Revisiting Health and Income Inequality Relationship:Evidence from Developing Countries

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Evidence from Developing Countries

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Abstract: In general, countries with more equal income distribution generally enjoy better health. Earlier empirical studies on the relationship between income distribution and health at country level present strong evidence that income inequality on an average impedes the improvement of population health. However, a majority of these empirical studies are based on data from either only developed countries or pooled data from developing and developed countries. They mainly study the relationship at a single point of time or at an average of several years. These studies also fail to control for country specific unobserved heterogeneity. Departing from the general trend of current literature, this paper examines the health-income inequality hypothesis using panel data from 31 low income and low middle income countries for the period of 1982-2002. The results from the simple pooled OLS analysis indicate that health and income inequality is negatively related in these countries. This finding is in line with the most of the earlier cross country studies. However, application of fixed effects and random effects model to control country specific heterogeneity provides contradictory results. In other words, my findings from this study confirm that there is a positive relation between health and income distribution in this set of developing countries over this period.

Key Words: Health, Fixed Effects, Income Inequality, Random Effects

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1.1 Introduction

In last couple of decades, there has been a rising trend in life expectancy and a declining trend in infant mortality and under-five mortality rates in the world. This large improvement in health outcome of population is more pronounced in developing countries as compared to developed ones. Meanwhile, income inequality has also increased in many countries. It is a common belief that countries with more unequal distribution of income usually lag behind in terms of many indicators of human development including health. In this context, more than 200 articles have already been published to understand the relationship between income distribution and health. The nexus between population health and income inequality was first brought about by Preston in his famous seminal paper in this fashion "…the distribution of income is clearly a likely source of variance in the basic relation between national life expectancy and average national income" (Preston 1975, p. 242). Though Preston did not directly claim that income inequality is detrimental to average health of population, a large body of empirical literatures in this field provides overwhelming evidence in this direction. For example, Wilkinson and Pickett (2006) have reviewed 155 peer published reports on the relationship between different measures of income distribution and health and found that 131 studies either completely or partially support the proposition that income inequality, in general is harmful to health.[1] Previous empirical works motivated Wilkinson (1996) to conclude that the distribution of income is "one of the most powerful influences on the health of whole populations in the developed world to have come to light" (as cited in Herzer and Nunnenkam, 2011, p. 1). Several other authors including Rodgers (1979) and Waldmann (1992) are also in favor of this view. However, Judge et al. (1998) states that aggregate cross country studies often suffer from inadequate samples, employing too simple bi-variate specifications without appropriate controls, consider only single point of time and lack high quality data for income inequality**.** Several recent works (Mellor and Milyo, 2001; Leigh and Jencks, 2007) have tried to overcome these limitations and have explored that the strong negative association between health and income inequality could be reversed. However, majority of these empirical studies are based on data from either only developed countries or pooled data from developing and developed countries. To the best of my knowledge, there is no single study, which solely makes use of cross sectional data for several time periods to assess how income inequality affects health of population in the developing countries.

Considering the above limitations of previous studies, this paper takes an attempt to examine the relationship between health and income inequality in low income and low-middle income countries over the period of 1982-2002 at aggregate level. Besides the objective of overcoming the drawbacks of earlier works, I have been motivated by several factors to undertake this research. To mention some of these, in many developing countries, it is frequently observed that both income inequality and average health are rising on the face of economic

[1] See Table 1 for the Wilkinson and Pickett s' classifications of the 168 analyses in "Income inequality and population health: A review and explanation of the evidence" in Social Science & Medicine 62 (2006)

development. For example, Bangladesh has been able to make significant progress in several health indicators such as improving life expectancy at birth and reducing infant mortality rate in past three decades. In contrast, income distribution has become more uneven over time. Again, countries with high poverty rate and with high inequality in income compared to their counterparts have made good progress in terms of average population health. For instance, proportion of people living on less than $2 per day income in Bangladesh is much higher than Pakistan but the former has been successful to reduce the under- five mortality rate at a greater speed than latter. Again income inequality measured by Gini index is higher in Ecuador than in Algeria but the under-rate mortality rate is higher in the latter country. Many other low income countries also show similar trends. So addressing the research question of the link between health and income distribution has important implications for these countries. My study contributes to the current literature of this field in several ways. First of all, this study uses panel data for 31 developing countries since the variation in income inequality in low income countries is higher as compared to high income countries. No other earlier work used paned data solely focusing on developing countries. Secondly, the difficulty of international comparison of income inequality data is solved using the best available measure of income distribution. I have used estimated household income inequality index (EHII), which overcomes the limitations of previously used income inequality indices. Thirdly, I have applied the standard panel data technique to account for the unobserved country specific effects. Finally, I have done a thorough sensitivity analysis using different indicators of health outcome to check the robustness of the findings. The results from the simple pooled OLS analysis indicate that health and income equality is negatively related in these countries. This finding is in line with the most of the earlier cross sectional studies in the field. However, I obtain contradictory results when I use the fixed effects and the random effects methods to control country specific effects. In other words, my findings from this study confirm that there is a positive relation between health and income distribution in this set of developing countries in the sample period.

This paper is organized sequentially as outlined here. The section after wards provides a non-technical over view of the main hypotheses relating income, income inequality and health. Chapter 2 discuses the previous literatures on the relationship between health and income distribution and I limit this review to the aggregate studies only. In chapter 3, I design the empirical framework of this paper and I also the present data and estimation strategies in different subsections. Especially, section 3.3 provides a detailed explanation of the panel data methodology applied in this paper. A short summary of the key statistics and a brief graphical analysis are given in chapter 4. I present the main empirical results and discuss the important findings in chapter 5. This chapter also includes a sensitivity analysis of the results obtained in this study. Section 6.1 focuses on the main limitations of this research and it highlights the scope for future research in this field. Finally, I conclude the paper in section 6.2.

1.2 Income, Income Inequality and Health: Different Hypotheses

Since 1960's researchers and scholars of several disciplines such as economics, sociology, public health etc. have been debating on the subject of relation among income, income inequality and health. The debate has become more intense in recent decades on the face of worldwide improvement in several indicators of health along with rising income inequality. Though several arguments in the related literature suggest that a more equal distribution of income is coupled with better average health outcomes such as higher life expectancy and lower mortality, there is a substantial theoretical ambiguity in many aspects. Much effort has been given to explore the relationship between income inequality and health. However, the debate is still open and agreement on many fundamental matters is not also obvious. In this regard, the focus of this section is to highlight the underlying hypotheses regarding the relationship between income distribution and health. The discussion of this part is mainly based on Wagstaff and Doorslaer(2000) and Deaton(2003).With respect to the previous literatures, the underlying mechanisms of income inequality and health is grouped under three broad titles :absolute income, relative income, and income inequality hypothesis.

Hypothesis 1: Absolute Income Hypothesis (AIH)

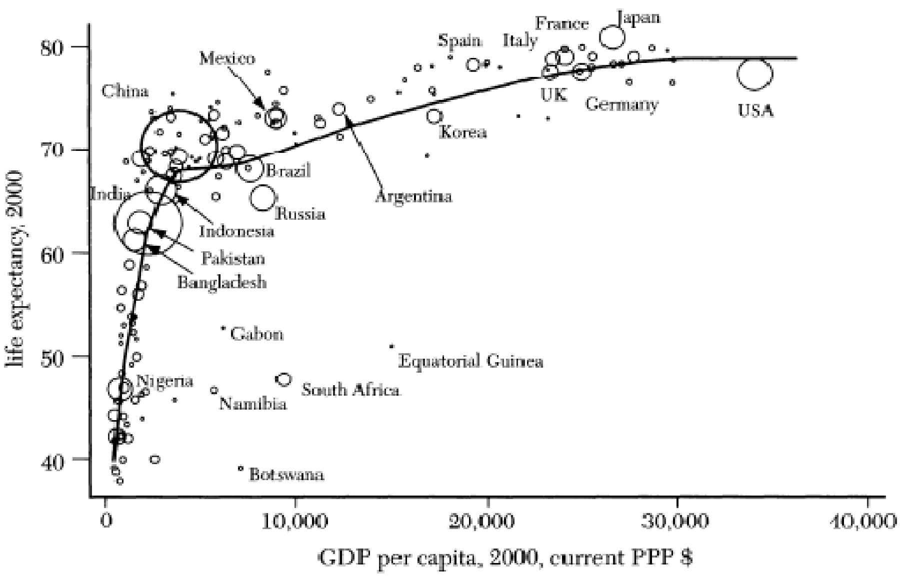
The absolute income hypothesis states that higher average income leads to better health but the improvement in health occurs at a decreasing rate. In other words, the relationship between income and health is concave. The famous seminal paper by Preston (1975) formulated the ground for the absolute income hypothesis. AIH postulates that people with higher incomes have better health outcomes, but income inequality or relative income has no direct effect on health. Deaton (2003) argues that bad health is an outcome of low income or intense poverty and it is known as poverty hypothesis also. The updated relationship between life expectancy and per capita GDP at international level are shown in Figure 1, which is well known as Preston Curve. Preston (1975, p.241) states "Increases in average income are strongly correlated with increases in life expectancy among poor countries, but as income per head rises, the relationship flattens out, and is weaker or even absent among the richest countries". Some scholars describe AIH in this way that lower tail of income distribution must be pushed up to a certain level from where income has strong impact on health. So, absolute income hypothesis reveals that average income is more important in poorer countries while income inequality matters more for health in wealthy nations.

Hypothesis 2: Income Inequality Hypothesis (IIH)

The income inequality hypothesis states that income inequality itself has an impact on the health of people within a country, holding their average incomes constant. According to the IIH, there is a direct link between health and income inequality. Mellor and Milyo (2002) identify two versions of this hypothesis; "strong" and "weak".

Argument of the strong version is that inequality affects all individuals in a society equally, regardless of their income levels. On the other hand, the weak version states that income inequality has more impact on the health of persons with lowest level of income in the society. Therefore, the IIH suggests that the extent of the difference between the rich and poor matters for population health and mortality. The key difference between the AIH and the IIH stems from the fact that the latter explicitly considers the effect of income distribution on health while the former manifests the concave relationship between health and income.

Figure 1: New version of Preston curve: Life Expectancy versus GDP Per Capita



Source: Deaton (2003, pp.116), Journal of Economic Literature, Vol. XLI

Hypothesis 3: Relative Income Hypothesis (RIH)

The relative income hypothesis is conceptually different from above two hypotheses. RIH states that it is neither average income nor income inequality affects individual's health, rather individual's health depends on his or her income relative to average income of one or more reference groups. Several aspects such as psychosocial stress and material deprivation may explain the connection between relative income and health. Sometime is difficult to distinguish between IIH and RIH but they are not similar. The relative income hypothesis is more or less parallel to the weak version of income inequality hypothesis in a sense that poor people suffer more than the rich when the income distribution spreads out more. But the strong version is more consistent with AIH. So it is important to unveil the subtle distinction among these three hypotheses.

This discussion thus comes to a conclusion that there is a direct link between income inequality and health implied by IIH. The RIH indicates that individuals' income relative to their social group average is important to determine their health. Relative income hypothesis can be only tested using individual level data. In this study, I employ aggregate data from developing countries to test the relevance of strong version of income inequality hypothesis.

Chapter-2: Survey of Previous Literature

There exists a growing body literature examining the relationship between health and income inequality. As noted already, the purpose of this study is to re-investigate the association between income inequality and health using aggregate level data from developing countries. So, the intention of this section is to provide a brief summary of the previous empirical researches in this topic confining the discussion only to economics literatures. Additionally, this discussion focuses only on the empirical findings and methodological debates. In line with Wagstaff and Doorslaer (2000), studies on the link between health and income distribution can be divided in to three broad categories by their levels of aggregation; individual level, community level and population level. Prior individual level studies both theoretically and empirically have almost reached a conclusion that poor people always have worse health because they are unable to afford goods and services such as better health care, better nutrition, good sanitation and housing to improve their health. However, the conclusion regarding this relationship is still open to the debate both at the community and aggregate level. With the purpose of not departing from the main objective this paper, I restrict my review only to the existing aggregate level studies. Those who are interested can consult Deaton (2003), Lynch et al. (2004), Wilkinson and Pickett (2006) and De Maio (2010) for an extensive and comprehensive review on methodological, theoretical and epistemological issues on the relationship between income and health. In aggregate studies, the objective is to investigate whether difference in income distribution can determine the differences in average health of population across countries. Life expectancy and infant mortality are the two most widely used indicators of health while Gini coefficient and different shares income distribution measure the degree of inequality in country level. Moreover, earlier studies on the relationship between inequality and health at national level can be divided into two groups as: cross-sectional evidence at a certain point of time and longitudinal studies, which simultaneously examine the relationship across countries and over several periods.

2.1 Country Level Evidence: Cross Sectional Studies

The most important feature of the previous literatures on population level is that most of the studies are done using data on a single year's cross section to investigate the association between inequality and health. This raises the question of methodological problem, sample coverage and quality of data in these studies. However, cross-country studies are the dominant part in the literature on income inequality and health. This why the the natural starting point in reviewing the earlier studies is to critically discuss the main findings of the most cited papers in this topic of research. International comparison of health and income distribution goes back to Preston (1975), in which he examined the international patterns of per capita GDP and life expectancy at birth for three different decades of the 20th century. Preston shows that life expectancy is positively related with national income but the effect of income on health diminishes at high level of income, which results in curvilinear relation between income and health. He suggests that that at least some of the variation in life expectancy among richer countries may be a result of variations in income distribution. Later on, Rodgers (1979) finds a statistically significant negative effect of the Gini coefficient on life expectancy at birth, life expectancy at age five, and positive effect on the rate of infant mortality in a sample of 56 countries in a simple regression model after controlling for income. The argument for including income inequality in aggregate models of health outcomes comes from the fact that the effect of income inequality reflects the individual-level nonlinear relationship between income and health. In sample of developing countries, Flegg (1982) shows that there is a significant positive association between income inequality and child mortality after adding maternal illiteracy rates and measures of the availability of nurses and physicians. In an influential paper, Waldmann (1992) looks into the link between infant mortality and income share held by sub-group of population in a pooled sample of 57 developing and developed countries. The main conclusion is that inequality directly affects the infant mortality rate; among the poor it increases when the rich get richer, even when their own incomes do not suffer. According to Wennemo (1993) and Duleep (1995), there is a significant negative relationship between income inequality and infant mortality and male mortality in several age cohorts. Wilkinson (1992) provides evidence of significant relationship between income inequality and life expectancy across a number of developed countries. However, Wilkinson's 1992 analysis has been heavily criticized by Judge (1995). Judge for an instance, argues that Wilkinson's findings are not robust to changes in the unit of income. De Vogli et al. (2005) in a more recent paper present evidence that the Gini index is inversely related with life expectancy after controlling for per capita GDP and educational attainments in 21 economically developed nations. A comparable research to previous one finds statistically significant relation between income inequality and mortality among men aged 15-29 using data of 126 countries (Dorling et al. 2007).Although the discussion highlights that the findings of many cross-country analyses support the proposition that income inequality has a hazardous impact on health, there are also exceptions to some extents. Pampel and Pillai (1986) are unable to get a significant effect of income inequality on infant mortality. Making use of updated data from World Bank's World Development Report (1993 edition), Baumbusch (1995) replicates Waldmann's study for the same period but finds that income accruing to the top 5 percent decreased infant mortality. Judge (1995) comes with new findings that there is no significant relationship between income inequality and health for a cross section of 13 countries. Judge et al. (1998) show that there is no significant correlation between changes in income inequality and changes in either life expectancy or infant mortality in a cross sectional study of 10 countries. In a sample of 75 countries, Gravelle et al. (2002) also fail to find any significant relation between income distribution and population health.

2.2 Country Level Evidence: Longitudinal Studies

Empirical studies using panel data are rare in the prior population level literature of health and income inequality nexus. The main reason behind this exception as compared to other fields of research is the unavailability of consistent data on income inequality for longer time horizon for many countries especially for less developed countries. The first study that attempts to make use of panel data to investigate this relationship is done by Mellor and Milyo (2001). Applying first-difference method, they try to control for country-specific effects in sample of 47 developing and developed countries. Their analysis brings us the evidence that the positive correlation between the gini coefficient and infant mortality disappears once secondary school enrolment is controlled for. Moreover, negative association between life expectancy and income inequality eliminates when income per capita is taken into account. The main limitation of this study is that time period cover is very short (four years only.) In a sample of 115 countries, Beckfield (2004) applies fixed effect model to consider unobserved heterogeneity but he finds no support for income inequality-health hypothesis. Recently, Shkolnikov et al. (2009) uses a country fixed-effect method for a set of comparable data from 17 developed countries and conclude that unequal income distribution cannot explain reduction in life expectancy losses over time. However, it can explain differences in life expectancy losses across countries.

2.3 Summary

To sum up, many of the cross national studies use straightforward bi-variate regression method without appropriate controls. Moreover, they do not consider for the possibility of unobserved country heterogeneity and the measures of income distribution used are often not internationally comparable (Beckfield 2004). Another problem of these studies is that they pool together rich and poor countries without considering different mechanisms through which income inequality affects health. I term this as a heterogeneous sample problem in this topic of research. Unobserved heterogeneity is not taken into account in many studies, which leads to bias the results. Though few studies have used panel data, time the period is usually in short many cases, which limits statistical power. Last of all, aggregate studies suffer from unreliable measures of income inequality at the country level and from inconsistent data from one period to other.

Chapter-3: Empirical Framework, Data and Methodology

This chapter is designed to present the empirical models, data and econometric strategies applied in this study. The first section outlines the empirical specifications. Data description is given in the next section and the third section finishes this chapter describing the methodology.

3.1 Empirical Framework

The purpose of this section is to introduce the empirical models to be estimated in this research to examine the association between health and income inequality in population level in developing countries. It is discussed in the previous section that majority of the existing literature studying the relationship between health and income distribution relies on comparisons across countries at a single point in time or on changes over time within one or two countries. In contrast, this paper takes an attempt to utilize panel or longitudinal specification, which takes into account unobserved heterogeneity among countries. There are several advantages to use panel data. For instance, it increases precision in estimation as there is more information and more degrees of freedom. More over, omitted variables problem can be dealt with sometimes and it captures the unobserved heterogeneity. It helps to take into account the issues that cannot be studied in either cross-sectional or time-series setting alone. Time series and cross-section studies not controlling this heterogeneity are at risk of obtaining biased results. Therefore, I start by specifying the following general representation of the panel model of this study:

$$lnH_{it} = \beta_0 + \beta_1 lnEHII\_Gini_{it} + \beta_2 lnGDP\_PC_{it} + e_{it} \quad \text{for } i = 1,2,.....,N \text{ and } t = 1,2,....,T \qquad (1)$$

In equation (1), subscripts i and t denote cross section entities and time series dimensions for each variable respectively. In the this empirical specification, H is the measure of health status such as life expectancy at birth, the infant mortality rate and the under-five mortality rate, while EHII_Gini stands for the proxy of income inequality. Average income is measured by real per capita gross domestic product, which is denoted by GDP_PC and e is the error term with classical properties. All the variables are in natural logarithm to ease the interpretation and comparison. It also helps me to achieve linearity and to control for heteroskedasticity in the data. This specification allows us to estimate the relationship between income inequality and health, holding average income constant. However, it must be considered that education is one of the key determinants of population health. It is evident in the prior researches that education has strong positive impact on health status. Empirical findings suggest that impact of education on health is almost as large as the impact of income. In a sample of 72 developing countries, Subbarao and Raney (1995) find that female literacy has a strong impact on infant mortality during the period of 1970 –1985. That is why a proxy for national educational attainment is included as a control variable. Additionally, a control term for year of observation is included in the regression models motivated by previous researches (Judge,1995; Mellor and Milyo, 2001). It takes into account for health improvements that accrue to development not captured by changes in real GDP (Wilkinson,1996) and it captures the spurious association between trending variables. So considering these facts, equation (1) can be reformulated as below:

$$lnH_{it} = \beta_0 + \beta_1 lnEHII\_Gini_{it} + \beta_2 lnGDP\_PC_{it} +_{it} \beta_3 \ln EDU\_Sec_{it} + \lambda_t + e_{it} \qquad (2)$$

Here the gross secondary school enrollment rate is used as a proxy for educational achievement denoted by EDU_Sec and λ_t is a period dummy capturing time fixed effects. In line with most of the previous findings, the expected sing of the coefficient associated with income inequality should be negative that postulates the negative relation between income inequality and average health outcome when measured by life expectancy. On the other hand, I expect that coefficients of real GDP per capita and education should be positive and it is established by previous studies. In fine, the hypothesis that I am going to test is that average health of population is negatively associated income inequality in developing countries i.e the higher the unequal income distribution the lower is the health status.

3.2 Data

This section provides a discussion on the choice of indicators used in this paper and their sources focusing a special attention to the proxy of income inequality variable. Due to the unavailability of the data on the good quality measurement of income inequality for the recent years, the time span covered in this study is 1982-2002(Twenty One Years). I have selected 31(Thirty One) low income and lower-middle income countries (Developing Countries) out of 91(Ninety One) countries according to the World Bank classification of economies worldwide[2]. A complete list of the countries is given in Table: A1 of the appendix. The reason to choose the above time period is that the most consistent data on income inequality and other variables is available only for these countries. In constructing panel data set, repeated observations on the same cross section are observed for several time periods. The above time period is grouped into seven periods by taking three-year average of all the variables. The rationale behind method is that different health indicators and income inequality do not change over short span. This procedure of constructing panel data set should provide me a balanced panel of 217 (n.t=N) country–period observations but I ended up with an unbalanced panel since data on some variables of different countries for few periods are unavailable. Data on all variables except income inequality are collected from World Development Indicator-2010 (WDI) database of the World Bank. Income inequality data comes from the UTIP-UNIDO project at the University of Texas[3].

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[2] http://data.worldbank.org/about/country-classifications

[3] University of Texas Inequality Project (UTIP) and the United Nations Industrial Development Organization (UNIDO)

Dependent Variables: Several indicators of health outcome at population are used in the previous studies of income inequality and health but life expectancy at birth (LEB) is the most common used measure of health status. Because it is not biased by age structure and data on life expectancy at birth are available for a reasonably large number of countries and time periods. In line with with prior researches, I also use two alternative measures of health status such as the infant mortality rate (IMR) and the under-five mortality rate ((MR_5) in order to test the robustness of the results. The definitions of the three measures of health are given below according to the World Bank:

Life Expectancy at Birth (LEB): Life expectancy at birth indicates the number of years a newborn infant would live if prevailing patterns of mortality at the time of its birth were to stay the same throughout its life.
Infant Mortality Rate (IMR): Infant mortality refers to the number of infants dying before reaching one year of age, per 1000 live births in a given year.
Mortality Rate Under-five (MR_5): Under-five mortality rate is the probability per 1,000 that a newborn baby will die before reaching age five, if subject to current age-specific mortality rates.

Independent Variables: It is discussed earlier that income inequality hypothesis will be tested in this study. I briefly discuss three independent variables below:

Income Inequality (EHII_Gini): The main difficulty in any income distribution related empirical work is to obtain reliable and comparable measure on income inequality, especially for developing countries. The most widely used measure of income inequality is Gini index, which shows how equally income is distributed across the population. It scales between zero and one; the higher the Gini, the more the extent of inequality is. To answer the research question in this kind of longitudinal study, it is essential to measure inequality in a consistent way for a large number of countries over time. As noted by Beckfield(2004), most of the previous cross- national studies suffer from using income inequality data from multiple sources, which limit international and inter-temporal comparability(e.g., Rodgers 1979; Waldmann 1992; Wilkinson 1992). There are several sources for income inequality database. For instance, Gini coefficient dataset constructed by Deininger and Squire (1996), hereafter D&S are used in a number of previous studies. But several problems are associated in D&S database. For example, the coverage of this dataset is sparse and unbalanced and the mixture of varied data types into a single dataset, thus limiting the comparability, not only across countries but also over periods. Another source is Luxembourg Income Study (LIS) database. LIS has data for longer periods but it covers mainly high income countries. Lastly, several researches depend on inequality data from the World Income Inequality Database (WIID). However, the use of different income definitions such as gross or net, different beneficiary units such as individuals or households and population coverage of urban or rural causes the Gini coefficient in WIID to be inconsistent. This results in serious problems of comparability that can challenge the robustness of the empirical evidences. But in this paper, I have opted for using Estimated Household Income Inequality (EHII) index, which is extracted from the UTIP-UNIDO project at the University of Texas. It has become an alternative but more reliable source of income inequality data in recent studies (Meschi and Vivarelli, 2009; Gimet and Lagoarde-Segot, 2011). I am not going to give details of the construction procedure of this index. Galbraith and Kum (2003) provide comprehensive explanation of the methodology to construct this index. This index is estimated by merging information from the D&S dataset with information from the UTIP-UNIDO dataset. To be specific, the EHII index is constructed by regressing the D&S Gini indices on the UTIP-UNIDO Theil inequality measures and then using the predicted values as estimated Gini coefficients (Herzer and Nunnenkam, 2011). The objective of this method is to detach the useful information from the doubtful information in the D&S dataset. The EHII inequality index ranges from 0 to 100 like the conventional Gini index. The higher the estimated household income inequality value, the more unequal the country is. I choose this index is as it is available for a reasonably large number of developing countries over a sufficiently long and continuous time period (Galbraith and Kum; 2005) and it sorts out the many limitations of the other measurements of inequality.

GDP per capita (GDP_PC): Real (price-adjusted) GDP per head (constant 2000 US$) is used as proxy for economic development, is the main control variable in my empirical models. It is the value of all final goods and services produced within the geographical area of a country during one year period divided by consumer price index.

Gross Secondary School Enrollment Rate (EDU_Sec) : It is a measure of the ratio of secondary school enrollment to the population of the age group that officially corresponds to the secondary level in percentage term.

3.3 Estimation Strategies

Since this paper widely applies various panel data estimation techniques, it is important to present a brief overview on their relevance and importance. Several empirical strategies exist in literature to estimate static and dynamic panel data models but I am confining this discussion on the static models as the number of countries far exceeds the number time periods. The following section discusses basically three commonly used panel data models giving attention to their advantages and disadvantages; Pooled Ordinary Least Squares (Pooled OLS) regression, panel model with fixed effects (FEM) and random effects (REM)

3.3.1 Pooled Ordinary Least Squares (Pooled OLS)

The natural starting for panel data analysis is estimating a pooled OLS model. Pooled panel method is more or less analogous to the method of standard ordinary least squares but pooled OLS estimation widens the database by pooling together cross sectional and time series observations of the sample to get more reliable estimates of the parameters. So it uses more information than standard OLS. Pooled estimators use both between (cross section) and within (time- series) variation in the data. The following pooled OLS model can be specified using the general panel specification model from the previous section:

$$lnH_{it} = \beta_0 + \beta_1 lnEHII\_Gini_{it} + \beta_2 lnGDP\_PC_{it} + \beta_3 \ln EDU\_Sec_{it} + \lambda_t + u_{it} \quad (3)$$

Here, β_0 is the overall intercept. It seems that there is no difference between equation (3) and (4). In fact the subtle difference is that in equation (4), we have the composite error term, $u_{it}= \alpha_i+e_{it}$ .Here α_i denotes unobserved factors that differ between countries but are constant over time for each country such as political system, climate conditions, geographical location, health system etc. and λ_t is the time fixed-effect or unobserved factor present in all countries at a specific point in time. So, e_{it} represents the net effect of omitted variables which change over both country and time. The above model can be easily estimated by ordinary least squares method. It provides more consistent estimators compared to simple OLS estimates as long as the composite error in the model is uncorrelated with regressors. However, the error, $u_{it}= (\alpha_i+e_{it})$ are most likely to be correlated over time for a given country. Additionally, this method ignores unobservable country fixed effects or α_i in equation (3). If a_i is correlated with any of the regressors, OLS estimates will be biased. These estimates will be also biased because e_{it} and α_i are likely to be correlated in this specification. So, we can say that heterogeneity of the countries under consideration for investigation can influence estimated parameters. Standard errors should be adjusted for any error correlation and it can be done using more efficient feasible generalized least squares (FGLS) estimation. In pooled FGLS individual effects are assumed to be random and averaged out. This is why it is also known as Population- Averaged (PA) regression. I estimate and present results from both method and compare the parameters.

3.3.2 Fixed Effects Model (FEM)

Unlike Pooled OLS, the fixed effects model takes into account country specific characteristics. So a two way fixed effects model, which allows intercept to vary over countries and periods can be stated as below:

$$lnH_{it} = \beta_1 lnEHII\_Gini_{it} + \beta_2 lnGDP\_PC_{it} + \beta_3 lnEDU\_Sec_{it} + \lambda_t + \alpha_i + e_{it} \quad (4)$$

In the above equation, u_{it} from the previous equation is replaced with $\alpha i+e_{it}$. So the basic difference between fixed effect and pooled OLS lies in a_i. The underlying assumption in the FEM is that individual effects are correlated with regressors or $E(X_{it}, a_i) \neq 0$. Under the strict exogeneity assumption of the explanatory variables, the fixed effect estimators will be unbiased, which implies that e_{it} must be uncorrelated with independent variables across all time period (Wooldridge, 2010). Moreover, e_{it} should be homoskedastic and serially uncorrelated across time. In FEM, the unobserved heterogeneity or a_i is eliminated using within transformation, which leads OLS estimates to consistent and unbiased. This method allows for a limited form of endogeneity. However fixed effect method is not without draw backs. For example, individual specific group wise heteroskedasticity or serial correlation over period can result into inefficient estimation.

3.3.3 Random Effect Model (REM)

The random effect model assumes that individual country effects are purely random, which means that ai is uncorrelated with the regressors. An ideal REM model incorporates all the FEM assumption plus the extra assumption that ai is independent of all explanatory variables in all time periods. So we can state the random effect model as below:

$$lnH_{it} = \beta_0 + \beta_1 lnEHII\_GINI_{it} + \beta_2 lnGDP\_PC_{it} + \beta_3 lnEDU\_Sec_{it} + \lambda_t + v_{it} \tag{5}$$

In the above model $v_{it}=\varepsilon_i+e_{it}$ where εi is the country specific random disturbance. We can write the underlying assumption of random effect model as $E(X_{it}, \varepsilon_i) = 0$, which implies individual effect are not correlated with any of regressors. The random effect estimators are consistent and completely efficient when it is appropriate but it is inconsistent if the fixed effect model is correct. It is worth noting that term "fixed effects" is sometime confusing because in both types of models level effects are random. Green (2008) gives a nice explanation in this context "…the crucial distinction between fixed and random effects is whether the unobserved individual effect embodies elements that are correlated with the regressors in the model, not whether these effects are stochastic or not" (Green, 2008, p.183). Finally, the problem of having an unbalanced panel in this study is not important as there is no attrition in the panel.

3.3.4 Model Selection and Dealing with Serial correlation and Heterosckedasticity

The starting point is to estimate a pooled OLS model. Nevertheless, we must consider the potential pitfalls of pooled OLS model such as failing to take into account the unobserved heterogeneity. So, the strategy is to proceed step by step to select the correct model. The first step is to test the presence of fixed effect in the Pooled OLS model. In this step, if the null hypothesis of no country specific intercept rejected, the conclusion is that there is unobserved heterogeneity in the panel or there is significant improvement in goodness-of-fit in the fixed effects model. So the fixed effects model is preferred to the pooled OLS. The second step is to test the null hypothesis of no random effect by Lagrange multiplier (LM) test (Breusch and Pagan's; 1980). Rejection of null hypothesis in this case indicates the existence of significant random effect and that the random effect model is able to deal with heterogeneity better than does the pooled OLS. When both hypotheses are rejected, the final step is to compare the fixed-effect model and random-effect model using the Hausman test. The Hausman specification test compares fixed and random effect models under the null hypothesis that individual effects are uncorrelated with any of the regressors in the model (Hausman, 1978). If the null hypothesis is rejected, the test concludes that correlation is important and a fixed effect technique is so far the best method to examine the relationship between health and income inequality. Lastly, the Baltagi-Wu LBI test (Baltagi and Wu;1999) implemented in STATA is used to the test for serial correlation of the residuals. In this test, the value for the test statistic below 1.5 indicates that there is serial correlation in the errors. As this study deals with short panel, I use country wise cluster-robust inference, which allows heteroskedasticity and general correlation over time for a given country in pooled OLS and and fixed effects models.

Chapter-4: Descriptive Statistics and Graphical Analysis

Ahead of formal empirical analysis, a short discussion on sample statistics and graphical representation of the key variables can give us important insights on the characteristics of the sample covered in this study. The following table 1 illustrates the key statistics of the dependent and independent variables separately for every period. It is apparent from the table that life expectancy at birth has steadily increased over the period in this sample of

Table 1: Decomposed Summary Statistics of the Sample by Periods

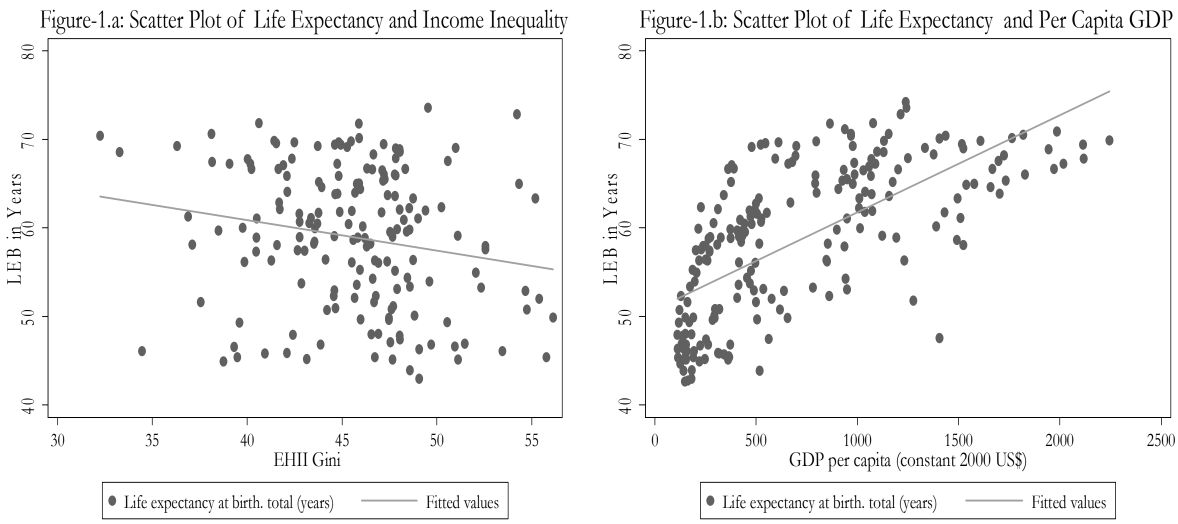
Period	Variables	Obs.	Mean	Std. Dev.	Period	Variables	Obs.	Mean	Std. Dev.
	LEB	31	56.621	7.5585		LEB	31	57.756	7.7488
	IMR	31	82.387	36.968		IMR	31	77.051	36.397
1982-84	MR_5	31	126.414	63.805	**1985-87**	MR_5	31	117.375	62.671
	EHII_Gini	26	45.236	3.3531		EHII_Gini	26	44.684	3.983
	GDPPC	28	662.205	483.936		GDPPC	29	687.218	488.629
	EDU_Sec	29	33.676	25.183		EDU_Sec	28	35.675	24.354
	LEB	31	58.725	8.126		LEB	31	59.216	8.514
	IMR	31	72.316	35.324		IMR	31	68.629	34.192
1988-90	MR_5	31	109.33	60.929	**1991-93**	MR_5	31	103.426	59.393
	EHII_Gini	27	44.923	4.713		EHII_Gini	31	44.713	5.327
	GDP_PC	30	698.517	496.767		GDP_PC	30	701.961	510.369
	EDU_Sec	26	38.543	27.685		EDU_Sec	26	41.026	27.795
	LEB	31	59.398	8.898		LEB	31	59.598	9.3691
	IMR	31	65.291	33.160		IMR	31	61.169	31.520
1994-96	MR_5	31	98.3462	57.954	**1997-99**	MR_5	31	91.861	55.053
	EHII_Gini	29	47.048	4.713		EHII_Gini	20	46.682	3.582
	GDP_PC	30	717.809	555.889		GDP_PC	31	753.08	573.652
	EDU_Sec	19	40.8371	25.481		EDU_Sec	27	43.850	26.266
	LEB	31	60.068	9.778					
	IMR	31	56.634	29.813					
2000-02	MR_5	31	84.483	51.634					
	EHII_Gini	12	47.002	2.7269					
	GDPPC	31	789.911	607.381					
	EDU_Sec	27	48.162	27.521					

countries while infant mortality rate has decreased by 25.75 per 1000 live births. However, there is also a considerable reduction in under-five mortality, which is almost 42 per live 1000. Per capita GDP has also risen moderately in this sample of developing countries over this period. It is not possible to comment on the overall trend of estimated household income inequality as there data some countries are randomly missing over covered period. It is noted that this variable is available for all countries only in the period of 1991-93. Simple correlation among the variables is presented in table 2. Income inequality is negatively correlated with life expectancy at birth are while it is positively correlated with both infant mortality and under-five mortality in

Table 2: Bi-variate Correlations between Variables

Variables	LEB	IMR	MR_5	EHII_Gini	GDP_PC	EDU_Sec
LEB	1.0000					
IMR	-0.9054	1.0000				
MR_5	-0.9493	0.9787	1.0000			
EHII_ Gini	-0.2428	0.2362	0.2411	1.0000		
GDP_PC	0.6853	-0.6734	-0.6955	-0.0380	1.0000	
EDU_Sec	0.7812	-0.8240	-0.8335	-0.2808	0.5305	1.0000

Figure-1: Cross-country scatter plots of GDP per capita, life expectancy and income inequality



this sample. Pair wise scatter plots of per capita GDP, EHII_Gini and life expectancy are shown in the above figure. From figure-1.a we can see that there is a weak but negative relation between income inequality and life expectancy at birth. However, there is a strong positive association between GDP per capita and life expectancy and it almost resembles the famous Preston curve (Figure-1.b) for this set developing countries also.

Chapter -5: Presentation of the Empirical Results

5.1 Empirical Results and Analysis

This section presents the econometric results and discussion of the main findings in line with earlier studies. To facilitate the comparison with the conclusions drawn in prior works on the relationship between health and income inequality, I first estimate the pooled OLS models along with pooled FGLS models and the results are reported in table 3. Pooled FGLS leads to more efficient estimates in short panel under the assumption that errors are independent across countries. Results of model-1 in the following table are the most consistent with the existing cross sectional results. It shows that life expectancy at birth is negatively related with the estimated household income inequality (EHII_Gini) and it is positively related per capita real GDP. Coefficients of both of the variables are statistically significant. The double log or constant elasticity model implies that estimated

Table 3: Dependent Variable--Log of Life Expectancy at Birth

	(1)	(2)	(3)	(4)
Estimation Method	Pooled OLS	Pooled OLS	Pooled FGLS	Pooled FGLS
Log (EHII_Gini)	-0.224*	-0.115	0.0292	-0.0115
	(0.130)	(0.101)	(0.0207)	(0.0189)
Log(GDP_PC)	0.130***	0.0814***	0.103***	0.109***
	(0.0146)	(0.0161)	(0.0155)	(0.0233)
Log(EDU_Sec)		0.0864***		0.0499***
		(0.0166)		(0.0186)
Constant	4.074***	3.688***	3.297***	3.247***
	(0.532)	(0.399)	(0.137)	(0.128)
Time Effects	Yes	No	Yes	Yes
F-Test:	2.45	1.07		
Observations	165	140	138	86
R-squared	0.602	0.774		
Number of country			24	18

Notes: 1. Robust standard errors clustered in country level are in parentheses

2. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels respectively

3. F-Test is a test for the joint significance of time effects.

elasticity of EHII_Gini is -0.224. It means that holding average income constant, a 1 percent increase in income inequality on an average leads to a 0.224 percent fall in life expectancy across these developing countries. However, adding secondary enrollment rate as a control variable in model-2 eliminates the statistical relationship between EHII_Gini and LEB, but the sign remains same as before. Thus, I can say that income inequality does not play any role in determining the average health of population. In this model, both average income and educational attainment are highly significant and has positive impact on health status of the population. The results also indicate that the effect of education is as great as income in these countries, as discussed earlier. Population average (PA) or pooled FGLS method produces the results, which are more or less similar as pooled OLS in the extended model (Model-4). But the problem is that this method takes into account a small number of countries, which may violate the asymptotic property of the estimates. The following table 4 illustrates the results of fixed effects and random effects estimations. Before proceeding, it should be noted that F-test for joint hypothesis of no country specific effect is rejected and it discards the use of pooled OLS. The test of null hypothesis of no random effect by Breusch and Pagan's LM test is also rejected in every case. So, there is random effect in the panel. Moreover, Baltagi-Wu LBI test of serial correlation of the residuals suggests the presence of serial correlation. That is why I prefer to use generalized least squares (GLS) random effect model with AR (1), which allows autocorrelation in the residuals. Finally, Hausman test is carried on to compare

Table 4: Dependent Variable--Log of Life Expectancy at Birth

	(5)	(6)	(7)	(8)
Estimation Method	Fixed Effect	Fixed Effect	Random Effect GLS with AR(1)	Random Effect GLS with AR(1)
Log (EHII_Gini)	0.139**	0.149**	0.0753**	0.0851**
	(0.0635)	(0.0615)	(0.0353)	(0.0425)
Log(GDP_PC)	0.0812**	0.0875***	0.111***	0.0859***
	(0.0307)	(0.0275)	(0.0142)	(0.0143)
Log(EDU_Sec)		0.00409		0.0684***
		(0.0340)		(0.0142)
Constant	3.005***	2.917***	3.056***	2.957***
	(0.346)	(0.381)	(0.170)	(0.187)
Time Effects	Yes	No	Yes	No
F-Test	2.59	1.13		
Country Effects	Yes	Yes	RE	RE
F-Test	35.75	15.62		
Observations	165	140	165	140
R-squared	0.370	0.355	0.5709	0.7539
Number of country	30	30	30	30

Notes: 1. Robust standard errors clustered in country level are in parentheses for fixed effect models

2. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels respectively

3. R-Squared is the within-R-Squared for fixed effects and the between-R-Squared for random effects

4. F-Test is a test for the joint significance of the country fixed effects or time fixed effects.

the fixed effects model with the random effects model. Though the fixed effects models are appropriate suggested by this test, I present the results from both models. In line with (Wooldridge, 2010), it can be stated that the random country and fixed period effect model are useful over the alternative with both effects fixed if the number of observations are relatively small. Moreover, fixed effects estimation tackles endogeneity problem to some extent, since unobserved county effects are swept away. Now, we see that there is a dramatic change in the results as compared to the previous results in table-3. The results show that there is a positive relation between income inequality and life expectancy at birth. The coefficients of EHII_Gini are significant at 5 percent level even after controlling for educational attainment in all models. For instance, if I analyze the results of model-8, life expectancy at birth increases by 0.0851 percent on an average when EHII_Gini rises by 1 percent, holding income and education constant. These results are against the income inequality-health hypothesis. One important point is that impact of GDP per capita on average health among these countries is positive and highly significant and it is confirmed by the all the four econometric techniques above.

Earlier studies on the relationship between health and income inequality using pure cross sectional data such as Rodgers (1979) and Wilkinson (1992) show that at country level income inequality and average health of people are inversely related. However, some of the recent studies (Judge et al. 1998; Gravelle et al. 2002; Dorling et al. 2007; Babones, 2008) provide mixed evidences for income inequality- health hypothesis. On the other hand, Mellor and Milyo (2001) shows that income inequality leads to better health once education is controlled for in samples of 12 to 47 countries. Additionally, Beckfield (2004) using panel data is unable give evidence in favor of this hypothesis. Leigh and Jencks (2007) have not denied the possibility that inequality increases life expectancy to some extent a panel of 12 rich countries. In a recent paper, Torre and Myrskylä (2011) have studied this hypothesis for 21 developed countries over the period 1975-2006 and have reached the conclusion that there is no statistical link between life expectancy at birth and income inequality measured by Gini Index. However, their study is subject to the criticism that it covers only the wealthy countries where income inequality is not as high as poor countries. Lastly, Herzer and Nunnenkam (2011) have lately made a novel attempt using panel co-integration method to deal with omitted country-specific factors, endogeneity, and cross-country heterogeneity to examine the impact of inequality on health. Their findings suggest that population health is positively affected by the inequality in income in a balanced panel of 35 countries during 1970-1995. This discussion encourages me to state that when unobserved country specific effects are not considered, my findings from pooled OLS analysis coincide with findings from prior cross country studies to some extent. In contrast, fixed effects and random effects estimations, which take into account unobserved county effects and time effects provide me the results similar to the most recent studies based on longitudinal data. Additionally, the relation between health and inequality becomes weak after controlling for educational attainment.

5.2 Sensitivity Analysis

Since the results in the previous section contrast with earlier empirical works of cross-sectional design, this section is devoted to check the robustness of my findings. Sensitivity of results is tested using alternative measures of aggregate health outcome. The first sensitivity test of my findings is presented in the table 5, where I replace the log life expectancy at birth with log infant mortality rate as the dependent variable. It is established in the empirical literature that higher income inequality tends to increase infant mortality. Similar results are obtained by pooled OLS as shown in the following table. It indicates that higher income inequality has significant positive relation with infant mortality while raising average income significantly reduces it. Adding education as control weakens the significance of the results to much in pooled OLS (see model 10). This result is more or less in line with Mellor and Milyo (2001), who find that the positive correlation between the Gini coefficient and infant mortality disappears once secondary school enrolment is controlled for. However, these

Table 5: Dependent Variable--Log of Infant Mortality Rate

	(9)	(10)	(11)	(12)
Estimation Method	Pooled OLS	Pooled OLS	Pooled FGLS	Pooled FGLS
Log (EHII_Gini)	1.367**	0.832*	-0.0519	0.00771
	(0.584)	(0.438)	(0.0360)	(0.0917)
Log(GDP_PC))	-0.474***	-0.268***	-0.248***	-0.268***
	(0.0665)	(0.0710)	(0.0712)	(0.0997)
Log(EDU_Sec)		-0.343***		-0.202**
		(0.0954)		(0.0907)
Time Effects	Yes	Yes	Yes	Yes
F-Test	4.69	2.37		
Observations	165	140	138	86
R-squared	0.566	0.715		
Number of country			24	18

Notes: 1. Robust standard errors clustered in country level are in parentheses

2. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels respectively

3. F-Test is a test for the joint significance of time effects.

results are not beyond doubt as unobserved heterogeneity is not captured in these models. Using the same strategy applied in the previous section, I re-estimate the fixed effects and random effects GLS models. The results are presented in table 6 in the next page. In fixed effects estimation coefficients of EHII_Gini is significant at 5 percent level in basic model as well as in the extended model but it is now negatively related with infant mortality. It implies that the more unequal the income distribution the lower is the infant mortality rate. However, this relationship is not statistically significant in Random Effect GLS models but the sign is same as it is in fixed effects models. For instance, results of model-14 for tells us that if EHII_Gini goes up by 1 percent, keeping average income and secondary education fixed the number of infant deaths per 1000 live birth in a year decreases by 0.356 percent on average. The effect of income and education reflect the existing findings.

Table 6: Dependent Variable--Log of Infant Mortality Rate

	(13)	(14)	(15)	(16)
Estimation Method	Fixed Effect	Fixed Effect	Random Effect GLS with AR(1)	Random Effect GLS with AR(1)
Log (EHII_Gini)	-0.312**	-0.356**	-0.150	-0.197
	(0.142)	(0.146)	(0.106)	(0.129)
Log(GDP_PC)	-0.255**	-0.273**	-0.355***	-0.292***
	(0.0987)	(0.100)	(0.0480)	(0.0531)
Log(EDU_Sec)		0.0275		-0.224***
		(0.106)		(0.0525)
Constant	7.069***	7.247***	7.073***	7.581***
	(0.988)	(1.074)	(0.535)	(0.607)
Time Effects	Yes	Yes	Yes	Yes
F-Test	27.61	15.10		
Country Effects	Yes	Yes	RE	RE
F-Test	102.70	52.49		
Observations	165	140	165	140
R-squared	0.752	0.748	0.4940	0.6460
Number of country	30	30	30	30

Notes: 1. Robust standard errors clustered in country level are in parentheses for fixed effect models

2. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels respectively

3. R-Squared is the within-R-Squared for fixed effects and the between-R-Squared for random effects

4. F-Test is a test for the joint significance of the country fixed effects or time effects.

I have also checked the sensitivity of the results using exclusion single country but the results remain almost similar .In addition, estimation of the models without time controls changes the results marginally. Table 7 and table 8 in the appendix provide the empirical findings using under-five mortality rate as the dependent variable. It also confirms that the results obtained in the previous section in testing health -income inequality hypothesis are robust to the change in the measurement of health. My sensitivity analysis thus concludes that income inequality causes a reduction in both infant mortality and under-five mortality. These findings are again different from the large body of existing studies in this field.

Chapter-6

6.1 Limitations and Further Research

It must be admitted that my study is not beyond limitations. First of all, the sample covered in this study is one third of the entire list of developing countries and the time period covered is not very recent. This is because of the unavailability of recent data on income inequality for these countries. My results may be biased due to exclusion of relevant variables, which affect health and it causes omitted variable problem. But it does not imply that findings are completely invalid. Moreover, the estimated household income inequality (EHII_Gini) as an index of income distribution is not without flaws. The robustness of the results could be checked in principle with other measures of inequality such as top 10 or bottom 10 percent share of income. This is again halted by the unavailability of data.

Most importantly, the endogenous nature of income inequality is not fully solved in this study, though an attempt is made to tackle it with the fixed effects models. In the fixed effects estimation, time-invariant unobservable factors correlated with income inequality are swept way but time-variant unobservable factors cannot be removed. Studies based on observational data like this one are not appropriate to draw causal inference. This happens as the endoegeneity problem is not tackled appropriately in the earlier studies in this field. Finding an appropriate instrumental variable in aggregate studies is always hard, which hinders to deal with possible correlation between income inequality and unobserved factors. Wagstaff and Doorslaer (2000) ideally point out that unavailability of high-quality data on inequality makes it difficult to apply best-available methods to get rid of spurious correlations and identify the causal effects in empirical research of inequality and health. Though findings from population level studies are informative to get a broad overview it is difficult to distinguish between the Absolute Income and the Income Inequality hypotheses. It is also impossible to test the Relative Income hypothesis using aggregate data to identify the true impact of inequality on health. These studies thus may not differentiate the "statistical artefact" (Gravelle, 1998) from the mechanisms in which income inequality has a direct effect on individual health. Gravelle (1998) emphasized that further research is necessary to estimate the direct impact of income inequality on health by combining individual and aggregate level data. Wagstaff and Doorslaer (2000) also support the use of individual level studies. They argue that "What seems to be required to discriminate between the various hypotheses are individual-level studies, because it is only at this level of aggregation that one can observe relationships that are consistent with one hypothesis and not with another." (Wagstaff and Doorslaer; 2000, p. 564). They also put emphasis on using natural experiments in this field. This discussion provokes the importance of several future researches. For example, the problem of endogeneity must be addressed properly in aggregate studies to get true causal effect of income inequality. Individual level studies in developing countries should be performed to distinguish between the Income Inequality and Relative income hypothesis.

6.2 Conclusion

It is well evident in the majority of the previous empirical works that income inequality on an average impedes the improvement in health of population. However, some recent studies have challenged the health and income inequality proposition and presented evidence that the relation between health and income inequality is far more ambiguous than it is supposed. Departing from the general trend of current literature, this paper reexamines health-income inequality hypothesis using population level cross country-time series data from 31 low income and low middle income countries over the period of 1982-2002. My results based on pooled OLS method show that health is negatively associated with income inequality. It is worth mentioning that when I add education as a control variable, statistical significance between health and income inequality disappears though negative relation still remains. This finding is consistent with majority of the literature, which manifests that inequality is detrimental to population health. However, this analysis fails to capture the country-specific fixed factors and thus the estimated coefficient on inequality may be biased. So, I go further to apply fixed effects and random effects methods to take in account for such unobserved heterogeneity. It allows me to identify the cross-national heterogeneity, while earlier approaches are based on usual restrictive assumption that the coefficients of the income inequality are same across all countries. Empirical results from these estimations confirm that life expectancy at birth is positively related with income inequality. Sensitivity analysis using different measures of population level health outcome provides evidence that my findings are robust indeed. Exclusion of single country from the sample or time control does not alter the result largely. So, it implies that there is a statistically significant positive relation between health and income inequality in developing countries over the study period at least. One possible explanation of this evidence is that multilateral donor (World Bank, IMF ADB etc.) funded health improvement initiatives help these countries to obtain better health outcome even in the face of rising income inequality. However, from a policy perspective it is important to understand that income inequality is an attribute of a social system while income is a characteristic of an individual person. My findings do not necessarily recommend that the inequality in income should be remained or widen to improve health of the population. In general, it is better to have more equal distribution of income in the society but overemphasizing income inequality as a determinant of population health is redundant from a policy perspective. Redistributive policy could be expensive or even useless when it has little or no impact on the target specific health outcome of the population in developing countries.

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Appendix

Table-A1: List of Countries

Bangladesh	India	Pakistan
Bolivia	Indonesia	Philippines
Burundi	Iraq	Senegal
Cameroon	Kenya	Sri Lanka
El Salvador	Malawi	Swaziland
Ethiopia	Moldova	Syrian Arab Republic
Fiji	Morocco	Tanzania
Ghana	Mozambique	Tonga
Guatemala	Nepal	Uganda
Honduras	Nigeria	Ukraine
		Zimbabwe

Note: As per World Bank Classification of Low income and Lower-middle income countries

Table-A2: Variables and Sources

	Variables Involved	Original Source
Response Variables	Life Expectancy at Birth (LEB) (In number of years)	World Bank : (World Development Indicators: WDI Online data base) http://data.worldbank.org (Accessed April 15, 2012)
	Infant Mortality Rate (IMR) (Per 1,000 live births)	World Bank: (World Development Indicators: WDI Online data base) http://data.worldbank.org (Accessed April 15, 2012)
	Mortality Rate Under-five (MR_5) (Per 1,000)	World Bank: (World Development Indicators: WDI Online data base) http://data.worldbank.org (Accessed April 15, 2012)
Explanatory Variables	Estimated Household Income Inequality (EHII_Gini): (Gini format: on a 0 to 100 scale)	University of Texas Inequality Project: (UTIP-UNIDO) http://utip.gov.utexas.edu/data.html (Accessed April 12, 2012)
	Real GDP per capita (GDP_PC) (Constant 2000 US$)	World Bank: (World Development Indicators: WDI Online data base) http://data.worldbank.org (Accessed April 17, 2012)
	Gross Secondary School Enrollment Rate (EDU_Sec) (Ratio in percentage term)	World Bank: (World Development Indicators: WDI Online data base) http://data.worldbank.org (Accessed April 17, 2012)

Note: Natural logs of all variables are taken after extracting from the original source.

Table-A3:Panel Summary Statistics

Variables		Mean	Std. Dev.	Min	Max	Observations
LEB	overall	58.7694	8.556726	42.67588	74.20952	N = 217
	between		8.232247	44.54415	71.44866	n = 31
	within		2.707427	47.5158	65.41218	T = 7
IMR	overall	69.06836	34.53991	14.73333	165.9667	N = 217
	between		33.3411	17.30952	140.8238	n = 31
	within		10.59504	38.08264	101.0112	T = 7
MR_5	overall	104.4633	59.63497	17.13333	248.3667	N = 217
	between		57.74067	20.27143	210.1905	n = 31
	within		17.74696	54.22995	159.93	T = 7
GDP_PC	overall	716.9979	527.8396	109.9252	2244.387	N = 209
	between		513.6139	125.2541	1860.858	n = 31
	within		125.1186	320.9516	1165.956	T-bar = 6.74194
EHII_Gini	overall	45.60841	4.355109	32.24508	56.1104	N = 171
	between		3.313718	36.50386	52.77485	n = 31
	within		3.150872	35.29205	56.95175	T-bar = 5.51613
EDU_Sec	overall	40.13535	26.33654	2.93529	107.7879	N = 182
	between		26.36754	4.21444	98.27731	n = 31
	within		5.297332	25.42823	60.1476	T-bar = 5.87097

Figure- 2: Scatter plot of Infant Mortality Rate against Income Inequality and GDP per Capita

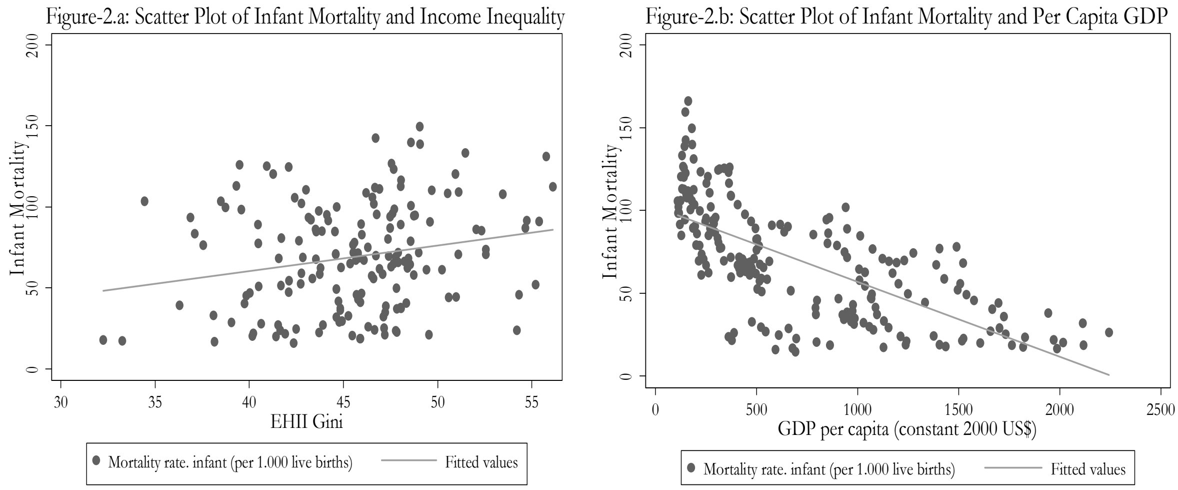

Figure-3: Scatter plot of Under Five Mortality Rate against Income Inequality and GDP per Capita

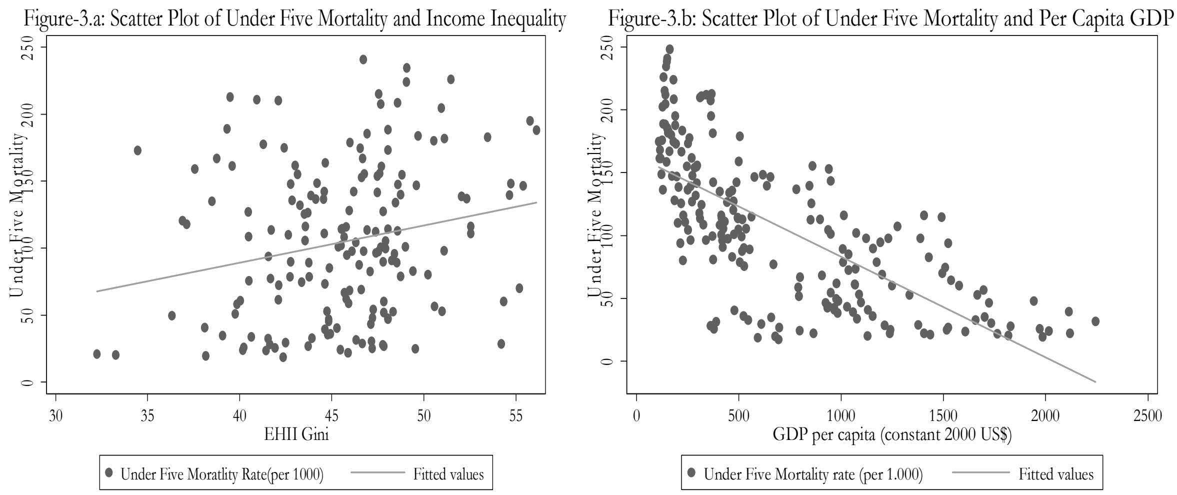

Table A7: Dependent Variable--Log of Under-Five Mortality Rate

	(17)	(18)	(19)	(20)
Estimation Method	Pooled OLS	Pooled OLS	Pooled FGLS	Pooled FGLS
Log (EHII_Gini)	1.614**	0.950*	-0.0700	0.0206
	(0.673)	(0.499)	(0.0429)	(0.109)
Log(GDP_PC)	-0.578***	-0.318***	-0.303***	-0.326***
	(0.0741)	(0.0771)	(0.0850)	(0.120)
Log(EDU_Sec)		-0.427***		-0.260**
		(0.112)		(0.112)
Constant	2.185	4.470**	6.766***	7.463***
	(2.696)	(1.989)	(0.606)	(0.859)
Time Effects	Yes	Yes	Yes	Yes
F-Test	4.02	2.60		
Observations	165	140	138	86
R-squared	0.582	0.738		
Number of country			24	18

Notes: 1. Robust standard errors clustered in country level are in parentheses
2. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels respectively
3. F-Test is a test for the joint significance of time effects.

Table A8: Dependent Variable--Log of Under-Five Mortality Rate

	(21)	(22)	(23)	(24)
Estimation Method	Fixed Effect	Fixed Effect	Random Effect GLS with AR(1)	Random Effect GLS with AR(1)
Log (EHII_Gini)	-0.382**	-0.433**	-0.184	-0.230
	(0.165)	(0.172)	(0.127)	(0.155)
Log(GDP_PC)	-0.286**	-0.308**	-0.428***	-0.345***
	(0.115)	(0.116)	(0.0570)	(0.0624)
Log(EDU_Sec)		0.0244		-0.287***
		(0.121)		(0.0616)
Constant	7.923***	8.157***	8.048***	8.632***
	(1.164)	(1.286)	(0.640)	(0.723)
Time Effects	Yes	Yes	Yes	Yes
F-Test	25.21	13.47		
Country Effects	Yes	Yes	RE	RE
F-Test	96.77	46.66		
Observations	165	140	165	140
R-squared	0.735	0.729	0.5127	0.6753
Number of country	30	30	30	30

Notes: 1. Robust standard errors clustered in country level are in parentheses for fixed effect models
2. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels respectively
3. R-Squared is the within-R-Squared for fixed effects and the between-R-Squared for random effects
4. F-Test is a test for the joint significance of the country fixed effects or time effects.