rate of intergenerational transmission of education from father is higher than from mother, which is similar to findings in existing literature. This might be obvious due to the fact of patriarchal family structure, where father's contribution is more than the mother in making decision of investment in kids. The results do not recommend any policy that only focuses on female education as rate of intergenerational transmission from mother is lower than father. It is also discussed in Behrman & Rosenzweig (2005), they mentioned about a policy in Bangladesh, which is designed to raise schooling only for female. However, rate of transmission from mother is also significantly high, it recommends gender unbiased educational policies. Policy makers should treat male and female students equally in designing the compulsory educational policy, educational subsidy program or study loan program in Thailand.

2.5.2 Child Education in Lower Income Households

This part discusses whether children from lower income families are worse off than children from higher income families. The results of both OLS and IV for equation (3) are shown in Table 3. It is found that the coefficient of family wage dummy is significantly negative, interpreted as children from lower income families are getting less schooling than their counterparts, controlling the effects of parents' education. Here, on an average, children from lower income families are getting 0.34 to 0.59 years less schooling than their counterparts. This is quite meaningful because credit market is not perfect or public education is not fully covered in all education levels. Lower income families face lower budget to invest in their kids. This is the reason why most of the countries are engaged in public education program or student loan program in higher education.

In Thailand, there are two types of public universities based on admission pattern, such as limited admission universities and open universities or unlimited admission universities. Moreover, there were two student loan programs by the government to support poor students. First one is Student Loan Scheme (SLS), started in 1996 by the "Student Loan ACT B.E. 2541". This program is providing fund to students whose family income is lower than 200000 Thai Baht per year. It covers the tuition fees and living allowance for the education level of Bachelor degree in universities and for vocational school. Second one is the income contingent loan based on Higher Education Contribution Scheme (HECS), started in 2006. Although, it is discontinued its operation after one year and SLS is implemented in new form in 2007. Together with SLS and public education program in Thailand benefit the students from lower income families in continuing their higher education. However, based on our findings, the children from lower income families are getting less education which implies that SLS might not be efficient. Ziderman (2002) concluded that SLS in Thailand is uncontrolled from the center, tight criteria of loan eligibility and weak targeting. They also criticized that it is beyond the original plan.

Our findings also argued that children from lower income families might start working or enter in the labor force earlier to support their family needs.

However, the education loan programs in developing countries might be beneficiary as poor families have lesser resources to invest in their kids. Based on the empirical findings of intergenerational income model in Brazil, Marchon, (2014) also suggested the policy of education loan program in Brazil. Our results suggest that the existing education loan program should be monitored in closer look to increase its efficiency.

2.5.3 Validity of Instrument

We already described our instrumental variable is $mean\_ysch_{asp}$ in the methodology section for the endogenous regressor parental education (h_{it-1}). To be a valid instrument, following two conditions must be satisfied.[11]

Condition 1: $\mathrm{corr}(mean\_ysch_{asp}, h_{it-1}) \neq 0$

Condition 2: $\mathrm{corr}\left(mean\_ysch_{asp}, u_{it}\right) = 0$

Condition 1 and 2 are commonly known as instrument relevance and instrument exogeneity respectively. The condition of instrument relevance is satisfied if variation in the $mean\_ysch_{asp}$ is correlated to the variation in h_{it-1}. And the instrument is

[11] See the Chapter 10 on Instrumental Variable Regression from Stock, J. H., & Watson, M. W. (2003). Introduction to econometrics (Vol. 104). Boston: Addison Wesley.

called more relevant if $\mathrm{corr}(mean\_ysch_{asp}, h_{it-1})$ is high. If condition 1 or instrument relevance is satisfied, we can call the instrument as strong instrument. Form the first stage regression (Equation 2) of 2SLS, null hypothesis of weak instrument could be rejected if F-statistic is high. For most of the cases, rule of thumb is F-statistic should be more than 10 to reject null hypothesis of weak instrument.[12] For our sample F statistics are reported in Table 3, 2954 and 2664 for the sample of father and mother respectively, which is high enough to reject the null hypothesis of weak instrument. We can conclude that the instrument, $mean\_ysch_{asp}$ is strong instrument or variation in parental education is explained by variation in $mean\_ysch_{asp}$. Intuitively, parents' education should be correlated with their cohorts in their respective provinces because they share the common shocks, facilities, educational reform policies and educational infrastructure.

The second condition, the instrument should be exogenous, if not, 2SLS estimates will be inconsistent. Statistically, it is not possible to test whether the instruments are exogenous. But it is possible to define intuitively or by expert's opinion that the instruments are not directly affecting the error term in the model. In our case, the instrument, $mean\_ysch_{asp}$ should be uncorrelated with u_{it}. u_{it} contains unobservable factors, mostly the idiosyncratic factors of parents and child. For instance, the factors are abilities, luck, genetic factors, etc. Thus, it is meaningful to argue that abilities, luck and genetic factors are uncorrelated with the $mean\_ysch_{asp}$. We can also conclude that $mean\_ysch_{asp}$ is exogenous in the model. By satisfying two conditions mentioned above, we argue that $mean\_ysch_{asp}$ is a valid instrument for parental education. In addition, Sargan-Hansen test for over-identification is performed, which shows that the equation is exactly identified because we have single instrument for a single endogenous regressor in the model.

[12] See Appendix 10.4 from Stock, J. H., & Watson, M. W. (2003). Introduction to econometrics (Vol. 104). Boston: Addison Wesley.

2.6 Conclusion

This paper concludes that rate of intergenerational transmission of human capital in Thailand is higher than developed countries, but quite similar to developing countries like Chile (see Celhay & Gallegos, 2015). We leave the reasoning issue of getting higher rate of transmission in developing countries compare to developed countries for further research. It is also found that rate of transmission from father is higher than from mother. The evidence recommends the policy to boost both male and female schooling in Thailand. Policy to boost only female education might be inefficient because of lower transmission rate from mother than father.

The estimated coefficient of family income dummy suggests that children from lower income families are getting lesser education than their counterparts, which implies that SLS in Thailand might not be fully functional or inefficient. These findings recommend the policymakers to rethink and redesign the SLS in terms of coverage and efficiency.

CHAPTER 3
INEQUALITY TREND AND RURAL-URBAN GAP IN EDUCATION: EVIDENCE FROM THAILAND

Abstract

Inequalities both within a country and across the countries are highly explained by rural-urban educational differences (A. Young, 2013). This paper aims to find the rural-urban educational gap and the trend in human capital inequality using the Labor Force Survey (LFS) in Thailand. Applying Two Stage Least Square (TSLS) method, this paper has found that the rate of transmission of human capital is higher from lower educated parents than that from higher educated parents. It implies that there is a decreasing trend in human capital inequality in Thailand. The coefficient of rural-urban gap indicates that rural children are getting less schooling than what urban children are getting. This study claims to be the first to find human capital inequality trend and rural urban educational gap intergenerational framework, which controls parental contribution in child education in the model.

Keywords: Rural-urban gap; Intergenerational transmission; Human Capital; Inequality; Instrumental Variable.

3.1 Introduction

The issue of inequality is widely discussed and human capital inequality is added as new dimension of inequality. Unlike income inequality, human capital inequality is decreasing in most of the countries (Castello-Climent & Domenech, 2014). This paper has two parallel aims in a single framework. First, it tries to investigate the trend in human capital inequality by adding parents' education dummy variable in intergenerational framework. Observing the trend in human capital inequality is more important than trend in income inequality as it has already been found that human capital inequality affects economic growth more robustly than income inequality (Castelló & Doménech, 2002). Second, this paper concentrates on the rural-urban gap in education. The educational gap between rural and urban area has been widely discussed in existing literature for both developing and developed countries.13 It has some adverse effect on educational attainment or human capital development. Moreover, about 40% of mean country's inequality and most of the cross country variation is explained by rural-urban gap (A. Young, 2013). Thus, findings of this paper might help in policy making to reduce rural-urban educational gap, hence to reduce overall human capital inequality in Thailand.

Thailand is an interesting country to conduct study about the trend in human capital inequality as well as rural-urban educational gap. First educational reform in Thailand took place in 1999 (Lounkaew, 2013). Government budget for education has been increasing, which nearly doubled in a decade, but the educational achievement is declining over time (Siamwalla et al., 2011). Decline in educational achievement might have effects on the distribution of human capital which triggered our interest on the trend in human capital inequality in Thailand. Due to the declining educational achievement, National Education Standards and Quality Assessment (NESQA) also conducted a study to investigate whether the quality of the schools meet the minimum standard. It has been found that more than 20% of schools could not meet the minimum quality benchmarks. Moreover, most of the disqualified schools in terms of quality are located in rural area (NESQA, 2008). As educational achievement was

[13] For developing countries, please see Lounkaew, 2013; Tayyaba, 2012; Wang, Li, & Wang, 2018; Zhang, 2017; Zhang, Li, & Xue, 2015. For developed countries, see Cresswell and Underwood, 2004; Fleischman et al., 2010; Thomson, 2011.

continuously declining, second education reform has been implemented in 2012, which incurred a cost of about $4.6 Billion (Ministry of Education, 2011). This study might help policymakers to implement further educational reforms as it contributes to find rural urban educational gap in Thailand. Although previous literature already studied about the rural-urban educational gap in Thailand (Lounkaew, 2013), this paper finds rural-urban educational gap using intergenerational regression model, which controls the effects of parents' education. It has been found that the rate of intergenerational transmission of education is higher in Thailand than in developed countries (Uddin, 2019). Thus, rural-urban educational gap in child generation might be affected by the previous generation. If we can control parents' education, the findings of rural-urban gap might become more robust and informative; indicating the effects in child education from outside of the households. Hence, policymakers can narrow their concentration to educational reform policies.

This paper contributes in several aspects. First, it measures the trend in human capital inequality in next generation in an intergenerational framework instead of observing time series trend of overall human capital inequality. Second, this paper finds the rural-urban educational gap in causal estimation, which controls parents' education and age. Based on our best knowledge, this paper claims to be the first measuring rural-urban gap by controlling parents' education and age, in education in intergenerational regression model.

This study is organized into six sections. In section two, we reviewed the existing literature. Section three is focused on the empirical model and methodology. Data used in this paper are discussed in section four. Results and discussion are provided in section five and section six is about conclusion.

3.2 Literature Review

Previous literature has observed rural-urban educational gap in both developing and developed countries. A large number of previous literature found that there is no significant gap between rural and urban educational achievement. Edington and Martellaro (1984) found that there is no significant differences between rural and urban students in Mathematics score. Ward and Murray (1985), and Howley & Gunn

(2003) also found similar results in evaluating mathematics skills of rural and urban students. Comparing with various subjects, Monk and Haller (1986) found similar results or no significant achievement gap between rural and urban students. Lee and Mclntire (2000) argued that the results varied at state level and found that there are significant differences in rural urban education, and no difference found in some states. Tayyaba (2012) reported similar findings with data from Pakistan, where rural children are achieving better schooling for one province in Pakistan, while in other provinces it is opposite. They argued that the reasons of these different results are schooling conditions, parents' background, and teachers' characteristics.

However, in general opinion or intuitively urban schools are comparatively better than rural school in terms of quality, teachers training, and school condition (D. J. Young, 1998). D. J. Young (1998) found that urban students perform better than rural students. Williams (2005) studied with 24 developed countries and reported that rural students' educational achievement is lower than that of the urban students' in 14 countries out of 24 countries. Wang, Li, & Wang (2018) studied with Chinese rural-urban literacy gap, collecting data from primary schools in two provinces. They found that educational achievement of urban children is significantly higher than the educational achievement of rural children.

Surprisingly, the findings of previous literature regarding rural-urban gap in education are contradictory, and the reason of this contradictions might lie in the factors that affect the educational achievement like parents' education. For instance, rate of intergenerational transmission in education differs a lot in different countries (Black et al., 2005; Holmlund et al., 2011; Uddin, 2019). Wang et al. (2018) found family education is the main mediating factor in defining rural-urban literacy gap in their study. Chiu & Chow (2015) also found that families' socio economic status affects more in students' achievement than classmates' characteristics. Dufur, Parcel, & Troutman (2013) found similar result--social capital in the family is more important that social capital in school in students' academic achievement. Family literacy has also been identified as an important factor to develop early childhood education in other studies (Chiu & Chow, 2015; Silinskas, Leppänen, Aunola, Parrila, & Nurmi, 2010). Other than family literacy, there are some other factors that may affect educational achievement through educational reform and school quality. For instance, management, autonomy, leadership, accountability, etc., which are as important as the educational infrastructure (Brunello & Checchi, 2005; Hanushek, 2003, 2005; Hanushek & Woessmann, 2011). These intangible factors are viewed as causes of failure of education reform in Thailand (Lathapipat, 2011; Siamwalla et al., 2011). Lounkaew (2013) reported that intangible factors are important in defining the rural-urban educational gap in Thailand.

In the view of above, family of parents' educational effect should be controlled to find the more robust rural-urban educational difference. Contrary to previous literature, this paper uses the framework of intergenerational transmission of education to find rural-urban educational gap, which controls both nature (genetically transmitted) and nurture effects from parents.

Trend in education inequality mostly observed in time series line of Gini coefficient or other measurement or by comparing two Gini coefficient of education in different years. Lopez et al. (1998) reported Gini coefficient of education for Thailand for the year 1980 and 1990. They found that education inequality in Thailand has been decreased by 8.6% in 10 years. They also found education inequality has been decreased in the Philippines by 19% from the year 1970 to 1990. The trend in education inequality is quite different and sometime opposite compared to income inequality. The inequality trend in educational achievement is downward in most of the countries, while there is a little change in income inequality, or in some cases it has been increased for last few decades.14 The trend in education inequality can also be observed by investigating intergenerational transmission of education (Becker & Tomes, 1986). If the rate of transmission is less than one, children are getting more education than their parents' education, which is lower than the average education and vice versa. Clark (2014) also mentioned that lower rate of transmission (i.e. 0.2 or 0.3) means descendants' schooling move faster toward average schooling whereas the process is very slow for higher rate of transmission. In this process, child education is compared with their parents' education. However, applying dummy variable approach, this paper analyzes the trend in education inequality by observing

[14] Castello-Climent & Domenech (2014) discussed about the change in human capital inequality and income inequality. They mentioned that average human capital inequality is dropped from 0.55 to 0.28 from the year 1960 to 2005 respectively whereas income inequality does not change much.

educational achievement between two groups of children in different provinces in Thailand, children from lower educated family background and children from higher educated family background.

3.3 Empirical Specification & Methodology

3.3.1 Empirical Specification

The theory of intergenerational mobility of human capital by Becker & Tomes (1986) explains that parents optimize their own consumption and investment on child's human capital with respect to given level of wealth. This model showed that there is intergenerational linkage or mobility of income. In other words, income of the child will be affected by the parents' and their grandparents' income. From the income mobility model, human capital mobility has been developed by using education instead of earnings to find the rate of intergenerational transmission (Holmlund et al., 2011; Plug & Vijverberg, 2005; Solon, 2014; Uddin, 2019). Following Holmlund et al. (2011) and Uddin (2019), we specified the reduced form empirical model as follows

$$h_{ic} = \beta_0 + \beta_1 h_{ip} + \beta_2 age_{ip} + \delta d_{ip}^h + \gamma d_i^R + \varepsilon \qquad 1$$

Let h_{ic} and h_{ip} be the child human capital and parents' human capital respectively. β_1 measures the intergenerational transmission rate, which is expected to be positive because return on investment in children is positive. age_{ip} be the age of parents in household i, which controls for the age specific characteristics of parents. Although Black et al. (2005) argued that age of child should be included if all children in the sample did not finish their study or some are currently studying, we excluded child age in the model because we excluded the children who are currently studying or did not finish their study during the survey.15 Let ε be the error term which captures unobservable effects such as genetic effect and luck.

[15] Black et al. (2005) suggested that if all children did not finish their schooling in the sample, should include child age in the model. They also suggested that child age might be endogenous because timing of birth is the parents' decision. So it is better to exclude child age from the model.

In the intergenerational framework, we first concentrated on the issue of human capital inequality using dummy variable approach. This paper tries to find whether the rate of intergenerational transmission is higher in lower educated families than their counter parts. Interestingly, from the coefficient of parental education dummy variable (d_{ip}^{h}), we can predict inequality of human capital over the generations. Parental education dummy, d_{ip}^{h}, can be specified as follows

d_{ip}^{h} =1 if $\bar{h}_{ip} < \bar{h}_{vp}$, 0 otherwise

$$\bar{h}_{ip} = (h_{ip}^{F} + h_{ip}^{M})/2$$

$$\bar{h}_{vp} = \sum (h_{jvp})/N_{jv}$$

Let d_{ip}^{h} be the parental education dummy, which is equal to 1 if average year of schooling of father and mother ($\bar{h}_{ip}$) for household i is lesser than the provincial level average year of schooling of all parents ($\bar{h}_{vp}$) and 0 otherwise. $\sum(h_{jvp})$ be the sum of years of schooling of all individual parents j in province v. N_{jv} be the number of individual parents j in province v. h_{it-1}^{F} and h_{it-1}^{M} represent schooling of father and mother of household i respectively. δ be the corresponding parameter for parents' human capital dummy. A positive value of estimated δ implies that intergenerational transmission rate from lower educated parents is comparatively higher, which also could be interpreted as inequality in human capital is decreasing over the generations. More specifically, the return on investment on child education is higher in lower educated households compare to higher educated households. We expect that estimated δ will be significantly positive because human capital inequality over the generation is decreasing (see Figure 2).

The rural urban dummy, d_{i}^{R} is equal to 1 if the household lives in rural area, otherwise is equal to zero. The estimated coefficient γ indicates the magnitude of rural-urban inequality in human capital. We expect that the sign of estimated γ will be negative because normally educational infrastructure is better in urban area.

3.3.2 Methodology

Estimating equation (1) is challenging due to endogeneity problem in the model. Because parental education is not exogenously determined, which might be affected by gene, luck of parents and other unobserved abilities (Black et al., 2005; Holmlund et al., 2011; Lindahl et al., 2014). Ordinary Least Square (OLS) method is unable to provide consistent parameter estimates because $Cov(h_{ip}, \varepsilon) \neq 0$. Most common solution of the endogeneity problem is instrumental variable (IV) or Two Stage Least Square (2SLS) method. The basic conditions of using IV are- there should have strong correlation between instrumental variable and endogenous regressor, and the correlation between instrumental variable and error term (ε_{it}) should be zero.16 Existing literature mostly used education reform policy as an instrument for parental education. Holmlund et al. (2011) argued that most of instruments are less convincing due to statistical weakness (tuition fees, college location) or less variation (exam quality, UK education reform policy). They also argued that education reform policies in US or Norway are more convincing because of more variability and statistical strength. Uddin (2019) used cohort's mean schooling of each parents in each province and argued that it has better statistical strength and more variation in the data.

Hence, following Uddin (2019), this paper used cohort's mean schooling of each parents in each provinces. We took average year or schooling by age, sex and province for all parents and used as instrument for parental schooling. Let $ysch_{asp}$ be our instrumental variable, which is mean year of schooling by age, sex and province. a, s and p represent age, sex and province respectively. In 2SLS, our first stage and second stage regression equations are in equation (2) and (3) respectively

$$h_{ip} = \alpha_0 + \alpha_1 ysch_{asp} + \alpha_2 age_{ip} + \alpha_3 d_{ip}^h + \alpha_4 d_i^R + \nu \qquad 2$$

$$h_{ic} = \beta_0 + \beta_1 h_{ip} + \beta_2 age_{ip} + \delta d_{ip}^h + \gamma d_i^R + \varepsilon \qquad 3$$

where $ysch_{asp}$ is the instrument for parents' education.

[16] For details please see Wooldridge, Jeffrey M. Introductory econometrics: A modern approach. Nelson Education, 2015. Page 507-516

3.4 Data

Thai Labor Force Survey (LFS) has been used in this paper, which is quarterly collected by the National Statistical Office (NSO), Thailand. In this paper, we selected the sample of all quarters for the year 2012.[17] Thai LFS covered the whole kingdom and sample size is relatively large, which is the one of the major advantages of it.

We generated the individual year of schooling for all respondents then separated into two generations. The survey is divided into parents' and children by the question of "What is the relation to the household head?" in the LFS questionnaire. The descriptions and summary statistics of all the variables including instrument are shown in Table 1 and Table 2 respectively.

Table 3.1 Description of Variables

Variables	Description
Children's Education ($\boldsymbol{h_{ic}}$)	Average year of schooling of children in a household i
Parents' Education ($\boldsymbol{h_{ip}}$)	Father's year of schooling.
Parental Education Dummy ($\boldsymbol{d_{ip}^{h}}$)	$d_{ip}^{h} = 1$ for household i if average year of schooling of father and mother is less than provincial average year of schooling, 0 otherwise
Rural-Urban Dummy ($\boldsymbol{d_{i}^{R}}$)	d_{i}^{R} = 1 if the household lives in non-municipal area, and d_{i}^{R} = 0 if the household lives in municipal
Instrument ($\boldsymbol{ysch_{asp}}$)	Average year of schooling of cohorts for mother and father in each province.

[17] Quarter 2, 2013 was the last available managed data but last available year for all quarters was 2012.

Table 3.2 Summary Statistics

Variables	Observations	Mean	Standard Deviation
Children			
Age	48155	34.77	9.41
Year of Schooling	48110	9.65	3.85
Father			
Age	31262	61.96	11.20
Year of Schooling	31197	4.99	3.18
Mother			
Age	43798	60.88	11.59
Year of Schooling	43746	4.25	2.77
Instrument ($\boldsymbol{ysch_{asp}}$)	31262	5.79	1.59
Parental Education Dummy	31262	0.75	0.43
Rural-urban Dummy	31262	0.51	0.49

From the data, it is observed that average year of schooling of children generation is much higher than the parents' generation, which implies faster growth in aggregate human capital over generations in Thailand. Provincial level average year of schooling of both parents and children are shown in Figure 1.

Figure 3.1 Provincial Average Year of Schooling of Parents and Children

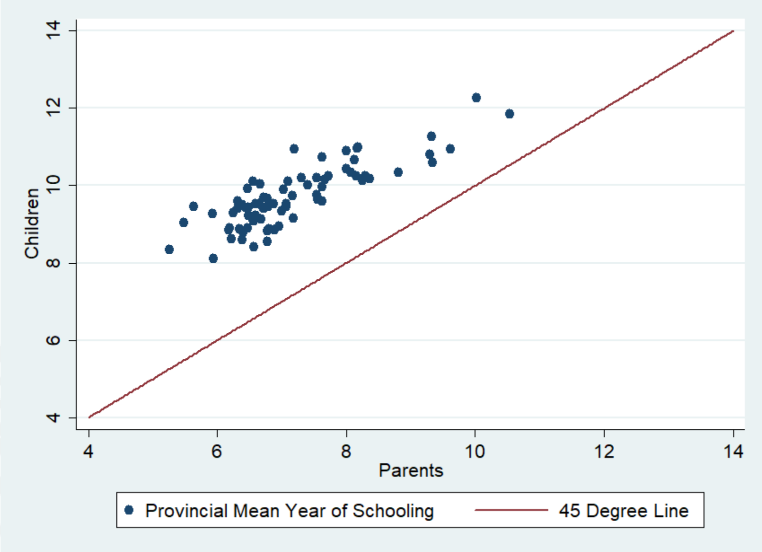


Figure 1 represents provincial average year of schooling for the year 2012.

Source: Author's own calculation from Labor Force Survey, National Statistical Office, Thailand.

In addition, we are interested to observe the human capital inequality of both parents' and children's generation. The coefficient of parental educational dummy in equation (1) can predict inequality of human capital over generations. In relation to this, we provided the provincial Gini coefficient of year of schooling for both generations in Figure (2). Following Castelló & Doménech (2002), we calculate the Gini index of year of schooling for parents' and children generation as follow

$$Gini^h = \frac{1}{2H}\sum_{i=0}^{21}\sum_{j=0}^{21}|x_i - x_j|n_i n_j$$

where H is the average year of schooling each generation. x_i is the cumulative average year of schooling of years of schooling i. x_j is the cumulative average year of schooling of years of schooling j. n_i and n_j are population share of i years of year of schooling and j years of year of schooling respectively of each generation. In year 2012, we calculated for $Gini^h$ for parents and child generation are 0.22 and 0.30 respectively in whole kingdom. Figure 2 shows the province level Gini index of year of schooling of each generation.

Figure 3.2 Provincial Human Capital Inequality of Parents and Children

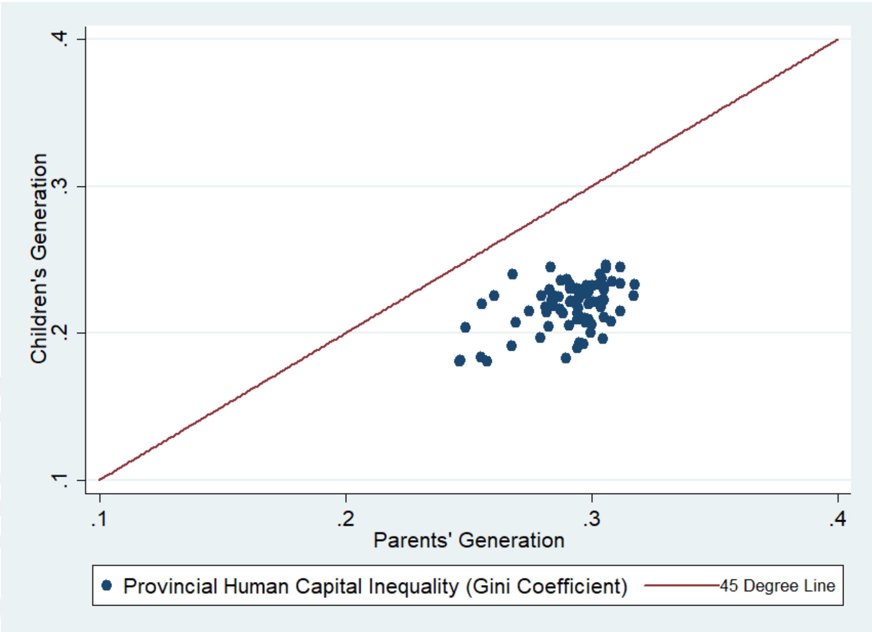


Figure 2 represents provincial Gini coefficient of year of schooling for the year 2012.

Source: Labor Force Survey, National Statistical Office, Thailand.

From the Figure 2, we observed the significant differences in human capital inequality between parents and children generation, which indicates sharp decrease in human capital inequality over the generation. Because of these findings, it is expected that the coefficient of parental education dummy in equation (1) or the estimated δ should be significantly positive.

3.5 Results & Discussion

Applying TSLS techniques we found the coefficient of each variable in equation (3). Surprisingly, it has been found that the estimated coefficient of parents' education dummy is positive. It implies that on an average, human capital transmission rate is higher or return on investment on child education is higher in lower educated household than higher educated household. This result suggests that inequality in human capital is decreasing in next generation. There can be several intuitions or reasons for our findings. First, lower educated parents might have lifelong experiences from being lower educated and not let their children in same situation like them. Hence, it may increase their investment to their children. Second, from the children's perspective, children from lower educated parents might have lesser wealth as bequest than children from higher educated parents. Thus, they could be less endowed than their counterparts (Conti & Heckman, 2014), which may increase their efforts in their own study to increase the endowments. However, this result supports the existing findings which indicate decreasing trend in human capital inequality.18 The detail results are provided in Table 3.

Table 3.3 Results

Dependent Variable: Children's Education	**OLS**	**IV**
Constant	9.76***	7.22***
	(50.48)	(11.95)
Parents' Education	0.45***	0.64***
($\boldsymbol{h_{ip}}$)	(38.04)	(14.19)
Parents' Age	-0.03***	-0.03***
($\boldsymbol{age_{ip}}$)	(-18.14)	(-13.63)
Parental Education Dummy ($\boldsymbol{d_{ip}^{h}}$)	0.36***	1.8***
	(3.42)	(5.27)
Rural-Urban Dummy	-0.73***	-0.67***
($\boldsymbol{d_{i}^{R}}$)	(-18.48)	(-15.89)
	N=31179 Adjusted R-squared: 0.16	N=31179 Adjusted R-squared: 0.16
	First Stage Regression (IV) Adjusted R-squared: 0.12 Partial R-squared: 0.09 F statistic: 2286 Sargan statistic: 0.00	

Note: $***$, $**$, $*$ indicates the significant level at 1%, 5% and 10% respectively. $\boldsymbol{N}$ be the number of observations in the regression. $\boldsymbol{t}$ and $\boldsymbol{z}$ statistics are in the parentheses for OLS and IV respectively.

[18] Lopez et al. (1998) found that Gini coefficient of education in Thailand declined by 8.6% in between year 1980-1990.

The result shows that there is significant gap between rural and urban education. The coefficient of rural-urban dummy explains that having same level of fathers' education, the children from rural area are getting 0.67 years of lesser schooling than that of urban children. Here, we found the rural-urban educational differences by controlling the effects of parents from both nature and nurture effects to their children. Nature and nurture effects are controlled by using IV and by including parents' education in the model respectively. With this intergenerational model, the findings of rural-urban educational gap indicate the outside household effects for this gap, like educational infrastructure, number of schools, teachers' quality, distribution and management of educational budget, etc. Our results pointed both tangible and intangible factors that are responsible for the rural-urban educational differences. However, previous literature regarding lower educational achievement in Thailand reported that intangible factors are responsible in Thailand (Lathapipat, 2011; Siamwalla et al., 2011). The findings of this paper clearly suggest that rural educational development should be concentrated to reduce inequality between rural and urban area.

Form the first stage regression (Equation 2) of 2SLS, null hypothesis of weak instrument is rejected if F-statistic is high. For most of the cases, rule of thumb is F-statistic should be more than 10 to reject null hypothesis of weak instrument.19 For our sample F statistics is 2286, which is high enough to reject the null hypothesis of weak instrument. We can conclude that the instrument, $ysch_{asp}$ is a strong instrument or variation in parental education is explained by variation in $ysch_{asp}$.20

3.6 Conclusion

This paper found that return on investment on child education is higher in comparatively lower educated household than their counterparts. It concludes that there is a decreasing trend in human capital inequality in Thailand. In addition to this, the estimated coefficient of rural-urban dummy suggests that there is a significant gap between rural and urban educational achievement. The non-household factors might

[19] See Appendix 10.4 from Stock, J. H., & Watson, M. W. (2003). Introduction to econometrics (Vol. 104). Boston: Addison Wesley.
[20] For details regarding the instrument validity, please see Uddin (2019).

be the reason for this rural-urban gap as family size and parental education have been controlled in the model. Human capital inequality should be explained by rural-urban educational gap (A. Young, 2013). The trend in rural-urban educational gap is yet to be investigated to compare with the trend in human capital inequality. We leave this issue for further research to find whether there exists a long-run association between human capital inequality and rural-urban educational gap.

Our model controls for both nature and nurture effects from the parents to investigate the educational difference between rural and urban area. As it controls for the parental effects in children's education, the magnitude of rural-urban educational difference in this paper could narrow the reasons like educational infrastructure, distribution and management of educational budget, etc. It can help policymakers to narrow down the focus on educational infrastructure in rural areas. Moreover, this paper investigates the trend in human capital inequality in intergenerational model that finds the inequality in next generation as well as the trend in intergenerational inequality in human capital.

Finally, the findings in this paper can help the policy makers to increase aggregate human capital as well as to reduce rural urban inequality. For instance, it suggests better educational infrastructure in rural area in Thailand to reduce rural urban inequality. This paper leaves room for further studying, whether the human capital inequality affects economic growth in the long run and apart from that, it also provides the research direction in investigating whether rural-urban inequality in human capital affects aggregate economy.

CHAPTER 4
HUMAN CAPITAL INEQUALITY AND ECONOMIC GROWTH: EVIDENCE WITH SUB-NATIONAL DATA FROM THAILAND

Abstract

This paper aims to find the effects of human capital inequality on economic growth using provincial panel data from Thailand. Thai Labor Force Survey (LFS) is used to generate provincial average year of schooling and Gini coefficient of year of schooling for the year 1995-2012. Econometric techniques have been employed to identify the effects of human capital inequality on economic growth. Economic growth is inversely affected by the distribution of human capital in Thailand. The coefficient of human capital inequality suggests that if Gini coefficient increases by 0.01 points, gross provincial product (GPP) will be decreased by about 0.02 percentage points in the long run. However, we found that the effect of average years of schooling in GPP is not significant. There is lack of strong theoretical background on the relationship between human capital inequality and economic growth to support the empirical study. The findings of the study help to design and analyze educational policies in developing countries like Thailand, considering the fact whether the educational policies can reduce human capital inequality. This paper is the first to analyze the effect of human capital inequality on economic growth with sub-national and annual data. In addition, it considers cross sectional dependence in panel model.

Keywords: Human Capital Inequality, Economic Growth, Cointegration, Cross Sectional Dependence.

4.1 Introduction

Is inequality the stumbling block in economic growth? There is a long debate answering this question over the last few decades but still it is far from getting a specific answer, both in theoretical and empirical literature. This issue has important implications in designing redistributive policies. On the one side of theoretical literature, income inequality boosts economic growth by increasing aggregate savings because marginal propensity to save of rich people is higher than that of poor people (Kaldor, 2006; Kuznets, 1955). Contrary, on the other side, income inequality could affect growth negatively by expansionary fiscal policy (Roberto Perotti, 1996), by inefficient bureaucracy (Acemoglu, Ticchi, & Vindigni, 2011) or political instability (Benabou, 1996). It could also hamper growth by lower investment in human capital in poor family or by hampering human capital accumulation (Galor & Moav, 2004). Halter, Oechslin, & Zweimüller (2014) identified that positive or negative effects of inequality in economic growth might depend on the time dimension, whether the effects are long term or short term. For instance, channels like expansionary fiscal policy or human capital accumulation take longer time to affect growth. Similarly, empirical results in existing results vary due to using different estimation techniques, depending on whether it captures long term or short-term effects of inequality. The inequality-growth theories are explained with the wealth inequality and most of the existing literature used income inequality as a proxy for wealth inequality (Aghion et al., 1999). This paper focuses on human capital inequality and its effects on economic growth, which is widely discussed in last decade. In a boarder concept, human capital includes abilities, skills and talent, build in a person through education, experiences and health (Sauer & Zagler, 2014; Goldin, 2016). As education through formal schooling system plays an essential role to obtain the components of human capital (Sauer & Zagler, 2014), most of the previous studies finding the nexus between human capital inequality and economic growth used average years of schooling data to represent human capital (Castelló-Climent, 2010; Castelló & Doménech, 2002; Sauer & Zagler, 2014). Though there is no concrete theory to explain the nexus of human capital inequality and growth (Castelló-Climent, 2010), researchers are concentrating on this issue because human capital inequality is decreasing along with the higher growth rate in most of the countries, while in contrast, there are negligible changes in income inequality for last few decades (Castello-Climent & Domenech, 2014; Easterly, 2007).

This paper contributes to the existing literature in four ways. First, it concentrates on cointegration test or long run association between human capital inequality and economic growth using Labor Force Survey (LFS), Thailand. Herzer & Vollmer (2012) claimed to be the first to apply panel cointegration technique to find inequality and growth nexus using income inequality. According to our best knowledge, this paper is the first to apply cointegration techniques to find long run association between human capital inequality and growth. Second, this paper uses annual sub-national data from developing country for the first time in analyzing human capital inequality and economic growth relationship. It is important to use sub-national data because the effects of human capital inequality might vary with the countries level of development (Castelló-Climent, 2010).21 Most of the existing inequality studies used cross country data with multi-year time intervals. Cross country dataset might be subject to heterogeneity, cultural and institutional differences. Dataset with more periodic intervals might be less reliable to track the inequality effects. Thus, it is suggested to have more studies with sub-national data (de Dominicis, Florax, & de Groot, 2008; Naguib, 2015) and with annual data (Kennedy, Smyth, Valadkhani, & Chen, 2017) in inequality-growth literature. Third, we consider cross sectional dependence (CSD) in panel model. In the existing panel study, CSD is ignored using both cross country dataset and sub-national dataset in human capital inequality and growth relationship, for which regression results could be inconsistent and less reliable (Pesaran, 2006; Zellner, 1962). In addition, our dataset is differed from existing study, especially in distribution of year of schooling of individuals. Existing literature used educational attainment data, distributed from 0 to 4 or 5. For instance, primary school is 1, secondary school is 2, Bachelor degree is 3 and Master degree is 4 (Castelló & Doménech, 2002; Sauer & Zagler, 2014). But in this paper, exact year of schooling has been used in generating inequality, which is

[21] Using the cross country data, Castelló-Climent (2010) found that the effects of human capital inequality in economic growth is significantly negative, whereas it is positive or sometime neutral in developed countries.

distributed from 0 to 21. We believe that with the exact year of schooling, inequality measurement will be more reliable and informative.

Most of the existing study regarding inequality-growth nexus used developed countries' sub-national data (Benos & Karagiannis, 2018; Kennedy et al., 2017). Resource allocation, ratio of return in human capital to physical capital (Galor & Moav, 2004), distribution of wealth and redistributive policies are different in developing countries than developed countries. As a result, effects of inequality might be different in developing country. As a developing country, Thailand is interesting country to study. In Thailand, there is increasing trend in income inequality from the 1960s to early 1990s and associated economic growth was moderately high in those periods. However, income inequality has come down after 1992 but the declining rate is very slow. Gini coefficient of households' income in 1960 was 0.413 and it increased to 0.536 by 1992, which again declined to 0.484 by 2011 (Phongpaichit and Baker, 2016). Asset or land inequality is even more than the income inequality; the land Gini index is 0.88 in Thailand (Laovakul, 2018). Moreover, there exists the Kuznets curve of inequality in Thailand (Jeong, 2008; Paweenawat & McNown, 2014).

This study is divided into six sections. The review of related literature are provided in section 2. Data and empirical model specification are in section 3. In section 4, we discussed the econometric techniques used as methodologies. Section 5 is about the results and discussion. Concluding remarks are in the last section.

4.2 Literature Review

Using the cross country regression, some early studies found negative effects of income inequality in economic growth (Alesina & Rodrik, 1994; Deininger & Squire, 1996; Roberto Perotti, 1996). In a cross country study, there is a mixture of developed and developing countries, which captures only the average relationship. But the effects of inequality might vary significantly in different countries (Robert J. Barro, 2000), which depends on countries' level of development (Galor & Moav, 2004). Thus, inequality-growth relationship with cross country data provides point in time estimators and it is not possible to observe how the effects vary in different countries (Kuznets, 1955). Inequality-growth relationship may have two-way causation. According to inverted 'U' shaped Kuznets curve, income inequality is positively affected by economic growth in the initial stage of development and negatively affected in the later stage of development. However, in some recent studies, regular 'U' curve has been observed instead of inverted 'U' curve. In other words, in the early stage of development, economic growth may affect income inequality negatively and positively in later stage of development (Blanco & Ram, 2019; Kim, Huang, & Lin, 2011). Moreover, using US data, Rubin & Segal (2015) found that both current economic growth and expected economic growth affect positively on income inequality. Contrary, Dollar, Kleineberg, & Kraay (2016) found that economic growth affects negatively to income inequality. In addition, some literature found the bidirectional causal relationship between income inequality and economic growth. R. Perotti (1992) investigates that there is two-way relationship between income inequality and economic growth. Using the data from Pakistan, Shahbaz, Rehman, & Mahdzan (2014) also found bidirectional causality between income inequality and economic growth. Although, using the US data Assane & Grammy (2003) found that there is unidirectional causality or economic growth causes to change in inequality. However, the relationship between inequality and economic growth is complex because of its bidirectional causation. As there is a very few evidences with the human capital inequality data, this paper tries to find the effects of human capital inequality on economic growth instead of effects of economic growth on inequality.

Because of the limitations in cross country study, researchers emphasized on cross country panel data to provide the evidence of inequality-growth relationship (e.g. Robert J. Barro, 2000; Forbes, 2000; Halter et al., 2014). Most of the existing literature using cross country panel used multiple years interval data (e.g. data with 5 years or 10 years interval) due to unavailability of yearly inequality series, subject to missing information (Nair-Reichert & Weinhold, 2001) and ignoring business cycle effects (Wan, Lu, & Chen, 2006). Because of the criticism of multi-years interval data, some existing studies put importance on annual data in inequality-growth nexus. For instance, Herzer & Vollmer (2012) used annual cross country panel data of 46 countries over the period of 1970–1995. Using the cointegration techniques, they found that the effects of income inequality in economic growth is significantly negative in the long run for whole sample and even for the sub-sample of developing countries and developed countries.

Another dimension in existing study is using subnational data instead of cross country data. Because of heterogeneity in cross country data, some studies emphasized on sub-national data in inequality and growth nexus (de Dominicis et al., 2008; Kennedy et al., 2017; Naguib, 2015). There are several studies found using subnational data from US (Benos & Karagiannis, 2018; Fallah & Partridge, 2007; Frank, 2009), from Sweden (Rooth & Stenberg, 2012), Australia (Kennedy et al., 2017), and Turkey (Gungor, 2010). Most of the existing study with subnational data used multi-years interval data and Kennedy et al. (2017) contributed in this issue, who used annual subnational data from Australia for the period of 1942-2013. They found that income inequality affects adversely to aggregate economy.

However, existing literature mostly concentrated on income inequality and growth relationship and a very few studies focused on human capital inequality and growth nexus. But the issue of human capital inequality and growth relationship got more attention because of two issues. First, human capital inequality is more robust than income inequality in growth regression (Castelló & Doménech, 2002). Second, there are negligible changes in income inequality (sometime increasing) while the trend is decreasing in human capital inequality over the time horizon (Castello-Climent & Domenech, 2014). Sauer & Zagler (2014) also used Robert J. Barro & Lee (2013) cross country dataset to compute human capital inequality. They contributed by introducing an additional interaction term between human capital inequality and average year of schooling to observe whether benefits from education in aggregate economy depend on the country's distribution of human capital. They found that in a country with very low level of average year of schooling, slight increment in human capital inequality might be beneficial for economic growth but harmful for a country with high level of average year of schooling. In their results, both OLS and system GMM estimates shows that human capital inequality significantly and negatively affects to economic growth. Castelló-Climent (2010) identified that the effects of human capital inequality in economic growth depends on country's level of development. Using system GMM techniques they found that the effects of human capital inequality is significantly negative in lower and middle income countries and positive or has no effects in high income countries. Gungor (2010) studied the education inequality and growth relationship with the provincial panel data from the labor force survey of Turkey for the period of 1975-2000. Using the fixed effect and random effect estimation, they found that education inequality and economic growth relationship is not linear. Provinces with higher Gini of education, human capital inequality affects economic growth positively and vice versa. However, they did not consider two facts: cross sectional dependence and cointegration between human capital inequality and economic growth. Senadza (2012) studied about the gender and spatial inequality in educational attainment in Ghana. They found positive correlation between poverty indices and educational inequality, which might have negative reflection in economic growth.

In existing literature, there is no study focusing on direct relationship between human capital inequality and economic growth in Thailand. In earlier inequality studies for Thailand, Meesook (1979) found that economic growth decreases the rural-urban and regional income inequality as well as poverty levels in Thailand. Using Pseudo panel data from Thai Socio-Economic Survey (SES), Fofack and Zeufack (1999) found that income inequality reduces with the increment of average education level. In recent study, Kurita & Kurosaki (2011) used provincial panel data from SES (1988-2004) and applied system GMM, they found that income inequality affects economic growth negatively in Thailand. Using synthetic cohort data for Thailand, Paweenawat & McNown (2014) found nonlinear relationship between average income and income inequality, which supports Kuznets hypothesis. They found that up to the level of 4000 Thai Baht per capita income, income inequality is positively related with growth and for income level higher than that, the relationship is negative. Jeong (2008) also found the evidence of Kuznets hypothesis but Motonishi (2006) found no evidence of Kuznets hypothesis in Thailand. A very few paper discussed about the human capital inequality or education inequality in Thailand. Lathapipat (2016) analyzed the short term and long-term factors affect in human capital inequality. Long term factors include parents' education, place of abode, socio-economic status of household, number of household members and family warmth. Short term factors include household income at the period of decision for their child education. They also found that inequality has been increased in access to education at tertiary level in Thailand.

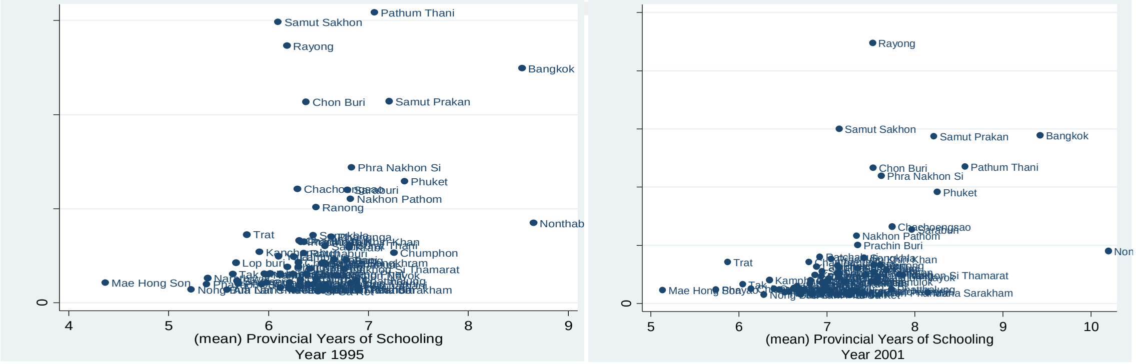
In the view of above, the research gaps can be summarized as follows. First, none of the existing literature aimed to identify long run relationship between human capital inequality and economic growth with sub-national data. Second, the issue of cross sectional dependence has been ignored. Finally, none of the literature studied this with developing countries' sub-national data.

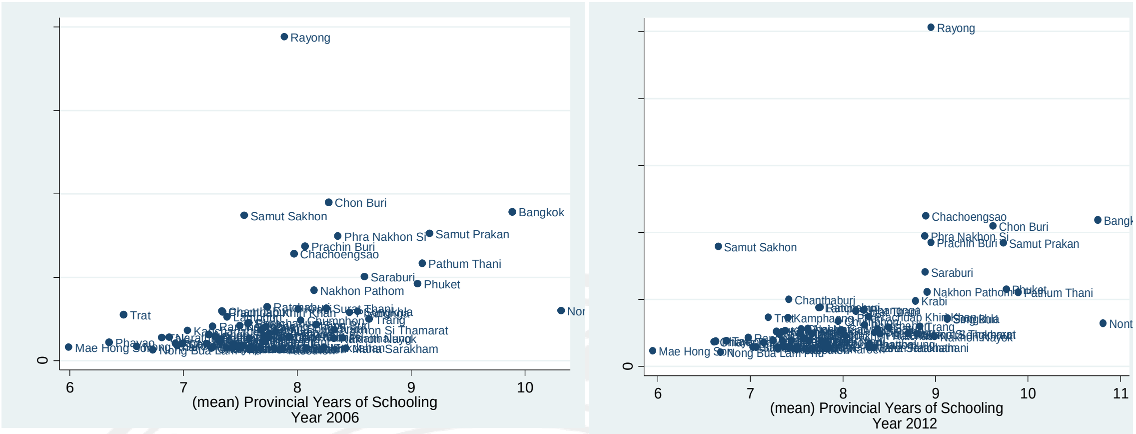
4.3 Data and Empirical Specification

4.3.1 Data

This study used Labor Force Survey (LFS) in Thailand for the period 1995-2012, conducted by National Statistical Office (NSO), Thailand. LFS is used to generate years of schooling of individuals from the raw data containing information about level of education. Then the provincial series of average year of schooling and Gini coefficient of year of schooling from individual year of schooling are generated. We excluded the individuals who are currently studying or has not finished their study from our sample. Because sample including students could mislead both the provincial mean year of schooling as well as Gini coefficient. Gross Provincial Product (GPP) data (1995-2012) of 76 provinces in Thailand are taken from the Office of National Economic and Social Development Board (NESDB), Thailand. Our panel dataset consists of 1368 observations, 76 provinces and 18 years. Figure 1 shows the mean year of schooling and GPP for the year 1995, 2001, 2006 and 2012.

Figure 4.1 Per Capita GPP and Provincial Mean Year of Schooling





Note: Horizontal axis and vertical axis represent the provincial average year of schooling and per capita gross provincial product respectively, for the year 1995, 2001, 2006 and 2012 out of 18 years sample.

The large sample size is one of the advantages of the LFS in measuring Gini coefficient of year of schooling. Second advantage lies on the distribution of the educational achievement data to generate years of schooling. In contrast to existing literature, the years of schooling is distributed from 0 to 21 years, has been used to calculate Gini coefficient. Existing literature used level of education dummy to calculate Gini coefficient. For instance, Castelló & Doménech (2002) calculated the human capital inequality with four levels of education: 0, 1, 2 and 3 for no schooling, primary, secondary and higher education respectively. In this approach, for example, even 4 years of schooling is considered as zero schooling, which might be less informative. Thus, we believe that Gini coefficient used in this paper will be more informative. There are two methods to calculate Gini coefficient, one is direct method and another is indirect method (traditional method). For income inequality, direct method has been developed by Deaton (1997)22 and the indirect method is based on Lorenz curve. Due to some limitations of traditional methods (for instance, year of schooling data is discrete whereas income data is continuous23) to calculate Gini of human capital, most of the previous literature used the developed version of direct method to calculate human capital inequality (Castelló & Doménech, 2002; Checchi,

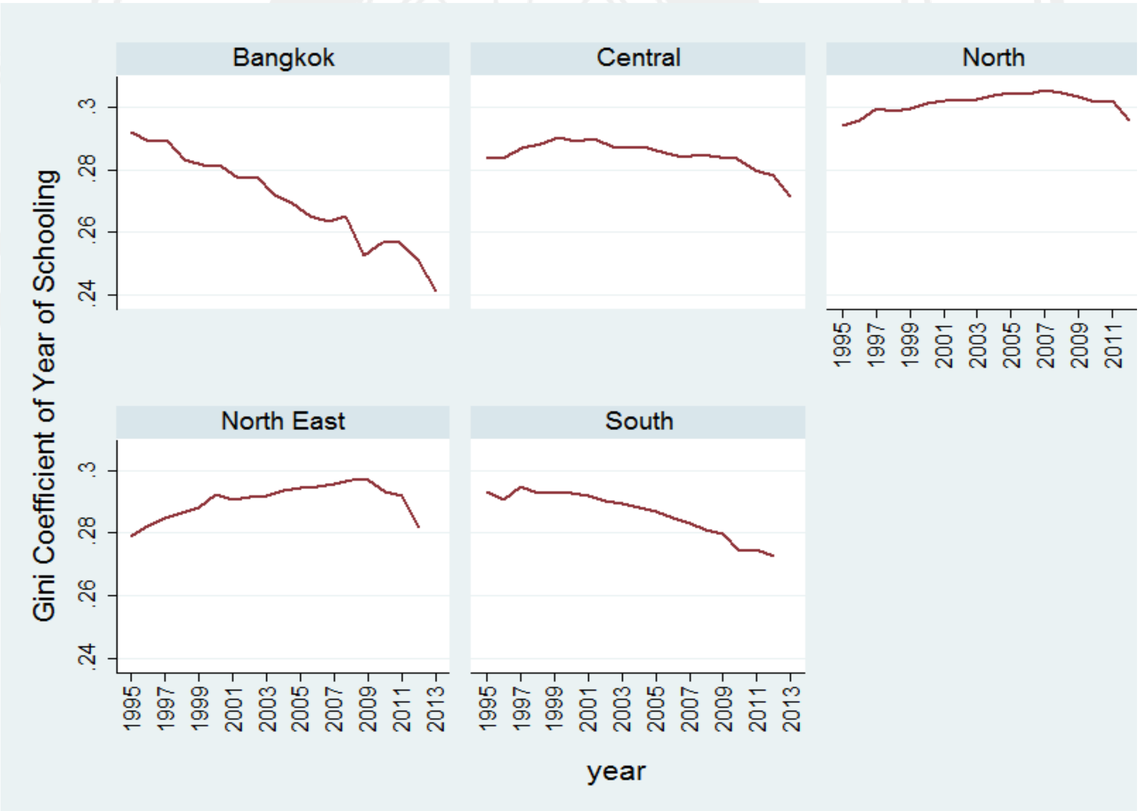
[22] "The ratio to the mean of half of the average over all pairs of the absolute deviations between [all possible pairs of] people" (Deaton 1997).
[23] For details, please see Thomas et. al (2001)

2004; Thomas, Wang, & Fan, 1999). This paper also used the similar direct method to calculate Gini coefficient.

$$Gini^h = \frac{1}{2H}\sum_{i=0}^{21}\sum_{j=0}^{21}|x_i - x_j|n_i n_j$$

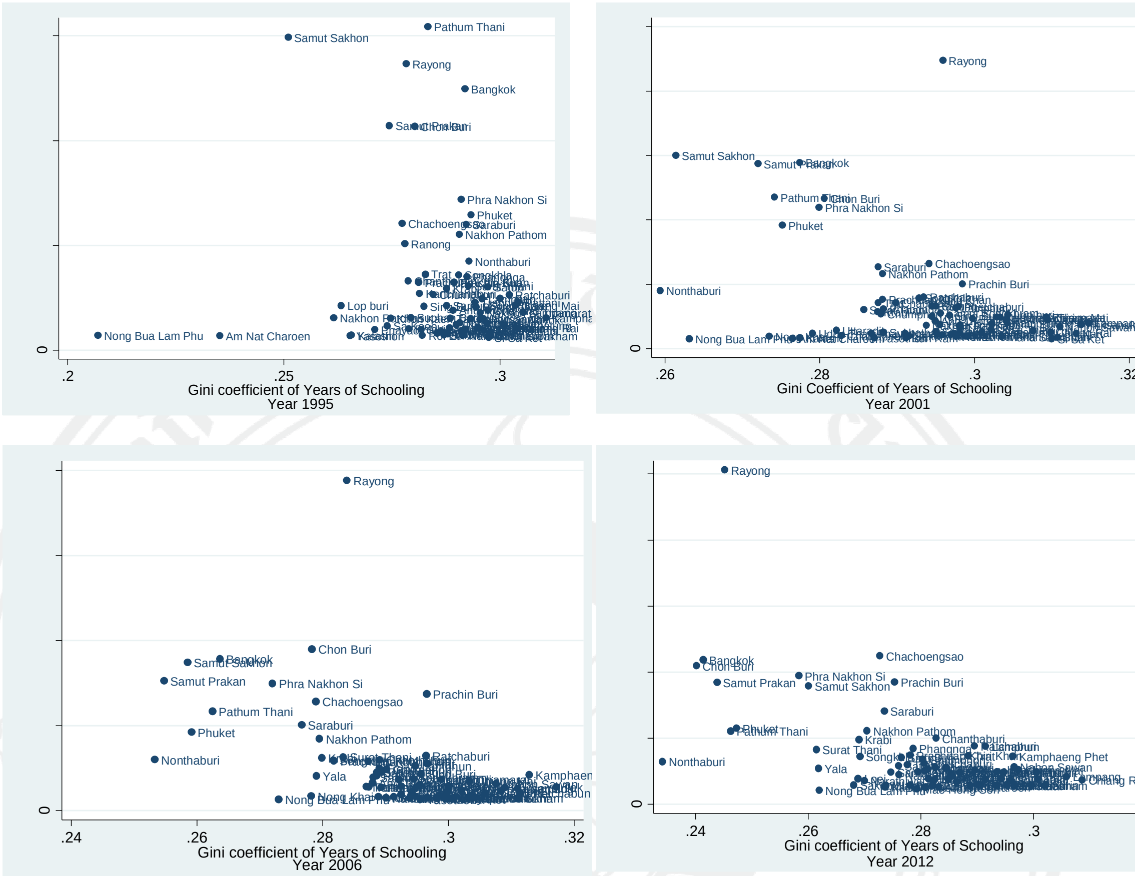
where H be the average year of schooling. x_i and x_j be the cumulative average year of schooling of years of schooling i and cumulative average year of schooling of years of schooling j respectively. n_i and n_j are population share of i years of year of schooling and j years of year of schooling respectively. There are 76 provinces, which are distributed in 5 regions. The regions are Bangkok, Central, North, Northeast and South region. Regional Gini coefficient and year of schooling for each sample year are presented in Figure 2.

Figure 4.2 Regional Human Capital Inequality



Provincial inequality in human capital and per capita GPP of each province are scattered in Figure 3.

Figure 4.3 Per Capita GPP and Provincial Inequality in Human Capital



Note: Horizontal axis and vertical axis represent the provincial Gini of year of schooling and per capita gross provincial product respectively, for the year 1995, 2001, 2006 and 2012 out of 18 years sample.

4.3.2 Empirical Specification

Most of the theoretical explanation are based on wealth inequality and due to unavailability of wealth data existing literature mostly used income, land, or human capital as a proxy of wealth to find the inequality and growth relationship (Alesina & Rodrik, 1994; Castelló & Doménech, 2002; Deininger & Squire, 1998). There is lack of theoretical explanation regarding the nexus between human capital inequality and economic growth in the existing literature. Castelló-Climent & Doménech (2008) discussed about the theoretical linkage between human capital inequality and economic growth through life expectancy. Moreover, Galor & Zeira (1993) theoretically examine that inequality affect economic growth through human capital accumulation.

The theory of wealth inequality and economic growth suggest that wealth inequality affects in economic growth through investment in physical capital or human capital. Income inequality has been used as a proxy of wealth inequality by Persson and Tabellini (1994), Clarke (1995), Roberto Perotti (1996), Robert J. Barro (2000), Banerjee & Duflo (2003), Forbes (2000) and Halter et al. (2014). However, using the human capital as a proxy of wealth in the underlying theory of wealth inequality and economic growth, we can specify our empirical model, similar to Halter et al. (2014). In addition, there are some other existing empirical studies regarding human capital inequality and economic growth used human capital as a proxy of wealth inequality (Castelló-Climent, 2010; Castelló & Doménech, 2002; Sauer & Zagler, 2014).

$$\ln GPP_{it} - \ln GPP_{it-1} = \alpha_{0i} + \alpha_{1i} \ln GPP_{it-1} + \alpha_{2i} \ln H_{it} + \alpha_{3i} GINI\_H_{it} + \varepsilon_{it} \quad 1$$

$$\ln GPP_{it} = \alpha_{0i} + (1 + \alpha_{1i}) \ln GPP_{it-1} + \alpha_{2i} \ln H_{it} + \alpha_{3i} GINI\_H_{it} + \varepsilon_{it} \quad 2$$

Here $\ln GPP_{it}$ be the log of per capita GPP of province i at period t. H_{it} and $GINI\_H_{it}$ be the average year of schooling and Gini coefficient of year of schooling for province i at period t. ε_{it} be the error term, captures unobservable effects. We did not include physical capital measurement into our regression, because of unavailability of provincial level physical capital data. One of the limitations of this study is the data availability for provincial level in Thailand. For instance, provincial level physical capital, level of corruption and institutional factors are not available to include in our regression model. Due to this limitation, the result may face omitted variable bias. To confirm the no omitted variable bias, this paper employed cointegration test. As long as the error term of cointegrated variables is stationary, we can omit the physical capital variable. Because in the cointegrating relationship, any non-stationary omitted variable reflect in the error term to be non-stationary too (Herzer & Vollmer, 2012). In addition, cointegration in set of variables also exists in extended variable set (Johansen, 2000). So omitting the physical capital variable might not be the cause of getting bias estimator in cointegrating vector estimation if error term (ε_{it}) is stationary. In addition, the lag of dependent variable will capture much of the information about physical capital variable.

4.4 Methodology

Because of the provincial panel data, we suspect that our panel model might face the problem of cross sectional dependence (CSD). In the presence of CSD in the model, the estimated parameter using ordinary least square (OLS) or Dynamic OLS (DOLS) will be inconsistent due to unobservable common shocks or cross sectional correlation (Pesaran, 2006; Zellner, 1962). Normally, sub-national dataset faces cross sectional dependence because of common shocks across the provinces or regions. The problem of cross sectional dependence might arise if provinces are geographically connected. (Jensen & Gleditsch, 2009; Tselios, 2009). However, (Jensen & Dall Schmidt, 2011) argued that it may arise because not only for geographical connection but also for social and economic linkage among provinces. In Thailand, provinces are socially and economically interlinked and economic shocks in any province may spill over the other provinces. For instance, GPP may moves in same direction for all provinces because of countries economic policies. Hence, this section first incorporates the CSD test and based on the results of CSD test, appropriate methodologies are discussed for panel unit root test, cointegration test, and cointegration estimation in the following subsections.

4.4.1 Cross Sectional Dependency Test

There are few alternative tests for identifying the CSD in panel data. Among them Lagrange Multiplier (LM) test by Breusch and Pagan (1980), CD test by Pesaran (2004), Friedman (1937) and Frees (1995) are mostly used. Breusch and Pagan (1980) proposed LM test to check the CSD and it is efficient for the panel in which number of cross sections (N) are few and very long time horizon (T). But for the panel with $N > T$, the test might exhibit size distortion and bias results. Contrary to this, the tests of Pesaran (2004), Friedman (1937) and Frees (1995, 2004) are suitable for the panel with $N > T$. However, Friedman (1937) and Frees (1995, 2004) tests do not fit with dynamic panel model.24 Hence, this paper applied the CD test of Pesaran (2004) as discussed in the following part.

Pesaran (2004) proposed an alternative test for cross sectional dependency, commonly known as Pesaran's CD test, as follow:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \quad 3$$

Here $\hat{\rho}_{ij}$ be the pair-wise correlation of the disturbances in the panel model. The rejection of null hypothesis of cross sectional independence indicates that there is dependency between the cross sections. Comparatively, Pesaran's CD test has more advantages than other tests because it allows heterogeneous, non-stationary and dynamic panel model. Thus, Pesaran's CD test has been used in this study.

4.4.2 Panel Unit Root Test

Unit root test is performed to check whether the series is stationary or non-stationary. It is used as the prerequisite of cointegration test or to test the convergence hypothesis. To be cointegrated, the variables should be non-stationary at level and integrated at some order. Panel Unit Root Test (PURT) are developed in two generations, popular first generation PURTs are Levin, Lin, & Chu (2002) (LLC); Im, Pesaran, & Shin (2003) (IPS) and Fisher's Augmented Dickey Fuller (ADF). First generation PURTs hold the assumption of cross sectional independence, which is unrealistic assumption because it could over-reject null hypothesis of having unit root or non-stationary if common sources are non-stationary. Thus, it could suffer from size distortion and power reduction (see Anindya Banerjee, Marcellino, & Osbat, 2004, 2005; Gengenbach, Palm, & Urbain, 2010; O'Connell, 1998). For the limitation of first generation PURTs in panel, the second generation PURTs are developed based on the assumption of cross sectional dependence. The popular form of second generation PURTS has been developed by Pesaran (2007), Bai & Ng (2004, 2010) and Moon & Perron (2004).

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[24] For details please see De Hoyos & Sarafidis (2006). They discussed about the comparative advantages and disadvantage of different types of cross sectional dependency tests.

In this paper, we applied cross sectional augmented Dickey-Fuller (CADF) developed by Pesaran (2007). They modified the ADF to CADF by assuming one common factor in the error term. The suggested the equation for CADF test as follow

$$\Delta Y_{it} = \rho_{0i} + \rho_{1i} Y_{it-1} + \rho_{2i} \bar{Y}_{t-1} + \rho_{3i} \Delta \bar{Y}_t + \varepsilon_{it} \qquad 4$$

Here i and t stand for cross sectional unit and time dimension respectively. ΔY and $\bar{Y}$ be the first difference and cross sectional mean of variable Y respectively. The lag of cross sectional mean ($\bar{Y}_{t-1}$) and first difference of cross sectional mean ($\Delta \bar{Y}_t$) are added as a proxy for unobserved common factor. Null hypothesis of unit root process in CADF is $H_0: \rho_1 = 0$ for all cross sectional unit i and alternative hypothesis is $H_1: \rho_1 < 0$ for $i = 1, 2, \ldots, N_1$ and $\rho_1 = 0$ for $i = N_1, N_2, \ldots, N$.

This paper also applied the unit root test proposed by Reese & Westerlund (2016), which is basically the combination of Bai & Ng (2004, 2010) and Pesaran (2007). Bai & Ng (2004, 2010) proposed the panel analysis of non-stationary and idiosyncratic components (PANIC) test using principal component (PC). Reese & Westerlund (2016) stated that there are some advantages and disadvantages of augmented cross sectional average (CA) of Pesaran (2007) and PANIC of Bai & Ng (2004, 2010). They modified PANIC test using CA instead of PC, which is PANICCA, formed with the strengths of both CA and PANIC. Arguably, PANICCA has better small sample performance than PANIC because it uses CA instead of PC. Like PANIC, it can perform the unit root test for both common factors and idiosyncratic components separately. Thus, this paper used both CADF and PANICCA for unit root test of each variable.

4.4.3 Cointegration Test

This paper used bootstrapped version of panel cointegration test proposed by Westerlund (2007), which can control CSD in the model. In addition, Westerlund (2007) proposed an alternative cointegration test by testing the error correction term of the panel model arguing that it has more power and lower distortion in small sample compare to other residual based tests. Data generating process of this test as follows

$$\Delta Y_{it} = \delta_i' d_t + \alpha_i (Y_{it-1} - \beta_i' X_{it-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta Y_{it-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij} \Delta X_{it-j} + e_{it} \quad 5$$

Here $(Y_{it-1} - \beta_i' X_{it-1})$ be the error correction term and α_i be the error correction parameter. i and t represents the cross sectional unit and time dimension respectively. As in the error correction model above all the variables must be stationary, error correction term, $(Y_{it-1} - \beta_i' X_{it-1})$ should be stationary. The dependent variable (Y_{it}) and independent variable (X_{it}) should be $I(1)$, meaning that their first difference will be stationary. If $\alpha_i < 0$, the variables come back to the equilibrium path in the long run in case of any error in the short run. It can be concluded that there is cointegration among variables if α_i is significantly negative. α_i can be estimated by least square if β_i' is known. But β_i' might not be similar and could be affected by nuisance parameter.25 Thus, Westerlund (2007) proposed to split error correction term and used the following equation, derived from equation (5)

$$\Delta Y_{it} = \delta_i' d_t + \alpha_i Y_{it-1} + \lambda_i' X_{it-1} + \sum_{j=1}^{p_i} \alpha_{ij} \Delta Y_{it-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij} \Delta X_{it-j} + e_{it} \quad 6$$

where $\lambda_i = -\alpha_i \beta_i'$. The null hypothesis of no cointegration is $H_0: \alpha_i = 0$ against the alternative hypothesis, $H_1: \alpha_i < 0$.

Based on the error correction model in equation 6, Westerlund (2007) proposed four tests of cointegration, symbolized as G_a, G_T, P_a and P_T. G and P refer to group mean statistics and panel statistics respectively. Group mean statistics and panel statistics follows the same null hypothesis ($H_0: \alpha_i = 0$ for all i), but the difference in alternative hypothesis. Alternative hypothesis for group mean statistics are formulated as $H_1^G: \alpha_i < 0$ for at least one i, rejection of null hypothesis could be interpreted as there is cointegration among variables at least one cross sectional unit. In panel statistics, alternative hypothesis is $H_1^P: \alpha_i < 0$ for all i, rejection of null indicates that there is cointegration among the variables for the panel as a whole. However, one limitation of Westerlund (2007) cointegration test is- there should be only one independent variable to perform the operation.

[25] See Pesaran (2007), Peter Boswijk (1994) and Zivot (2000)

4.4.4 Cointegration Estimation

There are several techniques to estimate the cointegrating vectors for the non-stationary panel. Fully-Modified Ordinary Least Square (FMOLS) by Pedroni (2000), Panel Dynamic Ordinary Least Square (PDOLS) by Stock, Watson, & Watson1 (1993) and Mean Group estimation (MG) by (Pesaran & Smith, 1995) are the popular forms of panel cointegration estimation techniques. However, all of them above assume cross sectional independence. Due to the effects of unobservable common shocks or CSD, estimated parameters might be inconsistent. Pesaran (2006) developed cointegration estimation techniques with the assumption of CSD, which is common correlated effects mean group estimators (CCEMG) and common correlated effect pooled estimation (CCEP), valid for both stationary and non-stationary panel model. In CCEP, cointegration coefficients are assumed to be homogeneous whereas in CCEMG heterogeneous coefficients are assumed. Alternatively, Bai & Kao (2006) and Bai, Kao, & Ng, (2009) developed Continuously Updated and Fully-Modified (CUP-FM) and Continuously Updated and Bias Corrected (CUP-BC) estimators respectively, both assumes CSD and allows the mixture of stationary and non-stationary series. The one of the limitations of CUP-FM and CUP-BC is size distortion in case of multiple common factors, whether stationary or non-stationary (See Birkel, 2014).

The CCEMG estimation technique has the following advantages. First, it allows CSD in the model. By Monte Carlo simulation, Pesaran & Tosetti (2011) investigated that CCEMG works well in the presence of strong or weak cross sectional dependence. Second, it also allows heterogeneous regression coefficients. Third, it is consistent in presence of multiple unobserved common factors, even the common factors are non-stationary or $I(1)$ (Kapetanios, Pesaran, & Yamagata, 2011). Fourth, it is suitable for both stationary and non-stationary panel. Lastly, it provides consistent estimators even for shorter time horizon or small T, but number of cross sectional units (N) should be moderately high. The model of Pesaran (2006) is specified as follows

$$Y_{it} = \alpha_i + \beta_i X_{it} + \varepsilon_{it}$$
$$\varepsilon_{it} = \lambda_i' F_t + u_{it}$$

Here Y_{it} and X_{it} be the dependent and independent variables respectively for cross sectional unit i at time t. ε_{it} be the error term contains unobservable common factors, F_t with $m \times 1$ vector. Cross sectional averages of Y_{it} and X_{it} could be the proxy of unobserved common factor F_t to take into account the CSD in the model. The model to estimate parameter as follows

$$Y_{it} = \alpha_0 + \alpha_1 X_{it} + a\bar{Y}_t + b\bar{X}_t + e_{it} \tag{7}$$

Where $\bar{Y}_t = \frac{1}{N}\sum_{i=1}^{N} Y_{it}$ and $\bar{X}_t = \frac{1}{N}\sum_{i=1}^{N} X_{it}$.

The CCEMG is further developed by Chudik & Pesaran (2015), which allows dynamic specification. To deal with endogeneity problem, Neal (2015) incorporated Generalized Method of Moments (GMM) and Two Stage Least Square (2SLS) techniques into CCEMG, which is simply called GMM version or 2SLS version of CCEMG. As Kuznets hypothesis suggested that Inequality might be a result of economic growth, the endogeneity problem might arise due to two-way relationship between dependent and independent variables in our model. Hence, we believe that CCEMG-GMM might be the best option to estimate our model. The instruments used for the endogenous regressors are the lag values of the respective regressors. In addition, we compared the results using CCEMG, CCEMG-2SLS and system GMM (see the table 5 in the following section).

4.5 Results

4.5.1 Cross Sectional Dependency Test

We tested CSD for all the variables in the panel model and the result shows that there exists CSD in all variables. The null hypothesis of cross sectional independence test of Pesaran (2004) is rejected at 1% level of significance for all three variables. It is very common to have cross sectional dependency in regional or provincial panel because of sharing the common shocks. As the results show that there is CSD in the panel, it should be considered in panel unit root test, panel cointegration test and panel cointegration estimation. Table 1 shows the details of the CD test results.

Table 4.1 Results for Cross Sectional Dependency test of Pesaran (2004)

Series	CD Test	P-Value
Log of GPP	201.46***	0.00
Log of YSCH	195.88***	0.00
Human Capital Inequality (GINI_H)	46.43***	0.00

Note: Null Hypothesis is Cross Sectional Independent. ***, **, * indicates the rejection of Null at 1%, 5% and 10% level of significance.

4.5.2 Panel Unit Root Test

This paper performed panel unit root test as a prerequisite for panel cointegration test. We used both CADF and PANICCA developed by Pesaran (2007) and Reese & Westerlund (2016) respectively. The results of CADF test are presented in Table 2, which shows that all variables contain unit root or non-stationary at level and stationary at first difference. Similar results are also found using the PANNICCA test, shown in Table 3. Based on PANICCA test, the $GINI\_H$ series is non-stationary at level with constant only and stationary at first difference, in both common and idiosyncratic components. And the series of $\ln GPP$ and $\ln YSCH$ are non-stationary at level with constant and trend and stationary at first difference, at least in idiosyncratic components. From the results of these two tests, it can be concluded that the variables are integrated at order one or $I(1)$, they might have co-movement in the long run or cointegration. To confirm the long run association among variables, panel cointegration is performed, discussed in section 5.3.

Table 4.2 Results for CADF Panel Unit Root Test

At Level with Constant			
Series	***t*-bar**	**Critical Value at 5%**	***P*-Value**
Log of GPP	-1.496	-2.070	0.976
Log of YSCH	-1.731	-2.070	0.498
Human Capital Inequality (GINI_H)	-1.641	-2.070	0.775

At First Difference with Constant			
Series	***t*-bar**	**Critical Value at 5%**	***P*-Value**
Log of GPP	-1.885*	-2.070	0.095
Log of YSCH	-2.382***	-2.070	0.000
Human Capital Inequality (GINI_H)	-2.407***	-2.070	0.000
At Level with Constant and Trend			
Series	***t*-bar**	**Critical Value at 5%**	***P*-Value**
Log of GPP	-1.627	-2.570	1.000
Log of YSCH	-1.690	-2.570	1.000
Human Capital Inequality (GINI_H)	-2.450*	-2.570	0.083

Note: Null Hypothesis is- has unit root. ***, **, * indicates the rejection of Null at 1%, 5% and 10% level of significance, indicating that variables are stationary.

Table 4.3 Results for PANICCA Panel Unit Root Test

Series	Common Factors (ADF Test Statistic)	Idiosyncratic Components (t-statistic)
At Level with Constant		
Log of GPP	4.24	-2.779***
Log of YSCH	-4.24***	-0.34
Human Capital Inequality (GINI_H)	3.61	-0.82
At First Difference with Constant		
Log of GPP	-4.12***	-3.90***
Log of YSCH	-0.79	-3.88***
Human Capital Inequality (GINI_H)	-3.83***	-2.79***

At Level with Constant and Trend		
Log of GPP	-3.96***	-1.303
Log of YSCH	0.14	-0.34
Human Capital Inequality (GINI_H)	1.40	-2.749***

Note: Null Hypothesis is- has unit root. ***, **, * indicates the rejection of Null at 1%, 5% and 10% level of significance, indicating that variables are stationary.

4.5.3 Panel Cointegration Test

Panel cointegration test confirms whether the variables move together in the long run. This paper used bootstrap version of panel cointegration test proposed by Westerlund (2007), discussed in section 4.3. As mentioned earlier in section 4.3 that it cannot perform with multiple independent variables, we took only Gini coefficient of YSCH or human capital inequality as independent variable to perform the test. Because the main aim of this paper is to find the relationship between human capital inequality and economic growth. The results of cointegration test are presented in Table 4.

Table 4.4 Results for Panel Cointegration test

	Critical Value	Robust P-value
$\boldsymbol{G_t}$	-1.034	0.160
$\boldsymbol{G_a}$	-1.054	0.790
$\boldsymbol{P_t}$	-7.377	0.010
$\boldsymbol{P_a}$	-1.253	0.020

Note: Null Hypothesis is no cointegration. ***, **, * indicates the rejection of Null at 1%, 5% and 10% level of significance, indicating that variables are stationary. $\boldsymbol{G_a}$ and $\boldsymbol{G_T}$ indicate group mean statistics; $\boldsymbol{P_a}$ and $\boldsymbol{P_T}$ indicate group mean panel statistics respectively.

The panel statistics, P_a and P_T are significant at 5% level, meaning that panel as a whole, there exists cointegration between GPP and Gini coefficient of YSCH. In the long run, these two variables move together or there exists long run association between these variables.

4.5.4 Estimation Results

We estimated the equation (2), discussed in section 3. The section provided the results from three estimation techniques, which are CCEMG-GMM, CCEMG-2SLS and CCEMG. It is considered that our independent variables are not strictly exogenous and in applying the CCEMG-GMM and CCEMG-2SLS, the first two lags of each independent variable has been used as instruments. The CCEMG-GMM and CCEMG-2SLS estimators in Table 4, show that inequality in human capital negatively affect GPP at 5% level of significance. The results support the findings in existing cross country studies, which found the negative effects of human capital inequality in economic growth for developing and least developed countries (Castelló-Climent, 2010). The coefficient of human capital inequality can be interpreted as if $GINI\_H$ increases by 0.01 points, GPP will reduce by about 0.02 percentage points in the long run in Thailand. The probability of Wald Chi2 indicates that the model is well fitted. The details estimated results and post estimations are provided in Table 4.

Table 4.5 Results for Parameter Estimation

	(1)	**(2)**	**(3)**	**(4)**
	CCEMG-GMM	**CCEMG-2SLS**	**CCEMG**	**System GMM**
ln $\boldsymbol{Y_{it-1}}$	0.16***	0.20***	0.13***	1.10***
	(3.02)	(3.41)	(4.29)	(28.51)
ln $\boldsymbol{H_{it}}$	0.14	0.13	0.08	0.13
	(0.96)	(0.86)	(0.70)	(1.27)
$\boldsymbol{GINI\_H_{it}}$	-2.13**	-2.17**	-1.50**	-1.61**
	(-2.07)	(-2.06)	(-2.47)	(-2.24)
Constant	-1.80	-1.70	-0.43	-0.66***
	(-1.46)	(-1.77)	(-0.44)	(-4.52)
Wald Chi2	18.92	20.88	24.25	109689
Prob.(Chi2)	0.000	0.000	0.000	0.000
Number of observations	1064	1064	1292	1064

Post Estimation Diagnosis				
Hansen J test for overidentification				Chi2=73.80 Prob.(Chi2)= 1.0
CD test	P-Value 0.07	P-Value 0.07	P-Value 0.045	P-Value 0.000
Autocorrelation test				
AR2	Chi2=15.34 Prob.= 0.00	Chi2=15.61 Prob.= 0.00	Chi2=65.21 Prob.= 0.00	Chi2=317.61 Prob.= 0.00
AR3	Chi2=0.02 Prob.= 0.88	Chi2=0.008 Prob.= 0.93	Chi2=23.68 Prob.= 0.00	Chi2=182.60 Prob.= 0.00

Note: The first two lags of each regressors are used as instruments in regression. Null Hypothesis is no cointegration. ***z***-statistics are in the parenthesis. ***, **, * indicates the rejection of Null at 1%, 5% and 10% level of significance, indicating that variables are stationary. Cumby & Huizinga (1992) test for autocorrelation has been used, which is suitable for IV-GMM estimation. For CSD test in residual series, CD test of Pesaran (2004) has been used.

To check the validity of our results, the test for CSD and serial correlation in the residuals has been performed. Null hypothesis of cross sectional independence cannot be rejected at 5% level of significance, which implies no CSD in the residual series in both CCEMG-GMM and CCEMG-2SLS estimation. Cumby & Huizinga (1992) test for autocorrelation has been used with two and three lags of residual series. The advantage of this test is the suitability for 2SLS or IV-GMM estimation (see Baum & Schaffer, 2015). Null hypothesis is of this test is there is no serial correlation at specified lag while alternative hypothesis is there is serial correlation at specified lag. For the model (1) and (2), Null hypothesis can be rejected at 1% level of significant at lag two while it cannot be rejected at lag three or there is no serial correlation in the error term at lag three. In addition, Hansen's J test cannot reject the null hypothesis and suggest that overidentification restriction is valid.

4.6 Conclusion

This paper tries to find the causal effects of human capital inequality and economic growth using sub-national annual data from Thailand. The methodologies used in this paper are unit root test with CSD, cointergration test with CSD and cointegration estimation using CCEMG, CCEMG-GMM and CCEMG-2SLS. We focused on CCEMG-GMM estimators because of endogeneity problem and cross sectional dependence in the panel. The estimated parameter of human capital inequality using CCEMG-GMM and CCEMG-2SLS are similar and significantly negative at 5% level, which implies that there is negative effects of distribution of human capital in aggregate economy. However, the effect of average year of schooling is insignificant.

The findings of the paper suggest that human capital inequality hinders economic growth in Thailand. Policy makers should undertake this view and make policy accordingly to reduce human capital inequality and foster economic growth in Thailand. Thailand initiated first education reform in 1999. Government budget for education has been increasing in Thailand, which nearly doubled in a decade, but the educational achievement is declining over time (Siamwalla et al., 2011). Moreover, the research conducted by National Education Standards and Quality Assessment (NESQA) in 2008 showed that 20% of the school are failed to maintain minimum quality requirements. As a result, second educational reform with six years plan initiated in 2012 (Ministry of Education, 2011; Lounkaew, 2013). Although there are some existing policies might help to reduce human capital inequality in Thailand. For instance, compulsory primary and secondary education, policy of education for all and student loan scheme (SLS). However, intangible aspects (i.e. management, autonomy, parental participation, leadership, accountability) should be counted to have successful educational reforms (Lathapitpat, 2011; Siamwalla et al., 2011). This paper suggests the policy makers to have more concentration on inclusive educational policies to reduce human capital inequality and hence to boost economic growth.

This paper also suggests to conduct research on human capital inequality and growth with the subnational data for other countries to confirm the findings. It also leaves the issue of policy based research for further study. More specifically, how efficient the existing educational reform policies in reducing human capital inequality.

CHAPTER 5
CONCLUSION

This dissertation has three main chapters regarding human capital, inequality, and economic growth in Thailand. Chapter two is about the intergenerational transmission of human capital. It found the rate of transmission of human capital as well as the comparative schooling attainment between lower income and higher income households. It also analyzed the efficiency of SLS in Thailand. Chapter three is about the trend and dimensions of human capital inequality. Using the rural-urban dummy in intergenerational framework, it tried to find the comparative schooling achievement between rural and urban children, which implies the rural urban dimension of human capital inequality in Thailand. In addition, it analyzed the trend of human capital inequality by using the parental education dummy. Chapter four is about the cointegration between human capital inequality and economic growth. Each chapter has some specific contributions to the existing literature. The main contribution of chapter two is in methodology, which is the alternative instrument to solve the endogeneity problem in estimating intergenerational transmission. It also contributes to analyze the policy of Thai Student Loan Scheme in the intergenerational framework. Chapter three contributes to analyze the trend in human capital inequality as well as the rural-urban dimension of human capital inequality. Lastly, chapter four claims to the first to find cointegration between human capital inequality and economic growth using sub-national annual data from Thailand.

The key findings in chapter two are- (1) the rate of intergenerational transmission for both mother and father are higher than the developed countries; and the rate of transmission from father is higher than the mother but gap between rate of transmission from father and mother is very low. The comparative findings regarding rate of transmission from father and mother support the existing evidences from different countries (J. R. Behrman & Rosenzweig, 2005). (2) Children from lower income families are getting less education than their counterpart, which implies that the existing student loan scheme in Thailand might not be efficient. Based on the findings in this chapter, it suggests some policies to the policy makers, such as compulsory public education should be designed irrespective of gender, redesign the student loan scheme to support the poor students' higher education. Moreover, this research also provides some further investigation, such as industry based intergenerational study to suggest more focused policies.

In chapter three, it has been found that intergenerational transmission rate of human capital in lower educated households are getting comparatively higher than higher educated households. It implies that there is a decreasing trend in human capital inequality in Thailand. In addition, this paper used rural-urban dummy variables to investigate comparative schooling achievement between rural children and urban children. It has been found that rural children are getting less education than the urban children. It might be helpful for the policy makers in making policies regarding rural educational infrastructure to reduce the human capital equality between rural and urban area.

Chapter four investigates the effects of human capital inequality in aggregate economy. This paper used second generation econometric techniques, which assume cross sectional dependence in the model. The techniques are panel unit root test with cross sectional dependence, panel cointegration test with cross sectional dependence and panel cointegration estimation with cross sectional dependence. It found that there is cointegration between human capital inequality and economic growth in Thailand. The long run effect of human capital inequality is significantly negative on economic growth in Thailand. This study confirms the existing evidences conducted with cross country data (see Castelló & Doménech, 2002). In addition, this chapter found that the coefficient of average year of schooling is not significantly different from zero. The findings of this paper recommend any policies those help to reduce human capital inequality to get higher economic growth in Thailand. The suggestions or policy recommendations from each chapter are in the following paragraph.

In conclusion, all the chapters recommend the policies those can help the education of poor children, compulsory education, gender unbiased educational policies. In addition, policy makers should concentrate on the policies to reduce human capital inequality as it is the stumbling block in economic growth. Chapter two suggests that the rate of intergenerational transmission is higher in Thailand than other developed countries. Policy makers can concentrate on educational policies focusing on the educational outcome particular generation as well as outcome of the next generations. In addition, gender unbiased educational policies are recommended in this chapter as it found the similar rate of intergenerational transmission from both father and mother. This chapter also suggests to redesign the Thai SLS to increase the educational outcome in poor households in Thailand. Chapter three recommends an important policy to reduce rural-urban inequality in human capital, which is to improve rural educational infrastructure in Thailand. Chapter four suggests any policies to reduce human capital inequality as it found that there are negative effects of human capital inequality in economic growth in the long run. Hence, policy makers should be aware of the trend of human capital inequality and take appropriate actions to increase aggregate human capital as well as to reduce human capital inequality.

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