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Income Inequality and Population Health: Regional Differences and New Evidence

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Abstract

This paper analyzes the link between income inequality and the health of the population. To do so I use both a cross-sectional and panel data econometric approach to look at the impact from income inequality, both globally as well as separated by region and income group as defined by the World Bank. The empirical analysis shows that there is a negative, statistically significant relationship between the Gini-index and health indicators when looking at the entire sample. This result is not robust to the introduction of variables which control for social infrastructure. However, the income inequality effect can be observed even when control variables are used in areas where the effect is particularly strong, Central & South America, as well as those countries that have an upper-middle level of income. These results point towards income inequality's relationship with the level of social infrastructure in a country being the largest driver of the link between income inequality and health.

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Introduction

How to handle rising income inequality and in what ways it affects the world are questions that have been brought to the forefront of the public debate, in large part due to the mainstream success of Thomas Piketty's Capital in the 21st Century (2014). There are confirmed economic effects from income inequality, such as reduced growth from lowered investment (Persson & Tabellini, 1994), but research suggest there are health effects as well. A meta-review by Wilkinson & Picket (2006) contain 155 studies which have mostly, but not exclusively, supported the idea that income inequality leads to poorer health. In general, the results from previous work is mixed and a clearer picture is needed to make the choice of public policy to address inequality simpler for lawmakers.
The main theory used in this paper is the income inequality hypothesis, which states that a more uneven distribution of income in society leads to poorer health regardless of other factors. There are two assumed mechanisms behind this relationship. The first is that increased inequality is associated with stronger separation between social classes in a society which amplifies negative psychosocial factors (Wilkinson, 1997). Higher inequality leads to less cohesion in society, which lowers trust and heightens stress which both have documented ill health effects. The second theorized mechanism is that countries with high inequality are associated with governments that underinvest in health and social infrastructure such as hospitals, schools, and the like (Lynch & Kaplan, 1997) which also affect the health of the population negatively. This social infrastructure pathway is the reason that my chosen control variables are the measles immunization rate and the school enrollment rate. These should serve as measurements of the availability of healthcare as well as education and should according to theory have a relationship with both health outcomes and the level of income inequality.

This paper provides evidence on how income inequality affects public health and adds to this debate by in three ways. First, finding support for the income inequality hypothesis on the aggregate level using a newer and larger dataset, as a way to confirm findings from seminal papers such as Rodgers (1979). Second, to find if this support is robust to the inclusion of relevant health and income inequality-related control variables which have been assumed to be time invariant in many previous analyses. Finally to find if there are differences in the income inequality effect between regions and income groups.

The empirical analysis uses both Ordinary Least Squares (OLS) as well as panel data with country fixed effects in order to study the income inequality hypothesis. The first measure of public health analyzed is life expectancy from birth for the total population and separated by sex. The next dependent variable is the mortality rates per 1,000 people for women, men and infants. These six health variables are analyzed using the entire sample. When the analysis is broken down by region and income group the analyzed variables are total life expectancy from birth and infant mortality per 1,000 live births. This paper uses the 2015 version of UNU-WIDER's World Income Inequality Database as well as data from the World Bank Databank in order to analyze the income inequality effect on health for the time period 1960 to 2013. This is the largest and most recent dataset available and includes 173 countries.

When using the standard model that controls only for income inequality and GDP per capita a significant negative relationship in line with theory between income inequality and life expectancy is found. It is statistically significant when looking at the global dataset with either cross-sectional analysis or with panel data country fixed effects. This is in line with the results from Rodgers (1979). However, this relationship does not hold up at the aggregate level to the introduction of two variables measuring social infrastructure, the enrollment rate and the measles immunization rate. The results are slightly different when the analysis is disaggregated by income group and region. The income inequality hypothesis holds even with these two control variables in the regions South & Central America as well as those countries classified as having upper-middle incomes. This same pattern is visible when the dependent variable is the mortality rate as well.

The main findings in this paper are that the income inequality hypothesis has varying levels of support and that the strength of the health impact of income inequality is different depending which part of the world is being analyzed. The significance of income inequality disappears in most regions when social infrastructure is controlled for. This indicates that the primary mechanism for income inequality affecting health may be in its relationship to poor social infrastructure. In the countries with upper middle income the mechanism dependent on psychosocial factor is possibly stronger since a negative relationship can be seen even when the new explanatory variables are included.

The following sections of this paper will first provide a theoretical background to the income inequality hypothesis and its mechanisms, then highlight some important previous studies on this topic, the analyzed data will be discussed followed by a review of the analysis and finally there will be discussion of the limitations of this paper as well as suggestions for future avenues of research.

Theoretical Background

There are three main theories about the relationship between income and health; the absolute income hypothesis, the relative income hypothesis and the income inequality hypothesis (Karlsson et al, 2009). These will all be discussed further in this section, but the central theory in this paper is that of the income inequality hypothesis.

The absolute income hypothesis claims that what matters for health outcomes is only absolute income (Wagstaff & van Doorslaer, 2000). National income reflects living standards in a country, which in turn influence health outcomes (Preston, 1975). This indicates that economic growth should lead to improved health, assuming no other changes. However, empirical findings by both Preston (1975) and Rodgers (1979) show that the relationship between income and health is concave. This is consistent with marginal utility theory, that is, increases in income "buys" more health gains, but at a decreasing rate. The conclusion drawn from this is that while increases in the average income does have positive health effects, the distribution of this income matters as well.

Due to this decreasing marginal health benefit of income shown by Rodgers (1979), if incomes increase by $ 1,000 in a country, having that thousand dollars go to the poorest in the country would lead to larger positive health effects than if it went to the richest, even though the national income has increased by the same amount in both scenarios. Wagstaff & van Doorslaer (2000) illustrate with another example; if a society starts with a completely equal distribution, and $100 is transferred from one person to another, the health benefits for the richer person are less than the health decreases for the poorer person, making society as a whole worse off than before.

The relative income hypothesis is that the incomes of other people in a given reference group can affect an individual's health. It can be affected either negatively by increased stress or positively where higher incomes among one's peers lead to better healthcare from increased taxation (Karlsson et al, 2009). The basis of this hypothesis is that one's own utility comes not only from individual consumption, but also from how individual consumption differs from the average consumption of others (Duesenberry, 1949). That is, being relatively worse off than peers leads to a lower level of utility regardless of personal consumption. The reference group which an individual compares themselves with can be either society as a whole, those living nearby or those with similar jobs or education (Ferrer-i-Carbonell, 2005). Thus individual wellbeing and by extension an individual's health then depends on the difference in the individuals income to that of the average (Wagstaff & van Doorslaer 2000). Whether the health outcome from income growth in a reference group is positive or negative can depend quite heavily on the structure of the healthcare system and how much of the government’s tax revenue remains in the local area (Miller & Paxson, 2006).

Finally the income inequality hypothesis states that a more uneven distribution of income in a group affects the health of everyone, regardless of individual income (Karlsson et al, 2009). The origin of this hypothesis is from the works of Preston (1975), and Rodgers (1979) where the mathematical proof that absolute income has decreasing marginal returns on health lead directly to the conclusion that the distribution of this income impacts health. Two main mechanisms have been theorized to be behind this negative relationship between income inequality and health. First the psychosocial mechanism where increases in income inequality lead to lower levels of trust, as well as higher levels of hostility, stress and anxiety, all of which are associated with poorer health outcomes (Marmot & Wilkinson, 2001). Countries with high inequality are expected to have a higher level of social stratification (i.e. be more hierarchical) which amplifies the cost of low social status (Wilkinson & Picket, 2006). Psychosocial factors associated with low social status affect health both in direct ways through the aforementioned higher stress and anxiety as well as through affecting behavior with health repercussions. In short this mechanism is summarized, “[if] greater inequality increases the burden of low social status while weakening social affiliations, health effects are to be expected” (Marmot & Wilkinson, 2001). The second mechanism works through the level of social infrastructure in a country. Countries with high levels of inequality, on average, have less public resources and inequality is associated with low investment in social and human capital, such as education, healthcare, environmental protection or basic infrastructure (Lynch & Kaplan, 1997). This is consistent with studies which show an association between high inequality and lower education outcomes, fewer library books, lack of medical insurance and the like (Kaplan et al, 1996). These factors serve to reduce the level of public health both through immediate effects such as lower availability of healthcare but also by leading to worse individual choices from either lack of information or limited options. Controlling for social infrastructure would hopefully lead to revealing how strong the psychosocial mechanism is.

While important, absolute material standards are not the key to understanding the differences in health outcomes between countries (Marmot & Wilkinson, 2001). It is a part of the explanation but the theoretical framework show that the distribution of income should also matter a great deal. Income inequality influences the social cohesion of a country negatively, resulting in poorer health due to several psychosocial factors. Furthermore, the decreasing marginal returns from income on health point to a more egalitarian society being healthier than a less equal one, if all other factors are the same. Lastly, large amounts of inequality is linked with poorer public institutions and less public spending which should result in worse health outcomes on average as well.

Literature Review

One of the earliest and most often cited papers in the area of income inequality and health is by G.B. Rodgers (1979). This was one of the first times the idea of income distribution and not only absolute income affecting social welfare was formulated. At the time of its writing there was not income distribution data available to the extent that there is today. The countries studied were limited to those with accurate data, 56 countries in total, in a cross-sectional analysis. He finds a statistically significant negative effect from income inequality (as measured by the Gini-coefficient) on life expectancy. The effect is present on life expectancy both from birth and from the 5th birthday, but the effect was smaller on the latter. Furthermore income inequality was found to have a positive relationship with the rate of child mortality. This study also finds that the effect is of a larger magnitude in those countries classified as less developed, defined as those with an income per capita below $1000. Rodgers (1979) concludes that the effect of income inequality on life expectancy can be as large as 5 to 10 years. He acknowledges that this effect is not only due to the spread of incomes but other socioeconomic factors that differ from country to country as well. His model does not control for these other factors and as such it is hard to claim these findings are generalizable. Another one of the seminal papers in this area is Preston (1975) which through cross-sectional analysis finds that higher income per capita is linked to higher life expectancies, but this relationship is slightly concave. Daalgard & Strulik (2014) use Preston's (1975) results to present a life-cycle analysis which cements the relationship between income and life expectancy. They also claim that this concavity is due to income inequality serving to lower life expectancies. Blakely et al (2002) also find that the absolute income hypothesis does not explain the entire relationship between health and income. Their results show that regardless of individual income, living in a high inequality area increases the odds of having poor self-reported health by up to 10%. These studies cement the idea that even if income inequality is the focal point of this study it is important to control for absolute income in some manner as it does have a documented impact on health outcomes. Recently Raghupathi & Raghupathi (2015) find a positive relationship between income per capita and several indicators of good health and a negative relationship between income and incidence of tuberculosis and HIV for example. Babones (2008) conducts a study similar to Rodgers but on a larger scale, using over 100 countries and looking at data from both 1970 and 1995 and performing cross-sectional analysis. He also finds a statistically significant negative effect of income inequality on life expectancy as well as a positive effect on infant mortality. This effect is present when looking at 1970 and 1995, both when controlling for GDP per capita and in the simple regression case with only income inequality in it. The author also finds a positive relationship between inequality and the murder rate. However much like Rodgers (1979) or Gravelle et al (2002) the analysis does not account for other factors except for the Gini-index and income per capita. There is a reasonable assumption that there are observable factors that differ depending on the country which should have an effect on the investigated health outcomes. Babones (2008) attempts to quantify whether the negative relationship between income inequality and population health is causal but there is little evidence found for this. He states that models assuming that all other factors influencing the relationship between health and inequality are time invariant (and therefore essentially zero in a fixed effects panel data model) confirms causality but this is a weak assumption. These findings are in line with the view that a correctly specified model is important in order to determine the actual effect of inequality, if any.

Cantarero et al. (2007) look at the income inequality effect using panel data for households and individuals inside the European Union instead of cross-sectional analysis as in the previously discussed papers. The data comes from responses to the European Community Household Panel for 15 member states from 1993–2000. The authors state the main advantage is that the information is homogeneous among the countries since the questionnaire is similar. The study focuses on two different dependent variables (life expectancy at birth and infant mortality) in order to test the effects of income inequality on population health. The panel data on income is used in order to calculate Gini-coefficients for the analyzed countries for each year. The authors use only the inverse of GDP per capita and its square as control variables and find strong support for income inequality affecting health indicators in the hypothesized manner, both when using fixed effects and random effects.

Myrskylä & Torre (2014) focus their analysis on only developed nations, using panel data for 21 nations for 1975-2006. They also find a statistically significant effect on life expectancy, and they further the analysis by breaking down the results by age and by gender. They find that the income inequality effect was the strongest for children and young adults and that the positive relationship between mortality and the Gini-coefficient was higher in female children aged 1-14 than for males. However, in young adults from 15-49 the effect on mortality was the largest for males. This model is one of few that accounts for a possible time trend by using both time and country fixed effects. It does assume that any differences between countries were time-invariant or that the developed countries would be homogenous enough that it would not matter. Analyzing the income inequality effect through different ages and by gender gives the authors the possibility to draw several conclusions about the way income inequality interacts with mortality. Myrskylä & Torre for example posit that the larger effect on young adult males is due to the fact that status is more important in finding a mate for males than for females. This then may intensify competition and stress when there is a high level of income inequality which would have negative effects on health.

Gravelle et al. (2002) suggest that there are empirical and methodological grounds for being doubtful of the usefulness of aggregate level evidence to test hypotheses about the effect of income and income inequality on the health of individuals. Their results attempting to replicate the previously discussed paper by Rodgers (1979) using more recent data do not show that income distribution is significantly associated with life expectancy. Gravelle et al. (2002) provide an explanation to why their results differ from Rodgers, namely that with the passage of time the countries are richer and the possibility of the effect of income and income distribution are different for high and low incomes.

Most aggregate studies appear to support the relative income hypothesis because they report a negative correlation between population health and income inequality. However, Gravelle et al. (2002) point to the fact that aggregate level evidence should be treated with extreme caution. Rodgers (1979) found evidence that income distribution had a significant negative association with life expectancy in almost all of his regressions. Gravelle et al. (2002) using both the same and other model specifications, found that the association in the data set could be positive and negative but never found to be statistically significant. According to the authors tests of income inequality can be contaminated by the non-linearity of the individual health– income relationship and they stress the importance of using individual as well as group data in order to get more reliable results and not only rely on aggregate data in order to answer such a complex relationship.

Income distribution is related to health when it can be seen as a measure of social class differences or segregation in a society (Picket & Wilkinson, 2005). The authors narrow down the two most important differences between the previous studies. The first being the different sizes of areas in which people have thought inequality most likely to be of importance and the second being what are regarded as legitimate control variables. They conclude that income inequality is less likely to be related to health in small areas since it does not reflect the class structure of that society. This points to the importance of choosing the proper level of aggregation in order to achieve robust results. Wilkinson and Pickett mention that the analyses that do not find support for the income inequality hypothesis use additional control variables, the common ones being the percent without a high school education, individual income, ethnicity and social capital. It has been suggested a number of times that the differences in health outcomes within countries is primarily a gradient of relative income or social status rather than a reflection of absolute material living standards. Wilkinson and Pickett also state that one of the most important points to come out of the analysis is that it looks like there are fundamentally important and measurable differences in the extent socioeconomic class structures are manifested in different societies. Karlsson et al. find that having a higher degree of education is associated with reporting very good health and also provides findings suggesting that the importance of income inequality effect increases with the level of development. The paper also suggests that there could be important differences in the support of the income inequality hypothesis between low/middle and high-income countries.

Data

The data comes from two sources. Health outcomes and macroeconomic variables are taken from the World Bank Databank. Information on income distribution comes from United Nations University World Institute for Development Economics Research (UNU-WIDER). The observations are separated by country and year and there is information on which region and income group each country belongs to. These income groups are classified according to the World Bank categories; low income countries are those with a gross national income(GNI) per capita below 1,045 USD , low-middle income is between $ 1,045 to $ 4,125, upper-middle are between $ 4,125 and $12,736 and high income countries are those with a GNI per capita above $12,736. All of these dollar values are in 2014 dollars. There are 158 countries in total in the sample. Below in table 1 is a brief summary of the descriptive statistics for the variables that are used in the subsequent analysis. These variables are discussed more in depth in this section. Figures describing the distribution of data is available in the appendix.

Table 1 Descriptive Statistics

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Life Expectancy from Birth Total	2536	69.40	8.81	32.46	83.42
Life Expectancy from Birth Male	2536	66.57	8.34	31.29	80.7
Life Expectancy from Birth Female	2536	72.37	9.44	33.68	86.7
Mortality Rate Male (per 1,000)	2513	222.88	96.40	63.413	680.721
Mortality Rate Female (per 1,000)	2513	137.80	92.78	31.98	687.023
Mortality Rate Infant (per 1,000)	2499	32.31	35.21	1.8	209.6
Gini-index	2888	37.69	10.67	15.9	74.3
GDP/Capita (2005 $)	2390	12561.09	15009.47	5.3	87772.69
Measles Immunization (%)	1848	84.1	17.26	1	99
Enrollment Rate (%)	1259	91.72	13.21	0.026	100

Dependent Variables

The dependent variables of interest are the health outcomes; life expectancy from birth, and the mortality rates. Life expectancy and mortality rate are analyzed for both men and women. Data on health outcomes is sourced from the World Bank Databank, so the data has been verified and as such the quality should not be an issue. The earliest observations are from 1960 and they span up to year 2013.

Life Expectancy

Figure 1 in the appendix shows the distribution of the total life expectancy from birth, defined by the World Bank as the number of years a newborn infant would live if all conditions are the same throughout its lifespan. This is then a measure of how healthy the country is in a given year, on average. There are two main observations about the total life expectancy, life expectancies resemble a negatively skewed normal distribution, and the mean being around 69 years. The graphs for life expectancy from birth for men and women show a similar pattern except the life expectancy in general is higher for women than for men. In 1960 the mean worldwide life expectancy from birth was 57.4 years and in 2010 it was 74.26.

Figure 2 shows the distribution of the mean of life expectancies by region. There are clear differences and similarities in the evolution of the region mean. The mean of life expectancy has been increasing almost every year, apart from the Post-Soviet region which has not changed very much for the majority of the analyzed time period. The highest life expectancies are in Europe, North America and Oceania while the lowest means are in Africa and the Middle East. The mean life expectancy in Africa was 41.4 years in 1960 and 59.05 in 2011 which is still the lowest mean but a very large increase. To contrast, in the same time period Europe has gone from a life expectancy of 69.7 years to 79.2. Since the patterns are so similar when looking at the life expectancies for men and women as well these graphs are not included.

Figure 3 shows the mean of life expectancy from birth for different income groups. Once again the pattern is clear here that life expectancy has been improving over time across the board, but the improvement is less visible in the OECD-regions which started off at an already high level of life expectancy. This is due to there being a maximum level of possible life expectancy and improvements cannot go on forever. The lowest life expectancies are in the low income regions and those same regions have also seen a lower amount of growth compared to the middle income regions. In 1960 the mean life expectancy in the low income regions was 41.9 years which by 2010 had grown to 64.2 years. The improvement was less marked in the OECD-nations which went from 70.1 years in 1960 to 80 years in 2010.

Mortality Rate

The next set of dependent variables are mortality rates, defined as the probability of a 15 to 60-year old dying for adults (measured per 1,000 people) and the probability of a newborn dying before reaching 1 year old in the case of infant mortality (per 1,000 live births). Figure 4 shows the infant mortality rate and the same general pattern of the world population becoming healthier over time is visible as the rate converges at a lower level as time passes. Mortality rates for men and women have also improved over time but infant mortality has seen a dramatic improvement from an average of 75 deaths per 1,000 live births in 1960 to 15.9 deaths in the year 2010. Since the pattern is similar only infant mortality is graphed.

This pattern of lowering infant mortality rates is also present when looking at the region means, which can be seen in figure 5. Asia, Africa and the Middle East has had significant improvement in the infant mortality rates while the areas were the mortality rates were already fairly low such as Europe, North America and Oceania has had some improvement but not any major differences from 1960 to 2013.

Figure 6 shows the evolution of infant mortality over time when organized by the mean of the income group. Lowered mortality rates is easily visible in every income group. The higher income groups started off at a lower rate and have therefore predictably not seen as much improvement.

Independent Variables

Gini-Index

The main independent variable is a measure of income inequality, which in this paper is the Gini-index. The Gini-index is calculated from the Lorenz curve, which is a measure of percentile distribution of income to households in a given area. The area between this curve and a 45-degree line (representing complete income equality) is then used to calculate the Gini-index which takes on values from 0 to 100 percent (Lesser, 2012). On this index 0 is a perfectly even distribution (everyone receives the same income) and 100 is maximum inequality (one person receives all the income). The measures of the Gini-index are taken from the World Income Inequality Database (WIID) which is published by the United Nations University World Institute for Development Economics Research (UNU-WIDER) and was updated to version 3.3 in September of 2015. This latest version includes observations up until the year 2013 and is the most accurate and largest spanning database of income inequality available. When multiple measures of the Gini-index where available for a given year it was narrowed down to one measurement by quality of data and if several measurements had the same level of quality then the latest revision was used. Furthermore, when available the choice of measurement was that which was calculated using the household as an economic unit, disposable income as the income measurement and which covered the entire country. When one of these criteria was not fulfilled then the choice was made to use the measurement which was calculated the same way and came from the same surveys for the time period for the country. For the special case of Germany the measurements pre-1990 are for West Germany and after that it covers the entire country. The relevant time period analyzed is 1960 through 2013. Other possible measures of income inequality are the income share of each quintile or percentile of the population but evidence from Kawachi & Kennedy (1999) show that the income inequality effect should be present regardless of the inequality indicator. Due to this and the amount and quality of data available the choice of inequality variable falls on the Gini-index.

Figure 7 shows a histogram of the Gini-indices included in the data set, which resembles a positively skewed normal distribution. Few countries have very low or extremely high levels of inequality but most have a relatively uneven distribution of income. The mean is a Gini-index of 37.7 with a standard deviation of 10.7.

Figure 8 shows the region means of the Gini-index. There is quite a lot of variation between the regions, with continents such as Oceania and Europe being relatively more equal in their income distribution while Africa as well as South & Central America have much higher levels of income inequality.

Figure 9 shows the mean of the Gini-index by income group. The most unequal distributions of incomes are in the low income countries, while the OECD countries have lower Gini-indices than the non-OECD members of the high income nations. There is a fair amount of variation from year to year which is important to making the Gini-index a worthwhile variable to analyze.

GDP per Capita

It is important to control for economic growth in some form, since it has been proven to be associated with improved health outcomes in several of the previously discussed empirical papers. In this case the chosen variable is GDP per capita (2005 US Dollars) which is the standard variable used to account for the absolute income hypothesis in previous studies. Figure 10 shows the GDP per capita graphed against time. There is a clear trend of economic growth, but also increased stratification. The richer countries in 2013 are much richer than the poorest countries compared to the difference between them in 1960, but on a whole the world is much more economically developed. In 1965 the mean GDP per capita was 7,383 2005 USD and in 2000 that mean was 13,583 USD. For the entire time period there are 2395 observations and the mean is 12,501 USD in 2005 dollars. In the econometric analysis GDP per capita is used in log form.

Measles Immunization

One factor which influences health outcomes is the availability of healthcare and one possible measurement of how available healthcare is to the population is the amount of people that have received common vaccinations, in particular the measles vaccine. This rate is defined as the percentage as children that are immunized for measles before the age of 12 months. In the paper by Jones et al (2003) the implementation of measles immunization is shown to reduce the number of child deaths by 1% per year, which is a significant amount and justifies its inclusion. Countries with high inequality also underspend on public resources, such as healthcare (Lynch & Kaplan, 1997) and as such the measles immunization rate should be related with the Gini-index.

Figure 11 shows the worldwide rate of measles immunization from year to year. The visible trend here is one of converging at a relatively high level. The percentage of infants that are immunized for measles there are 1854 observations and the mean is 84 percent.

Figures 12 and 13 shows the income group and region means of the measles immunization rates respectively. There are clear differences both by region as well as by income group. The high income countries have a much higher percentage of immunized infants but all the groups have a clear upward trend in the accessibility of vaccines. A positive trend is observable when looking at the region level as well. The regions with the highest percentage immunized infants across the time period is North America and Europe while Africa and South America are the lowest.

Enrollment Rate

Another factor which influences population health is education. The chosen variable to represent population education is the net adjusted enrollment rate, which is a measure of the ratio of students enrolled in primary or secondary education relative to the size of the school-aged population. In both Turra et al. (2016) as well as Crimmins & Saito (2001) education is shown to have a very large impact on both total and healthy life expectancy. The positive effect on health from education is more significant when females receive more education (more educated mothers have healthier children) but it is present for society at a whole as well. The same theoretical justification as with the measles immunization rate applies here: high inequality is connected to less public resources and social infrastructure. Therefore the Gini-index and the enrollment rates should be linked. Figure 14 shows the development of this rate over time. More and more countries are reaching higher levels of enrolment as the years pass, likely as a result of economic growth which allows young people to attend school rather than working or being caretakers at home. The mean enrollment rate is 91.8 percent and there 1254 observations across the time period of interest.

Time Variance

Several studies on income inequality and health claim that many of the differences that influence general health between countries are time invariant (for example Myrskylä & Torre, 2014). Some factors, such as geographical ones do not change over time but others do and therefore deserve to be looked at further. The prevalence of Measles-vaccinations in Africa in Figure 15 show clear differences from year to year in the time for which there are observations available. Figure 16 is the adjusted Enrollment rate for Asia and this also clearly shows variation. All the variables included in the analysis are time variant for every country and therefore deserving to be included in a model analyzing health outcomes instead of simply being assumed to affect each country in the same way for each year.

Empirical Strategy

The first aim of this paper is to replicate the findings of previous studies at the aggregate level, using the largest possible available data set. This is done with the baseline model, presented in equation 1. The model is run as a cross-sectional pooled Ordinary Least Squares analysis and as a panel data regression using country fixed effects. Country fixed effects account for any time invariant country heterogeneity[1]. The country fixed effects are not shown in the following equations but are used in every non-OLS regression. Figures 17 and 18 show life expectancy from birth graphed against both the Gini-index and the log of GDP per capita respectively and the expected relationship is present and appears linear so a square term is not necessary in the model. In all the equations below Y is total life expectancy from birth, female life expectancy from birth, male life expectancy from birth, female mortality rate, male mortality rate and the infant mortality rate. The coefficient of interest is $\beta_1$which shows the relationship between income inequality and health outcomes. The theoretical framework shows that increased inequality should be associated with worse health outcomes and as such the coefficient is expected to be negative when the dependent variable is life expectancy from birth and positive when the dependent variable is the mortality rate.

Equation 1:

$$Y_{it} = \beta_0 + \beta_1 * Gini_{it} + \beta_2 * Log\left(\frac{GDP}{Capita}\right)_{it} + \varepsilon_{it}$$

Next, as an extension to previous work the model is expanded with two explanatory variables which can be thought to both have an effect on health outcomes and be related to inequality. The chosen ones are the percentage of children receiving measles vaccinations, which should serve to indicate the level of healthcare availability in the country and the percent of those of school-going age that are enrolled in either primary or secondary school which is a measure of

[1] A Hausman test indicates that fixed effects would be preferable to random effects.

how educated the population is. This should control for some level of social infrastructure in the country. Figures 19 and 20 show the results of graphing both of these variables together with life expectancy and it is both clear that they are positively associated with health and there is no indication that the relationship is non-linear. Once again the models are run both as a cross-sectional and as a panel data regression. The new model is given in Equation 2.

Equation 2:

$$Y_{it} = \beta_0 + \beta_1 * Gini_{it} + \beta_2 * Log\left(\frac{GDP}{Capita}\right)_{it} + \beta_3 * Measles_{it} + \beta_4 * Enrollment_{it} + \varepsilon_{it}$$

Finally in order to verify that any correlation is not only due to the variables trending in the same direction over time a possible trend is accounted for using time dummies (Wooldridge, 2009). The final model is presented in Equation 3.

Equation 3:

$$Y_{it} = \beta_0 + \beta_1 * Gini_{it} + \beta_2 * Log\left(\frac{GDP}{Capita}\right)_{it} + \beta_3 * Measles_{it} + \beta_4 * Enrollment_{it} + \beta_5 * Year + \varepsilon_{it}$$

The analysis is also disaggregated by region and income group to look at heterogeneous effects. In this part of the analysis only total life expectancy from birth and infant mortality per 1,000 live births are used as dependent variables.

To verify the robustness of the results both standard errors and errors clustered by country will be used for every regression. If clustered errors are not used the possibility of deceptively small errors, and therefore overestimated significance, is very large (Cameron & Miller 2015). The literature also points towards clustering at the country level instead of at the region level in order to minimize any potential bias.

The expected result is that there should be a negative impact on health outcomes from increased inequality, but that the inclusion of explanatory variables that have documented health effects should make this impact smaller. By including these variables which are linked with public sector investment some level of social infrastructure should be controlled for. According to the theorized mechanisms any remaining income inequality effect should hopefully only be stemming from the psychosocial factors. Further, it is expected that there will be differences in the results once the analysis is broken up by region and income group.

Stationarity

Stationarity implies that the "probability distribution is stable over time" (Wooldridge, 2009). If this is not fulfilled any relationship between variables will be hard to quantify. Stationarity for this data set is verified by performing a Fisher test for unbalanced panels. The results of that test show that all the included variables have a low enough p-value to reject the null hypothesis of a unit-root or non-stationarity[2].

Results

This section contains analysis on the effect of income inequality on several health variables. First life expectancy from birth, starting with a global aggregated sample and using total, male and female life expectancy from birth. Then the data is disaggregated and total life expectancy from birth is analyzed broken up by region and by income group. The next section also starts with the global aggregated sample and looks at male, female and infant mortality rates. Finally the same region and income group breakdown is done analyzing the effect from income inequality on the infant mortality rate per 1,000 live births.

All results are presented in summary tables (Table 2 through 9) structured in the following way; column 1 is the base model (equation 1), column 2 is the model with the chosen explanatory variables included (equation 2) and column 3 is the same but with a time trend accounted for (equation 3). Columns 4 through 6 follow the same pattern except they use robust errors clustered by country instead of standard errors. In the summary tables only the coefficient on the variable of interest, the Gini-index, is displayed as well as the number of observations and the R-squared. When using the total dataset each set of rows represent a different health variable and in the disaggregated results each set of rows correspond to a region or income group. The summary tables for the global analysis are separated by econometric technique as well, first the OLS results are shown, followed by the results of country fixed effects. For the analysis on income groups and regions only fixed effects is used. Full regression tables for the global samples as well as summary tables for the OLS regressions by income group and region are available in the appendix.

Correlation

Some preliminary analysis can be done by analyzing the patterns when the variables are graphed out. From plotting life expectancy at birth against the Gini-index there seems to be a

[2] The only p-value above 0 was for the log of GDP per capita which had a p-value of 0.07.

definite pattern of those countries with lower Gini-indices having better health outcomes. The largest cluster of data points can be found between 65 and 80 years life expectancy from birth and a Gini from 20 to 30. The life expectancy outcomes are much more spread out as the Gini-coefficient increases and at a generally lower level. The same patterns shows up in life expectancy when split up for men and women and when mortality rates are used as the dependent variable.

The same expected pattern of health outcomes relative to the other independent variables is present as well when plotted against the health outcomes. That means the enrollment rate, the rate of measles immunization and the log of GDP per capita all have a positive association with life expectancy and a negative one with mortality rates. These can be seen in figures 17 through 20 in the appendix.

Life Expectancy

Table 2 OLS Results of Income Inequality on Life Expectancy

	1	2	3	4	5	6
Total Life Expectancy from Birth	LEBTot	LEBTot	LEBTot	LEBTot	LEBTot	LEBTot
Gini	-0.101***	-0.0210*	-0.0173	-0.101**	-0.0210	-0.0173
	(0.0118)	(0.0122)	(0.0122)	(0.0392)	(0.0323)	(0.0326)
Observations	2,344	1,075	1,075	2,344	1,075	1,075
R-squared	0.649	0.810	0.822	0.649	0.810	0.822
Male Life Expectancy from Birth	LEBMale	LEBMale	LEBMale	LEBMale	LEBMale	LEBMale
Gini	-0.0935***	-0.0101	-0.00616	-0.0935**	-0.0101	-0.00616
	(0.0112)	(0.0129)	(0.0128)	(0.0367)	(0.0322)	(0.0325)
Observations	2,344	1,075	1,075	2,344	1,075	1,075
R-squared	0.648	0.777	0.794	0.648	0.777	0.794
Female Life Expectancy from Birth	LEBFem	LEBFem	LEBFem	LEBFem	LEBFem	LEBFem
Gini	-0.109***	-0.0325**	-0.0289**	-0.109**	-0.0325	-0.0289
	(0.0130)	(0.0127)	(0.0128)	(0.0438)	(0.0363)	(0.0367)
Observations	2,344	1,075	1,075	2,344	1,075	1,075
R-squared	0.633	0.812	0.821	0.633	0.812	0.821
Explanatory Variables		X	X		X	X
Year Dummies			X			X
Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

In the OLS regression in table 2 the predicted result is found when looking at the base and the explanatory variable model (columns 1 and 2) for total life expectancy (LEBTot), namely that increased inequality is linked to a lower life expectancy. Once a time trend is added this result is no longer statistically significant. The base model retains a significant effect from income inequality even when cluster-robust errors are used which generally makes the error larger. However in the explanatory variable model in column 5 the Gini-index is no longer statistically significant when using cluster errors. The magnitude of the coefficient of the Gini-index is almost 5 times smaller when the explanatory variables are added in column 2. The base-model has an income inequality effect of -0.101 meaning that an increase in the Gini-index by one represents a decrease in life expectancy by 0.1 years (approximately 36 days) assuming all other factors remain the same. Once measles immunization and enrollment rate are accounted for this effect is down to -0.02.

The OLS results when using sex-specific life expectancy as the dependent variable are further down in the same table and the results are very similar to using the total life expectancy from birth. Statistical significance is found in columns 1-4 in the OLS regression for female life expectancy from birth (LEBFem) but only in the base models for the OLS regression for male life expectancy from birth (LEBMale). The magnitude of the coefficient is slightly higher for women than the total population when the explanatory variables are included, -0.0325 instead of -0.02, and it is -0.029 when year dummies are included in the regression. In the base model there is no real difference in magnitude when comparing men, women and the total population. Only when restricting the analysis to female life expectancy is a significant income inequality effect found in all three specifications. The result from the base model holds up when cluster-robust errors are used for all of the three analyzed life expectancy variables. The added explanatory variables are significant in all specifications and have the expected signs. These results point towards social infrastructure being a large part of the income inequality effect.

Table 3 Fixed Effects Results of Income Inequality on Life Expectancy

Total Life Expectancy from Birth	1 LEBTot	2 LEBTot	3 LEBTot	4 LEBTot	5 LEBTot	6 LEBTot
Gini	-0.0219*	0.0120	-0.00411	-0.0219	0.0120	-0.00411
	(0.0123)	(0.0120)	(0.0107)	(0.0253)	(0.0209)	(0.0193)
Observations	2,344	1,075	1,075	2,344	1,075	1,075
R-squared	0.467	0.662	0.769	0.467	0.662	0.769
Number of Countries	158	125	125	158	125	125
Male Life Expectancy from Birth	LEBMale	LEBMale	LEBMale	LEBMale	LEBMale	LEBMale
Gini	-0.0219*	0.00733	-0.0147	-0.0219	0.00733	-0.0147
	(0.0119)	(0.0130)	(0.0113)	(0.0244)	(0.0227)	(0.0201)
Observations	2,344	1,075	1,075	2,344	1,075	1,075
R-squared	0.482	0.650	0.772	0.482	0.650	0.772
Number of Countries	158	125	125	158	125	125
Female Life Expectancy from Birth	LEBFem	LEBFem	LEBFem	LEBFem	LEBFem	LEBFem
Gini	-0.0220*	0.0171	0.00710	-0.0220	0.0171	0.00710
	(0.0131)	(0.0116)	(0.0108)	(0.0269)	(0.0203)	(0.0198)
Observations	2,344	1,075	1,075	2,344	1,075	1,075
R-squared	0.442	0.650	0.740	0.442	0.650	0.740
Number of Countries	158	125	125	158	125	125
Explanatory Variables		X	X		X	X
Year Fixed Effects			X			X
Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3 shows the results from the same analysis using country fixed effects instead of OLS. For all three life expectancy variables the hypothesized result from income inequality is only found in the base model with standard errors. The significance disappears when either explanatory variables are used or if cluster errors are used. The magnitude of the effect on total life expectancy is -0.022 which represents a decrease in life expectancy of about one week if the Gini-index increase by one percentage point. Once again the added independent variables, GDP per capita, measles immunization and enrollment rates, are all highly significant and of the expected signs and remain significant even when cluster-robust errors are used. The fixed effects results of male and female life expectancy from birth and the results are in principle identical to using total life expectancy as the dependent variable, both in terms of statistical significance and magnitude. The only significant effect is in column 1, using the base model with standard errors and the size of the effect is around -0.022.

In general, the Gini-index is statistically significant in more specifications in the OLS regressions. In fact the Gini-index is only statistically significant in the base model using standard errors when a panel regression with fixed effects was used. In those cases were income inequality had a significant effect the magnitude was much lower in the fixed effects regression than in the ordinary least squares regressions. This difference between the two estimators indicates that unobserved country heterogeneity is a problem that might make the OLS analysis biased. The added explanatory variables are significant in every tested specification and have the expected signs in all cases which show that they are important to include in an analysis of the income inequality effect. These variables serve as an indicator of the level of social infrastructure in a country, which is a theorized mechanism for the income inequality effect. The fact that significance disappears in most cases when these variables are included point to the relationship between inequality and social infrastructure being a large part of the income inequality and health link.

Life Expectancy Regressions by Region

Table 4 Fixed Effects Results of the Effects of Inequality on Life Expectancy from Birth by Region

		1 LEBTot	2 LEBTot	3 LEBTot	4 LEBTot	5 LEBTot	6 LEBTot
Africa	Gini	-0.162***	0.114	-0.0258	-0.162***	0.114	-0.0258
		(0.0478)	(0.0782)	(0.108)	(0.0558)	(0.0718)	(0.0692)
	Observations	252	83	83	252	83	83
	R-squared	0.103	0.349	0.699	0.103	0.349	0.699
	Number of Countries	45	33	33	45	33	33
Asia	Gini	-0.0414	0.0281	-0.00404	-0.0414	0.0281	-0.00404
		(0.0383)	(0.0402)	(0.0509)	(0.0531)	(0.0694)	(0.0635)
	Observations	321	105	105	321	105	105
	R-squared	0.774	0.913	0.951	0.774	0.913	0.951
	Number of Countries	18	16	16	18	16	16
Central America	Gini	0.114	-0.0420	-0.0965***	0.114	-0.0420	-0.0965**
		(0.0715)	(0.0504)	(0.0240)	(0.101)	(0.113)	(0.0329)
	Observations	109	53	53	109	53	53
	R-squared	0.660	0.793	0.995	0.660	0.793	0.995
	Number of Countries	6	6	6	6	6	6
Europe	Gini	-0.0192**	-0.0226	-0.0219**	-0.0192	-0.0226	-0.0219
		(0.00784)	(0.0154)	(0.00861)	(0.0194)	(0.0219)	(0.0160)
	Observations	816	471	471	816	471	471
	R-squared	0.831	0.753	0.935	0.831	0.753	0.935
	Number of Countries	37	31	31	37	31	31
Middle East	Gini	-0.547***	-0.0215	0.104	-0.547*	-0.0215	0.104*
		(0.141)	(0.0963)	(0.0675)	(0.250)	(0.0830)	(0.0511)
	Observations	92	44	44	92	44	44
	R-squared	0.524	0.902	0.997	0.524	0.902	0.997
	Number of Countries	12	9	9	12	9	9
North America	Gini	0.0441*	0.110***	0.0712	0.0441**	0.110*	0.0712
		(0.0240)	(0.0191)	(0.0513)	(0.00123)	(0.0116)	
	Observations	95	35	35	95	35	35
	R-squared	0.942	0.953	0.999	0.942	0.953	0.999
	Number of Countries	2	2	2	2	2	2
Oceania	Gini	0.121*	-0.119***	0.0520**	0.121	-0.119***	0.0520***
		(0.0650)	(0.0427)	(0.0239)	(0.163)	(0.0112)	(0.00322)
	Observations	86	52	52	86	52	52
	R-squared	0.338	0.918	0.998	0.338	0.918	0.998
	Number of Countries	5	3	3	5	3	3
Post-Soviet	Gini	0.0284*	-0.00659	-0.00612	0.0284	-0.00659	-0.00612
		(0.0169)	(0.0212)	(0.0184)	(0.0396)	(0.0336)	(0.0260)
	Observations	202	84	84	202	84	84
	R-squared	0.238	0.652	0.868	0.238	0.652	0.868
	Number of Countries	12	10	10	12	10	10
South America	Gini	-0.0855*	-0.130***	-0.0421*	-0.0855	-0.130**	-0.0421
		(0.0462)	(0.0295)	(0.0244)	(0.0993)	(0.0564)	(0.0332)
	Observations	264	110	110	264	110	110
	R-squared	0.506	0.762	0.960	0.506	0.762	0.960
	Number of Countries	11	9	9	11	9	9
West Indies	Gini	-0.0259	0.0176	0.00551	-0.0259	0.0176	0.00551
		(0.0310)	(0.0282)	(0.0192)	(0.0463)	(0.0217)	(0.0176)
	Observations	107	38	38	107	38	38
	R-squared	0.697	0.575	0.990	0.697	0.575	0.990
	Number of Countries	10	6	6	10	6	6
	Explanatory Variables		X	X		X	X
	Year Fixed Effects			X			X
	Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Moving on from the aggregate regressions to analyzing each region separately there is some evidence that there is a statistically significant difference in the effect of income inequality depending on the region. For readability's sake and due to the previously mentioned unobserved country heterogeneity being significant only fixed effects is used in this section. Summary tables of the OLS regressions are available in the appendix. Table 4 summarizes the fixed effects regressions for total life expectancy from birth separated by region. The table has the same structure as the previous summary table except that only one dependent variable is analyzed. Measles immunization and the enrollment rates were statistically significant for almost all regions and model specifications where they were included and had the expected positive effect on total life expectancy from birth.

Just like the global sample, much less significance is found when looking at the Gini-index when using panel data regressions as compared to the OLS-regressions. In fact, for both Asia and the West Indies there is no statistically significant effect from the Gini-index in any model specification, and the Post-Soviet region only shows a small positive significant effect using the base model with standard errors in column 1.

The results for Africa show a negative effect from income inequality on life expectancy in the base model that retains its significance even when cluster-robust errors are used. Introducing the measles immunization and enrollment rates makes the significance disappear, regardless of if year fixed effects are used together with country fixed effects. The size of the coefficient is -0.16 when it is significant. This magnitude means that in Africa an increase in the Gini-index by one percentage point would lead to a decrease in the life expectancy by almost 2 months on average assuming the other variables remain at the same level.

In Europe there is a small, statistically significant, negative effect from income inequality on life expectancy in both columns 1 and 3, the base model and the regression with explanatory variables, country fixed effects and year fixed effects. This effect does not retain significance when cluster-robust errors are used instead of standard errors.

Central America has the predicted negative effect and it is statistically significant in columns 3 and 6, when the full model is used. The size of the coefficient on the Gini-index is -0.0965 which is the strongest effect found in the country fixed effect regression when explanatory variables are used in combination with year fixed effects. The interpretation is that an increase in the Gini-index by one percentage point corresponds with a decrease in life expectancy by just over one month if no other changes occur in the region.

North America has a statistically significant positive effect on life expectancy from birth in the base and explanatory variable model that retains significance even when cluster-robust errors are used which can be seen in columns 1,2 4 and 5. However, the robust errors suffer from the problem where the low number of countries in the region make the errors much smaller than the true estimate of the error coefficient. This is the case in Oceania as well where the cluster-robust errors are significantly smaller than the standard errors. In Oceania the predicted negative income inequality effect is observable in column 2 and 5, but both the base model and the full model accounting for time fixed effects show a positive relationship as in North America.

The Middle East shows the strongest negative income inequality effect in the base model presented in column 1. The size of the coefficient is -0.547, meaning that an increase in the Gini-index in the Middle East by one point would correspond to a decrease in life expectancy from birth by over 6 and a half months assuming no other changes occur in the same time. The Gini-index also has a significant effect even when cluster-robust errors are used and it is almost 5 times larger than the second biggest coefficient from column 1 which is found in Africa. However, this effect loses its significance once time fixed effects as well as measles immunization and enrollment rates are introduced in columns 2 and 3. A small statistically significant positive effect is seen in column 6, but this suffers from the previously mentioned issue of the robust errors becoming too small when there are not enough countries in the region. The standard error is larger than the robust error and since there is no significance in column 3 the significance in column 6 with cluster-robust errors is most likely due to this issue.

South America is the only region that shows the predicted negative statistically significant effect on life expectancy from income inequality in all three model specifications with standard errors. The size of the effect in column 1 is larger than in Europe, but smaller than the Middle East and Africa which are the four regions where there is a statistically significant negative effect in the base model. In column 2 South America has a stronger negative effect than Oceania, -0.130 compared to -0.119, and these are the only two regions where the predicted relationship had statistical significance. In column 3 with the explanatory variables and time fixed effects income inequality has a statistically significant negative effect on life expectancy in three regions; Europe, Central & South America with the largest magnitude being found in Central America. When cluster-robust errors are introduced to the regressions run for South America, only column 5 shows any statistical significance.

In general, there is evidence that the effect of income inequality on life expectancy is different in the regions of the world. The strongest effect found in the Middle East, Africa and South America. Asia, the West Indies and the Post-Soviet countries do not show any consistent significant relationship between life expectancy and income inequality. On the whole, significance is found in more model specifications in the region breakdown regressions than when looking at the aggregate level, most likely due to the difference in the strength of the effect between the regions. In those regions where there is a significant effect on life expectancy from the Gini-index even when controlling for social infrastructure (Central & South America, Europe and Oceania) it can be theorized that the secondary mechanism for the income inequality hypothesis is stronger. That is, psychosocial factors related to income inequality such as such as increased stress and anxiety as well as lowered trust and social cohesion could have a relatively larger effect on health in these areas. Regions such as Africa and the Middle East where there is a strong negative effect in the base model but no significant effect in the other specifications most likely have a strong health effect stemming from the social infrastructure mechanism and a smaller effect from the psychosocial pathway. This is consistent with the theoretical framework, due to the marginal returns from income on health the relationship between health and income should be different depending on the level of economic development.

Life Expectancy Regressions by Income Group

Countries that are located in the same part of the world may not necessarily have similar factors that determine health outcomes. Therefore, analyzing the income inequality effect on life expectancy separating countries by their level of economic development should lead to observable differences as well. The countries are classified by income group as low, low-middle, upper-middle or high income countries. The high income countries are also divided whether they are members of the Organization for Economic Co-operation and Development (OECD) or not. Just like the previous section only the fixed effects results are discussed here, with a summary of the OLS results available in the appendix.

Table 5 Fixed Effects Results of the Effects of Inequality on Life Expectancy from Birth by Income Group

		1 LEBTot	2 LEBTot	3 LEBTot	4 LEBTot	5 LEBTot	6 LEBTot
Low Income	Gini	-0.101*	0.0814**	0.0369	-0.101*	0.0814*	0.0369
		(0.0604)	(0.0303)	(0.0657)	(0.0503)	(0.0394)	(0.0504)
	Observations	160	55	55	160	55	55
	R-squared	0.089	0.903	0.975	0.089	0.903	0.975
	Number of Countries	27	20	20	27	20	20
Low Middle	Gini	0.122***	0.0673*	0.0669	0.122*	0.0673	0.0669
		(0.0319)	(0.0401)	(0.0463)	(0.0625)	(0.0633)	(0.0661)
	Observations	462	181	181	462	181	181
	R-squared	0.362	0.411	0.585	0.362	0.411	0.585
	Number of Countries	40	32	32	40	32	32
Upper Middle	Gini	-0.125***	-0.0770***	-0.0650***	-0.125*	-0.0770**	-0.0650***
		(0.0297)	(0.0225)	(0.0201)	(0.0650)	(0.0332)	(0.0220)
	Observations	636	283	283	636	283	283
	R-squared	0.434	0.620	0.773	0.434	0.620	0.773
	Number of Countries	45	36	36	45	36	36
High Income OECD	Gini	-0.0106	0.0384**	-0.0201**	-0.0106	0.0384	-0.0201
		(0.0101)	(0.0151)	(0.0102)	(0.0166)	(0.0231)	(0.0201)
	Observations	885	485	485	885	485	485
	R-squared	0.822	0.844	0.951	0.822	0.844	0.951
	Number of Countries	30	27	27	30	27	27
High Income Non-OECD	Gini	0.0182	0.0589	-0.0881*	0.0182	0.0589	-0.0881***
		(0.0225)	(0.0414)	(0.0440)	(0.0347)	(0.0640)	(0.0248)
	Observations	196	70	70	196	70	70
	R-squared	0.786	0.741	0.952	0.786	0.741	0.952
	Number of Countries	14	10	10	14	10	10
	Explanatory Variables		X	X		X	X
	Year Fixed Effects			X			X
	Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5 is a summary table of the results when using panel data with country fixed effects and divided by income group. Only the upper middle income group shows the hypothesized results in every model specification, having the predicted negative sign and being statistically significant regardless if standard or cluster-robust errors are used. In the base model in column 1 only the upper middle and low income countries show a statistically significant negative coefficient on the Gini-index and it is the largest for the upper middle income countries at -0.125. This magnitude means that an increase in the Gini-index by one point represents a decrease in total life expectancy from birth by 1.5 months. In the low income countries the effect is comparable but slightly smaller at -0.1. The high income countries do not show any statistically significant effect in column 1 while the low middle income countries have a significant effect of about the same magnitude as the upper middle income countries but with the opposite sign.

In column 2 of table 5, when the model is expanded with the measles immunization and enrollment rates only the upper middle income countries have the predicted result. The Gini-index has a coefficient of -0.077 for these countries which means that an increase in the Gini by one should decrease life expectancy by 28 days on average. This effect is still statistically significant when cluster-robust errors are used. The other groups which show significance; low, lower middle and OECD high income countries all have coefficients of similar magnitudes or lower but they are unexpectedly positive. However only the low income countries retain statistical significance when cluster-robust errors are used instead of standard errors. The low income countries are also the group with the fewest amount of observations so too many conclusions should not be drawn from this counter-intuitive result.

Column 3 shows the effects on life expectancy from income inequality when the full model is used and time fixed effects are used in conjunction with country fixed effects. There is no significant effect found in the low and lower middle income countries but the remaining three groups all show the predicted negative relationship between the Gini-index and total life expectancy from birth. The high income OECD countries has the smallest magnitude, with a coefficient on the Gini-index of -0.02, while the largest is the high income non-OECD countries with an income inequality effect that is over 4 times larger at -0.088. These represent a decrease in life expectancy of around 7 and 32 days when the Gini-index increases by one point respectively. Both the non-OECD and the upper middle income countries still have a statistically significant coefficient when cluster-robust errors are used, but the high income OECD countries lose the significance.

The same general conclusions as in the regional analysis apply here, namely that there is observable evidence that the income inequality differs between different types of countries. Even when controlling for education and healthcare availability there are other region and income-specific differences that lead to significant heterogeneity in the size of the income inequality effect on life expectancy. The statistical significance and magnitudes also differ greatly depending on if the analysis is performed with panel data techniques or cross-sectionally. Both this and the region breakdown point toward the psychosocial mechanism of the income inequality effect being the most significant for life expectancy in countries with moderate economic development, and less significant in the poorest countries. In the low income countries the significance of the income inequality effect disappears when the explanatory variables are included. Both absolute income and inequality have a relationship with social infrastructure and this infrastructure seems to be more important for health effects in the less developed regions. This is consistent with previous findings that absolute income is more important for health than income distribution in lesser developed countries (for example Deaton, 2003). In the upper middle countries the income inequality effect is still quite significant when social infrastructure is controlled for, and judging from the magnitudes in table 5, this infrastructure mechanism stands for around half of the income inequality effect in that income group. In the high income countries there is only a statistically significant negative effect once this mechanism is controlled for, indicating that the psychosocial mechanism might be the most important once a certain level of absolute income is reached.

Mortality Rates

The next dependent variables of interest are the mortality rates for the population. Using the entire sample the three dependent variables are male mortality rate, female mortality rate and infant mortality, all expressed as the number of deaths per 1,000 people or live births in the case of infant mortality. The theoretical framework hypothesizes that the effect from the Gini-index on the mortality rates should be positive.

Table 6 OLS Results of Income Inequality on Mortality Rates

	1	2	3	4	5	6
Male Mortality Rate	MortMale	MortMale	MortMale	MortMale	MortMale	MortMale
Gini	1.230***	0.239	0.186	1.230**	0.239	0.186
	(0.156)	(0.253)	(0.256)	(0.566)	(0.658)	(0.655)
Observations	2,297	1,045	1,045	2,297	1,045	1,045
R-squared	0.499	0.534	0.552	0.499	0.534	0.552
Female Mortality Rate	MortFem	MortFem	MortFem	MortFem	MortFem	MortFem
Gini	1.522***	0.911***	0.878***	1.522***	0.911	0.878
	(0.147)	(0.194)	(0.198)	(0.554)	(0.564)	(0.564)
Observations	2,297	1,045	1,045	2,297	1,045	1,045
R-squared	0.521	0.608	0.619	0.521	0.608	0.619
Infant Mortality Rate	MortInf	MortInf	MortInf	MortInf	MortInf	MortInf
Gini	0.332***	0.124***	0.121***	0.332**	0.124	0.121
	(0.0518)	(0.0359)	(0.0362)	(0.161)	(0.108)	(0.106)
Observations	2,281	1,073	1,073	2,281	1,073	1,073
R-squared	0.569	0.842	0.850	0.569	0.842	0.850
Explanatory Variables		X	X		X	X
Year Dummies			X			X
Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6 present the OLS results of income inequality on the mortality rate. The only statistically significant effect from the Gini-index for the male mortality rate (MortMale) is found in columns 1 and 4. That is, in the model that only includes the Gini-index and the log of GDP per capita the predicted statistically significant positive effect on mortality from inequality is found and it remains significant when cluster-robust errors are used. The magnitude of this coefficient is 1.23 and the interpretation is simply that an increase in the Gini-index by one point leads to 1.23 more male deaths per 1,000 people on average. The next dependent variable is the female mortality rate (MortFem), and here there is a significant positive effect from the Gini-index in the first three columns that use standard errors. When cluster-robust errors are used instead only the base model in column 4 retains its significance.

Predictably, when more factors are controlled for the magnitude of the income inequality effect shrinks, from 1.52 in column 1 to 0.88 in the full model in column 3.

The final set of rows in table 6 shows the results from OLS regressions using the infant mortality rate (MortInf) as the dependent variable. With standard errors in column 1, there is a statistically significant effect on infant mortality. The effect is positive, i.e. more inequality is associated with more infant mortality. The effect is still statistically significant but of a lesser magnitude when the explanatory variables are introduced and when a time trend is accounted for in columns 2 and 3, shrinking from 0.33 in column 1 to 0.12 in column 3. The interpretation is that when accounting for time as well as the enrollment and measles immunization rate an increase in the Gini-index by one corresponds to 0.12 more infant deaths per 1,000 live births on average, assuming that all other factors remain the same. Using cluster errors there is only statistical significance in the base model. The added explanatory variables are once again all significant and have the expected negative sign both with standard and with cluster-robust errors.

Table 7 Fixed Effect Results of Income Inequality on Mortality Rates

	1	2	3	4	5	6
Male Mortality Rate	MortMale	MortMale	MortMale	MortMale	MortMale	MortMale
Gini	0.0210	-0.0925	-0.0123	0.0210	-0.0925	-0.0123
	(0.137)	(0.218)	(0.223)	(0.261)	(0.327)	(0.377)
Observations	2,297	1,045	1,045	2,297	1,045	1,045
R-squared	0.380	0.375	0.434	0.380	0.375	0.434
Number of Countries	158	125	125	158	125	125
Female Mortality Rate	MortFem	MortFem	MortFem	MortFem	MortFem	MortFem
Gini	-0.185	-0.396**	-0.463**	-0.185	-0.396	-0.463
	(0.142)	(0.190)	(0.196)	(0.285)	(0.281)	(0.329)
Observations	2,297	1,045	1,045	2,297	1,045	1,045
R-squared	0.278	0.233	0.295	0.278	0.233	0.295
Number of Countries	158	125	125	158	125	125
Infant Mortality Rate	MortInf	MortInf	MortInf	MortInf	MortInf	MortInf
Gini	0.174***	0.0196	0.0289	0.174	0.0196	0.0289
	(0.0612)	(0.0444)	(0.0453)	(0.135)	(0.102)	(0.0930)
Observations	2,281	1,073	1,073	2,281	1,073	1,073
R-squared	0.281	0.561	0.605	0.281	0.561	0.605
Number of Countries	155	124	124	155	124	124
Explanatory Variables		X	X		X	X
Year Fixed Effects			X			X
Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7 shows the fixed effects results of the same analysis and the results are quite different. The Gini-index is never significant for males and for females there is a significant negative relationship between the mortality rate and the Gini-index in columns 2 and 3. The Gini-index in all other columns show no statistical significant effect on the mortality rates for adults. This is the opposite of the hypothesized relationship and seems to point towards more inequality leading to fewer deaths for women. Column 1 shows no significant effect of income inequality on the female mortality rate however as well as this negative relationship not holding up to the introduction of cluster-robust errors.

The last set of rows show the results when using a fixed effects panel regression and the infant mortality rate as the dependent variable. The only statistically significant effect from the Gini-index is in column 1, the base model using standard errors. The magnitude in column 1 is almost half as large as column 1 in table 6, 0.17 compared to 0.33. The interpretation of the coefficient is the same as in the OLS results. The R-squared is almost 50% smaller in the base model when using fixed effects compared to a standard OLS regression and still significantly smaller when including explanatory variables as well as a time trend. The control variables are all of the expected signs and are statistically significant regardless if standard or cluster-robust errors are used. Only the infant mortality rate shows the theorized result when using fixed effects and the significance disappears when social infrastructure is controlled for. Intuitively it makes sense that the state of hospitals, how educated parents are and similar measures of health and social infrastructure have a larger effect on an infant's probability to survive rather than increased stress and other psychosocial factors. The large difference between the OLS and the fixed effects estimates indicate that there is a problem with bias when using cross-sectional analysis.

Infant Mortality Regressions by Region

In order to gain insight on the income inequality effect the next step is to disaggregate the analysis and break it down by region. Just like the case with life expectancy from birth there is evidence that the impact that income inequality has on population has significant differences between regions even when controlling for country heterogeneity. The fixed effects results from the previous section indicates that infant mortality would be the most interesting to study. As before only the fixed effects results are discussed here and the summary of the OLS results are available in the appendix.

Table 8 Fixed Effects Results of the Effects of Inequality on Infant Mortality by Region

		1 MortInf	2 MortInf	3 MortInf	4 MortInf	5 MortInf	6 MortInf
Africa	Gini	1.046***	-0.239	-0.0712	1.046***	-0.239	-0.0712
		(0.217)	(0.206)	(0.295)	(0.300)	(0.276)	(0.270)
	Observations	244	83	83	244	83	83
	R-squared	0.187	0.658	0.831	0.187	0.658	0.831
	Number of Countries	45	33	33	45	33	33
Asia	Gini	0.522**	-1.193***	-0.784**	0.522	-1.193**	-0.784**
		(0.255)	(0.250)	(0.324)	(0.322)	(0.429)	(0.364)
	Observations	278	103	103	278	103	103
	R-squared	0.545	0.785	0.875	0.545	0.785	0.875
	Number of Countries	16	15	15	16	15	15
Central America	Gini	-0.342	0.239	0.449**	-0.342	0.239	0.449
		(0.373)	(0.239)	(0.174)	(0.641)	(0.594)	(0.313)
	Observations	109	53	53	109	53	53
	R-squared	0.537	0.689	0.984	0.537	0.689	0.984
	Number of Countries	6	6	6	6	6	6
Europe	Gini	0.0582**	-0.0885***	-0.0818***	0.0582	-0.0885	-0.0818
		(0.0240)	(0.0219)	(0.0214)	(0.0627)	(0.0584)	(0.0658)
	Observations	820	471	471	820	471	471
	R-squared	0.710	0.756	0.803	0.710	0.756	0.803
	Number of Countries	37	31	31	37	31	31
Middle East	Gini	3.059***	-0.153	0.527	3.059*	-0.153	0.527
		(0.814)	(0.332)	(0.326)	(1.429)	(0.375)	(0.306)
	Observations	87	44	44	87	44	44
	R-squared	0.499	0.894	0.994	0.499	0.894	0.994
	Number of Countries	12	9	9	12	9	9
North America	Gini	0.354***	-0.0514*	0.0316	0.354	-0.0514*	0.0316
		(0.0520)	(0.0261)	(0.0541)	(0.116)	(0.00491)	
	Observations	95	35	35	95	35	35
	R-squared	0.941	0.909	0.999	0.941	0.909	0.999
	Number of Countries	2	2	2	2	2	2
Oceania	Gini	-0.0917	0.0867	-0.00545	-0.0917	0.0867*	-0.00545
		(0.104)	(0.0552)	(0.0220)	(0.168)	(0.0217)	(0.00753)
	Observations	86	52	52	86	52	52
	R-squared	0.358	0.852	0.998	0.358	0.852	0.998
	Number of Countries	5	3	3	5	3	3
Post-Soviet	Gini	-0.437***	0.00233	0.0171	-0.437**	0.00233	0.0171
		(0.104)	(0.113)	(0.108)	(0.178)	(0.244)	(0.145)
	Observations	202	84	84	202	84	84
	R-squared	0.137	0.727	0.873	0.137	0.727	0.873
	Number of Countries	12	10	10	12	10	10
South America	Gini	0.274	0.591***	0.283**	0.274	0.591*	0.283*
		(0.229)	(0.130)	(0.123)	(0.487)	(0.304)	(0.125)
	Observations	261	110	110	261	110	110
	R-squared	0.501	0.721	0.939	0.501	0.721	0.939
	Number of Countries	11	9	9	11	9	9
West Indies	Gini	0.244*	-0.0567	0.0681	0.244	-0.0567**	0.0681
		(0.134)	(0.0455)	(0.0573)	(0.141)	(0.0178)	(0.0392)
	Observations	99	38	38	99	38	38
	R-squared	0.606	0.822	0.986	0.606	0.822	0.986
	Number of Countries	9	6	6	9	6	6
	Explanatory Variables		X	X		X	X
	Year Fixed Effects			X			X
	Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results of the fixed effects regressions analyzing the effect of income inequality on infant mortality by region are summarized in table 8, and as was the case with the life expectancy results, generally less significance is found for the income inequality effect once fixed effects are used. The two regions where the effect is the strongest; Africa and the Middle East only show significance in the base model, in columns 1 and 4. These two regions have the largest magnitudes of the coefficients on the Gini-index by far, with 1.05 in Africa and 3.06 in the Middle East. This coefficient is interpreted as a one point increase in the Gini-index in that region corresponds to 1.05 and 3.06 more infant deaths per 1,000 live births on average, assuming all other factors remain the same.

Asia has the predicted positive relationship in the base model in column 1, and also shows the third largest coefficient, almost half as large as the second largest in Africa. However once the enrollment and measles immunization rates are controlled for in the following columns Asia instead shows a negative relationship between the Gini-index and infant mortality. This negative relationship is still statistically significant when cluster-robust errors are used, but the positive relationship from the base model is not. This same pattern can be seen in Europe as well where there is a statistically significant but low magnitude positive effect in the base model and significant but equally low magnitude negative effect in the models in columns 2 and 3, however none of these are significant once cluster-robust errors are used. The size of the coefficient on the Gini-index in Europe is the smallest of any of the coefficients that are statistically significant. In column 1 for Europe the magnitude is 0.058 which is almost 10 times smaller than the magnitude in Asia.

Several regions show the predicted positive relationship between income inequality and infant mortality in the base model in column 1 but the only region to show a statistically significant positive effect in column 2 is South America. Once time fixed effects are used as well as country fixed effects in column 3 the predicted positive relationship can be seen in both South and Central America with the magnitude being the largest in Central America. In South America the statistical significance found in these models also remains when cluster-robust errors are used in columns 5 and 6, but this is not the case in Central America.

The Post-Soviet region is the only region that shows a negative relationship between the Gini-index and the infant mortality rate in the base model in column 1 but there is no significant effect once the explanatory variables are added in columns 2 and 3. Oceania as well as Central & South America are the only regions where no statistical significance is present at all in the base model in column 1. Central & South America show a significant income inequality effect in other model specifications as previously discussed but Oceania only has a statistically significant coefficient on the Gini-index in column 5 and this is once again due to the cluster-robust error becoming smaller than its “true” value due to a low number of countries to cluster over. This is also the case with the statistically significant negative effects found in column 5 for the West Indies. The negative effect in the explanatory variable model in North America is statistically significant in both column 2 and 5.

In general the base model in column 1 of table 8 support the income inequality hypothesis for most of the analyzed regions but the relationship only holds for Central & South America once the measles immunization and enrollment rate are controlled for. This once again seems to support both the idea that the primary mechanism for the income inequality effect is through the relationship between inequality and underspending on public resources, at least in most of the analyzed regions. Much like in the results for total life expectancy from birth there is clear evidence that income inequality does not have the same effect in every region, even when other possible health affecting factors are controlled for.

Infant Mortality Regressions by Income Group

The next level of analysis is separating the countries by the World Bank classification of income groups, as defined earlier.

Table 9 Fixed Effects Results of the Effects of Inequality on Infant Mortality by Income Group

		1 MortInf	2 MortInf	3 MortInf	4 MortInf	5 MortInf	6 MortInf
Low Income	Gini	0.968***	-0.433**	-0.725**	0.968***	-0.433	-0.725***
		(0.315)	(0.170)	(0.253)	(0.281)	(0.271)	(0.150)
	Observations	157	55	55	157	55	55
	R-squared	0.170	0.897	0.987	0.170	0.897	0.987
	Number of Countries	27	20	20	27	20	20
Low Middle	Gini	-0.428**	-0.140	-0.185	-0.428	-0.140	-0.185
		(0.170)	(0.117)	(0.118)	(0.352)	(0.144)	(0.141)
	Observations	431	179	179	431	179	179
	R-squared	0.294	0.708	0.828	0.294	0.708	0.828
	Number of Countries	39	31	31	39	31	31
Upper Middle	Gini	0.430***	0.217***	0.203***	0.430	0.217	0.203**
		(0.140)	(0.0718)	(0.0621)	(0.291)	(0.142)	(0.0882)
	Observations	624	283	283	624	283	283
	R-squared	0.413	0.699	0.833	0.413	0.699	0.833
	Number of Countries	45	36	36	45	36	36
High Income	Gini	0.132***	-0.103***	0.00363	0.0975	-0.103*	0.00363
OECD		(0.0301)	(0.0203)	(0.0177)	(0.0929)	(0.0545)	(0.0320)
	Observations	883	485	485	883	485	485
	R-squared		0.718	0.852	0.729	0.718	0.852
	Number of Countries	30	27	27	30	27	27
High Income	Gini	-0.154	-0.133*	-0.0186	-0.154	-0.133	-0.0186
Non-OECD		(0.108)	(0.0676)	(0.0623)	(0.117)	(0.126)	(0.0519)
	Observations	177	70	70	177	70	70
	R-squared	0.408	0.887	0.984	0.408	0.887	0.984
	Number of Countries	12	10	10	12	10	10
	Explanatory Variables		X	X		X	X
	Year Fixed Effects			X			X
	Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 9 is a summary table of the fixed effects results of income inequality on infant mortality and again shows that there are clear differences between the income groups. Column 1 shows a very strong income inequality effect in the base model for low income countries. According to this result a one point increase in the Gini-index in the countries with low income would correspond with an increase in infant deaths by 0.97 infants per 1,000 live births on average.

The magnitude for the Gini-index in low income countries is more than twice as large compared to any other coefficient in column 1 and the significance is robust to the use of cluster errors instead of standard errors. However when the measles immunization and enrollment rates are included in column 2 the sign of the coefficient becomes negative and even more negative once time fixed effects are used as well. A large difference between the base model and the other models is expected in the low income countries since previous research has pointed towards social infrastructure being incredibly important in less developed countries, but this result is slightly surprising. This group does have the fewest number of observations, so this result could be due to that issue.

A statistically significant negative effect is also found in column 2 for both groups of high income countries as well in the base model in column 1 for the countries classified as lower-middle income. Just like the results from the life expectancy analysis there is significance in all three model specifications in the upper middle income countries. Only equation 3 retains significance when cluster-robust errors are used in column 6. The results seem to indicate that the income inequality effect is the strongest overall in those countries with moderate economic development.

The same pattern as with the region breakdown is evidenced here, that there are more specifications that show the hypothesized relationship between income inequality and health outcomes than when looking at the aggregate level. This is most likely because of the effect differing in magnitude when comparing regions or income groups which there is definitive evidence for. The theory predicts effect should be weaker in countries with stronger social safety nets which comparing the results from the group of high income OECD-countries or the European region with the middle income groups or the Middle Eastern or Africa regions seem to support. However this result does not always hold up to the introduction of other control variables, using country fixed effects regressions or the use of cluster-robust errors which points to there being more to the income inequality effect hypothesis than a straightforward relationship between health and the Gini-index. In general the results points to much of the income inequality effect on health being derived from the second theorized mechanism, the underfunding of social infrastructure such as hospitals, schools and the like. When this mechanism is controlled for by including an education and a healthcare variable much of the effect from income inequality loses statistical significance except for in certain regions. This possibly means that in these regions the psychosocial factors such as lowered trust or increased anxiety which are associated with higher level of inequality has a larger health effect than in those regions where the Gini-index has no significance once social infrastructure is controlled for. Especially infant mortality seems to be very strongly associated with social infrastructure since the predicted relationship is found in the base model in most areas but the significance disappears when the control variables are used.

There is strong evidence that both region-specific and income-specific analysis shed more light on the income inequality effect than aggregate analysis alone. In some groups of countries the income inequality effect seem to disappear completely or work in the opposite direction that theory would predict while it seems very strong in other parts of the world. The upper-middle income countries see the strongest impact on health from income inequality while the relationship is less clear for the other regions. On the whole, income group analysis seems more fruitful than a regional breakdown, pointing towards there being more likeness between countries of similar economic development rather than between countries with geographical similarities.

Limitations and Potential Future Research

The main issue with a study like this is deciding the optimal sample size. A balanced panel could provide less biased results, but would severely limit the available sample, either in the amount of years analyzed or the number of countries. Data on economic inequality stretch back over 60 years in most European countries while countries with more turbulent recent history may only have a few years with quality data. There are measures of the Gini-index that are approximated from other macro-economic measurements that could be used to "fill in the gaps" in order to make a balanced panel. For this study the choice was made to use the Gini-index stemming from the highest possible survey quality and constructed using the same income measurement but it is a balancing act and a study that uses lower quality sources for the Gini-index in order to maximize the amount of observations would not be misguided. Most of the previous studies have been cross-sectional in nature so any study using panel data and especially large samples would lead to interesting results.

The choice of explanatory variables apart from those dictated by the literature; Gini-index and GDP per capita, can also be debated. Once again sample size played into the decision to use the measles immunization and enrollment rates as measurements of social infrastructure. The measles immunization rate has a clearly established link to better health and inequality but there are other possible variables that could have been used instead that have stronger relationships such as the number of health workers per capita or healthcare spending, but these are available with much fewer observations than the immunization rate. In the same way there are other measurements of how educated the population is that can be used instead of the net adjusted enrollment rate chosen here. Literacy rates of mothers has been shown to have a very strong impact on the average health outcome. However in the developed parts of the world where there is a lot of high quality data this literacy rate is high and shows very little variation while those countries with lower rates have a lot of missing observations. There are other education variables that could be used instead such as average educational attainment but there should not be a significant difference from enrollment figures in the impact they would have on the population health. One potential issue with all of the data is that countries with high inequality and low development may not have the highest quality data collection and in fact could have a vested interest in downplaying poor health outcomes or low education results but this issue should be minor since only data vetted by the World Bank is used. Using time dummies in the base model as well as in the model with control variables could have been illuminating, but previous studies have performed similar forms of analysis. The main focus of this paper was on the model with control variables accounting for the level of social infrastructure and as such I did not want to focus too extensively on the base model.

There are several interesting avenues for future research in the area of income inequality and health outcomes. Since the theory behind income inequality affecting health is that it raises the cost of low social status controlling for different sorts of social security nets should lead to interesting results. Possible variables are percentage of people receiving some form of benefits, public healthcare expenditure, general measures of how content the population are with welfare measures and the like. High levels of income inequality are also linked with a poor quality of state institutions, so including strength of institutions in some measure should also have a definitive impact on the results of income inequality analysis. The amount and quality of data available grows every year which means that more sophisticated analysis can be performed in the future. As it is now certain interesting variables such as the corruption index, transparency indices and other governance indicators are available but for a limited amount of years which makes the sample size for a possible analysis very small. However these are indicators that are measured more thoroughly and more often than they have been historically so the possibility of including variables like this and finding significant and robust results increases as time goes on. Panel data measuring perceived trust or anxiety could potentially be used to control for the psychosocial mechanism of the income inequality hypothesis as an extension to this study. It would be very interesting to see if the opposite results were found when controlling for psychosocial factors instead of the level of social infrastructure.

Furthermore, as was shown in the results section, the income inequality effect becomes more clear once the data is disaggregated which indicates that analyzing smaller regions could be beneficial to the understanding of the link between income inequality and health. Possible levels of analysis could be looking at panel data from different cities with significant variation in income dispersal in a country, or even municipalities within a given city. Finding other measures to separate the countries in the analysis apart from income group and region, such as primary industries either by employment or by share of GDP, growth rates, unemployment levels and the like could also be a fruitful path for analyzing the income inequality effect.

Conclusion

There are two theorized mechanisms behind how income inequality affects health; either through its relationship with psychosocial factors (stress, anxiety) or through its connection with social infrastructure (public schools, hospitals). This study analyzes the link between income inequality and the health of the population with a larger sample than previous studies, using both cross-sectional and panel data techniques. This study also includes new explanatory variables which should control for the health effect from the social infrastructure mechanism. A negative link between the Gini-index and life expectancy from birth is shown when only GDP per capita is controlled for which confirms findings from seminal papers such as Rodgers (1975) with a larger and more recent data set. Next this paper introduces the enrollment and measles immunization rates as explanatory variables to study how significant the income inequality effect is once some level of social infrastructure is controlled for. These variables show clear variation over time which challenges the assumption of some previous works that country heterogeneity is time invariant (for example Myrskylä & Torre or Cantarero et al.) Adding these two variables changes the results when using the entire sample and the significance of the negative relationship between life expectancy disappears. This is not the case when the sample is separated by either region or income group, however, as the negative significant relationship is present and statistically significant in Central & South America as well as in the upper-middle income group. The same pattern of results is found when analyzing the relationship between income inequality and mortality rates. There is evidence that the income inequality effect differs from region to region and between the income groups which indicates the limitations of studies that research the link between income inequality and health on the aggregate level. While outside of the scope of this thesis there are other disaggregation methods that would be interesting to pursue in the future.

Another new contribution is the usage of robust errors clustered by country which in several but not every case removes any significant income inequality effect found. When significance is found even with cluster-robust errors the effect is particularly strong, such as in the upper middle income countries or the South American region. The general findings are that the income inequality hypothesis holds when the variables used are the Gini-index and GDP per capita. However, the relationship becomes muddied when the school enrollment and measles immunization rates in the country are included. A possible explanation is that the primary mechanism for the income inequality effect is through its relationship with social infrastructure. According to theory, countries with high inequality generally spend less on healthcare, education, public housing and the like. When the level of social infrastructure is controlled for by using the measles immunization and enrollment rates most of the income inequality effect disappears from the results. This points to this social spending mechanism being the primary driver of the negative relationship between income inequality and health found at the aggregate level in this and several other studies. Those areas where the negative relationship retains significance with these factors controlled for, such as the upper-middle income countries, could be hypothesized to have a stronger income inequality effect from the psychosocial mechanism.

Overall the results suggest that the model specification and the type of countries in the analysis matter for the results. When the data is disaggregated it becomes clear that the income inequality effect is not the same the world over. By looking at those groups of countries where it is the strongest and the weakest a clearer picture of the magnitude and mechanism behind the negative relationship between income inequality and population health should emerge. The analysis points towards the psychosocial and social infrastructure mechanisms having different strength depending on the area analyzed. While the results are not clear cut, the findings speak in favor of disaggregating by income, rather than region and that fixed effects is preferable to pooled OLS. The differences between the OLS and fixed effects results point towards there being some bias in the OLS estimators, likely stemming from unobserved heterogeneity between countries. The included explanatory variables show both that social infrastructure is not time invariant and that it has a very large effect on the results of income inequality studies. There are several other measurements of public spending which could be used in future studies to prove whether this is in fact the driving mechanism behind most of the income inequality effect. The opposite type of analysis in future studies, where the psychosocial mechanism is controlled for instead, could also be very useful to fully understanding the relationship between income inequality and health.

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Appendix

Figures and Tables

Figure 1 Life Expectancy at Birth

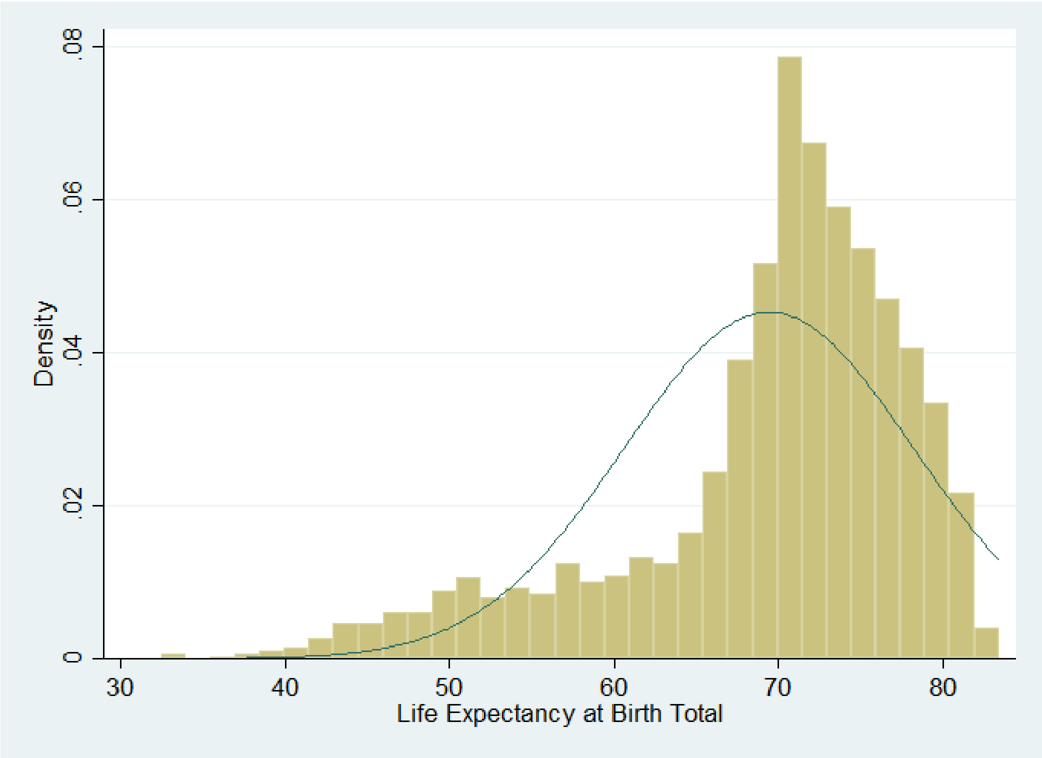

Figure 2 Region Mean of Life Expectancy

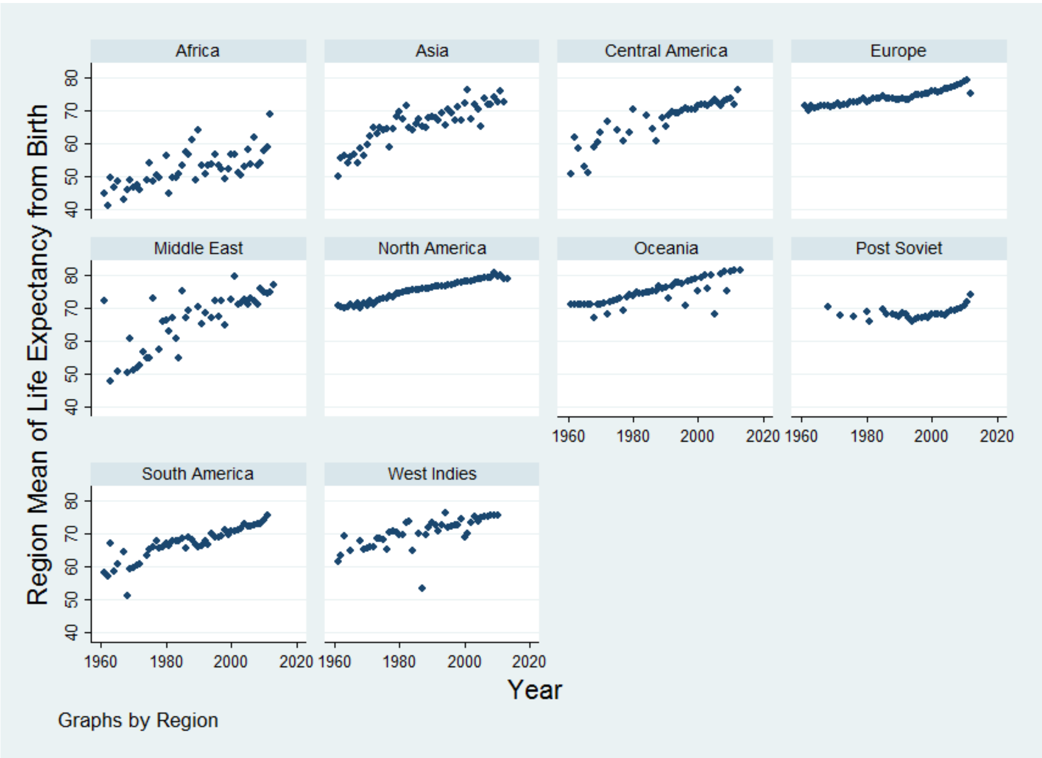

Figure 3 Income Group Mean of Life Expectancy

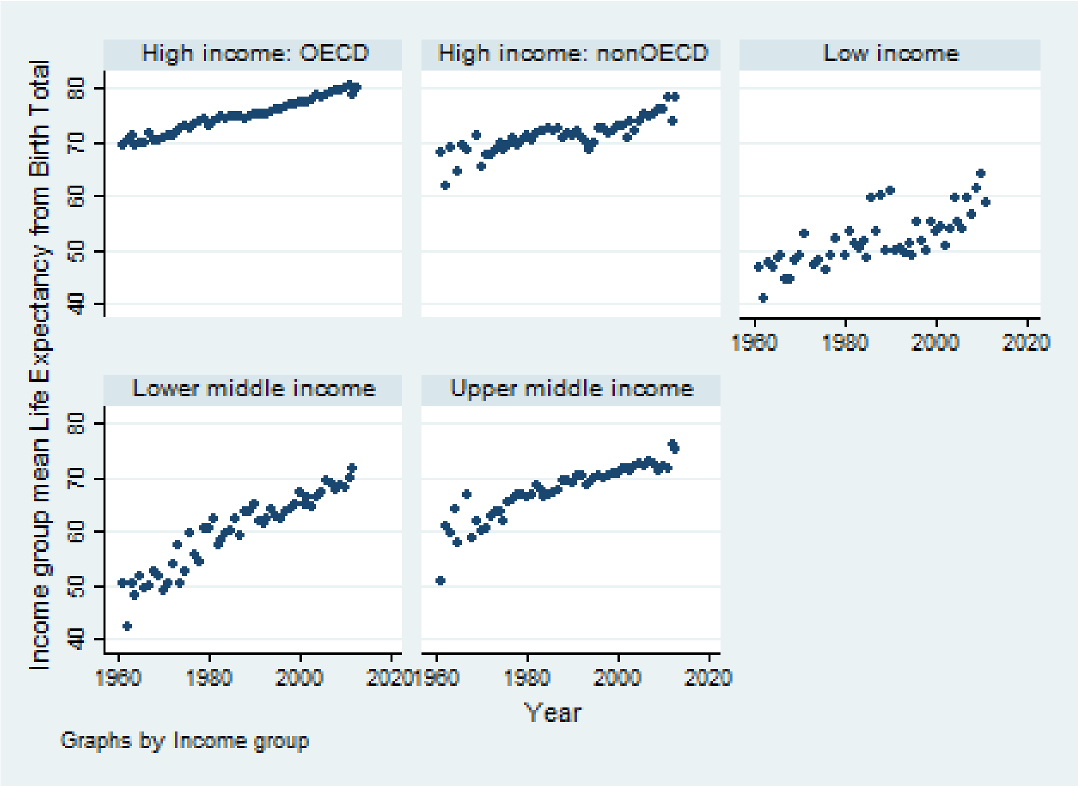

Figure 4 Mortality Rate Infants

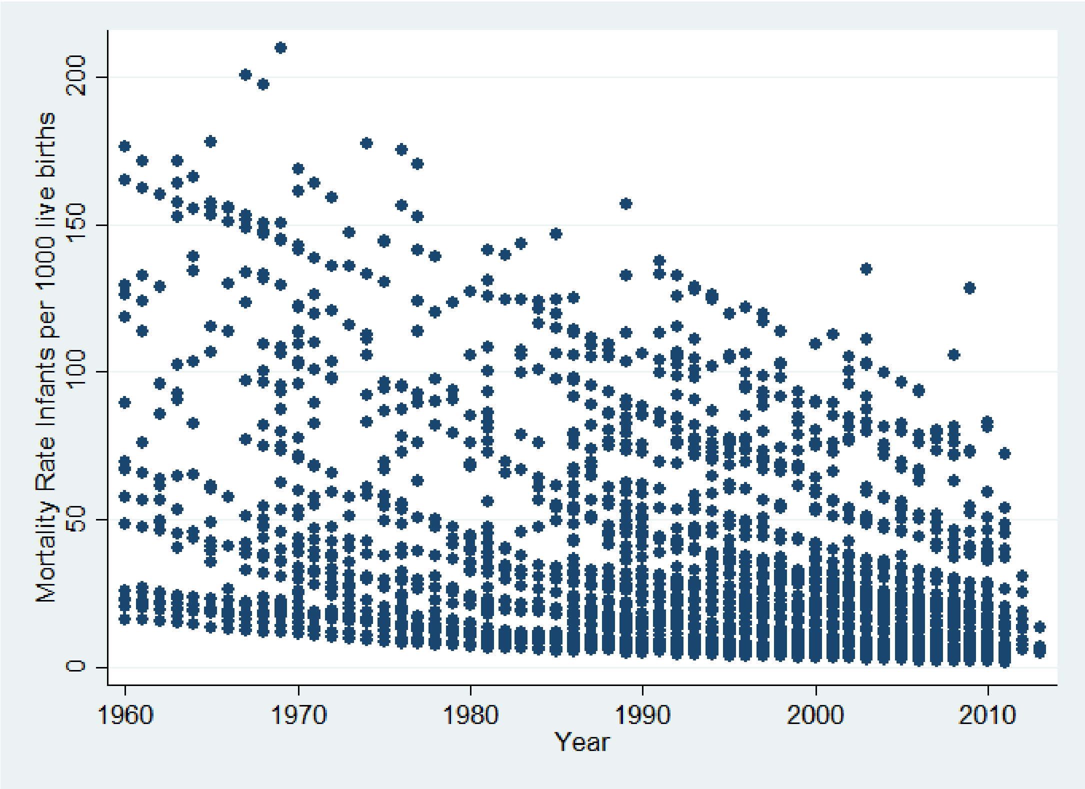

Figure 5 Region Mean of Infant Mortality Rate

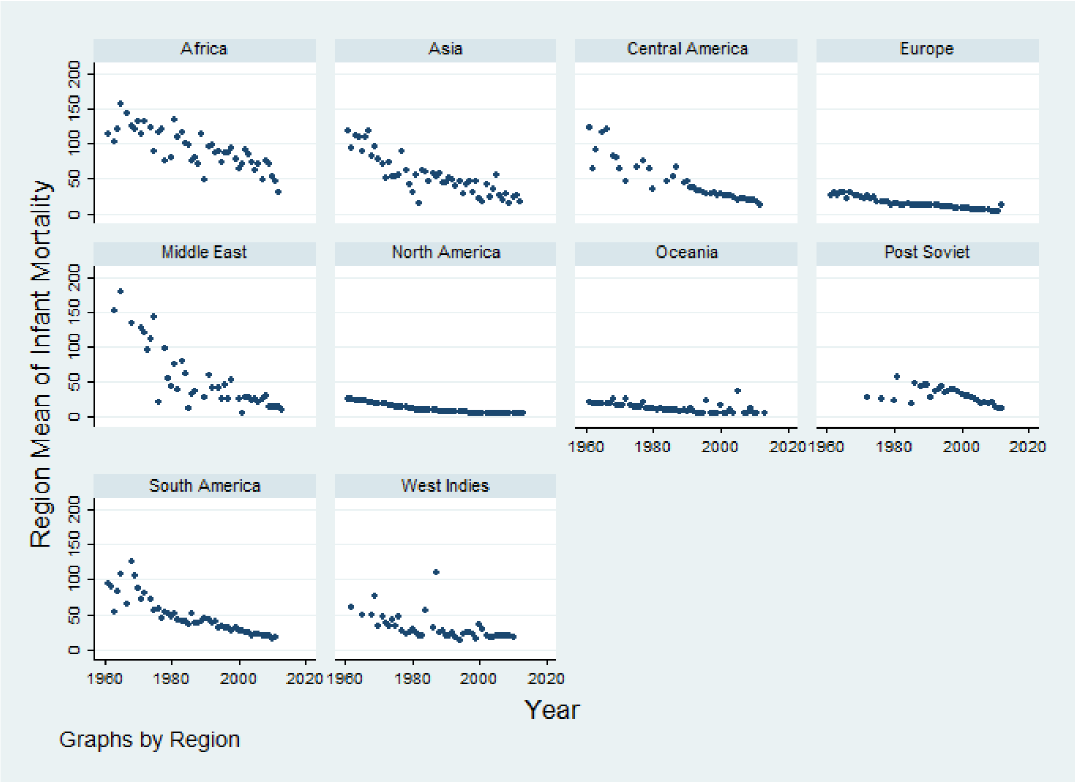

Figure 6 Income Group Mean of Infant Mortality Rate

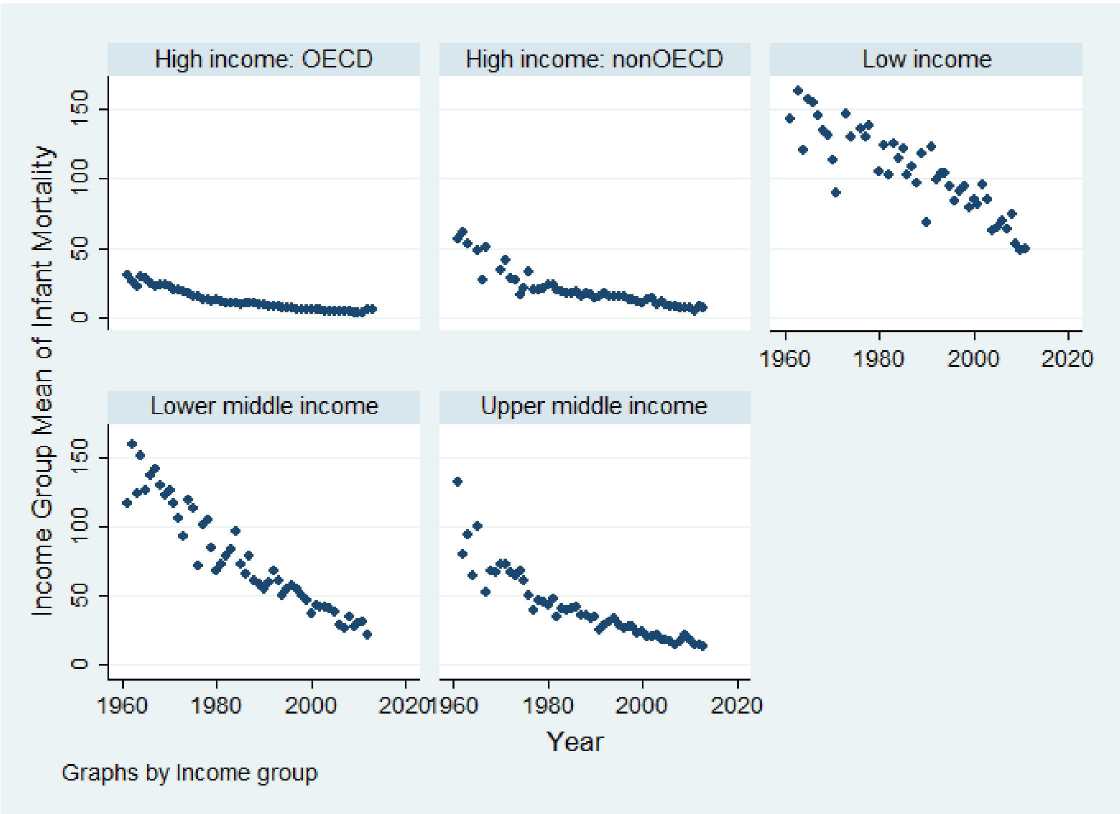

Figure 7 Gini Indices

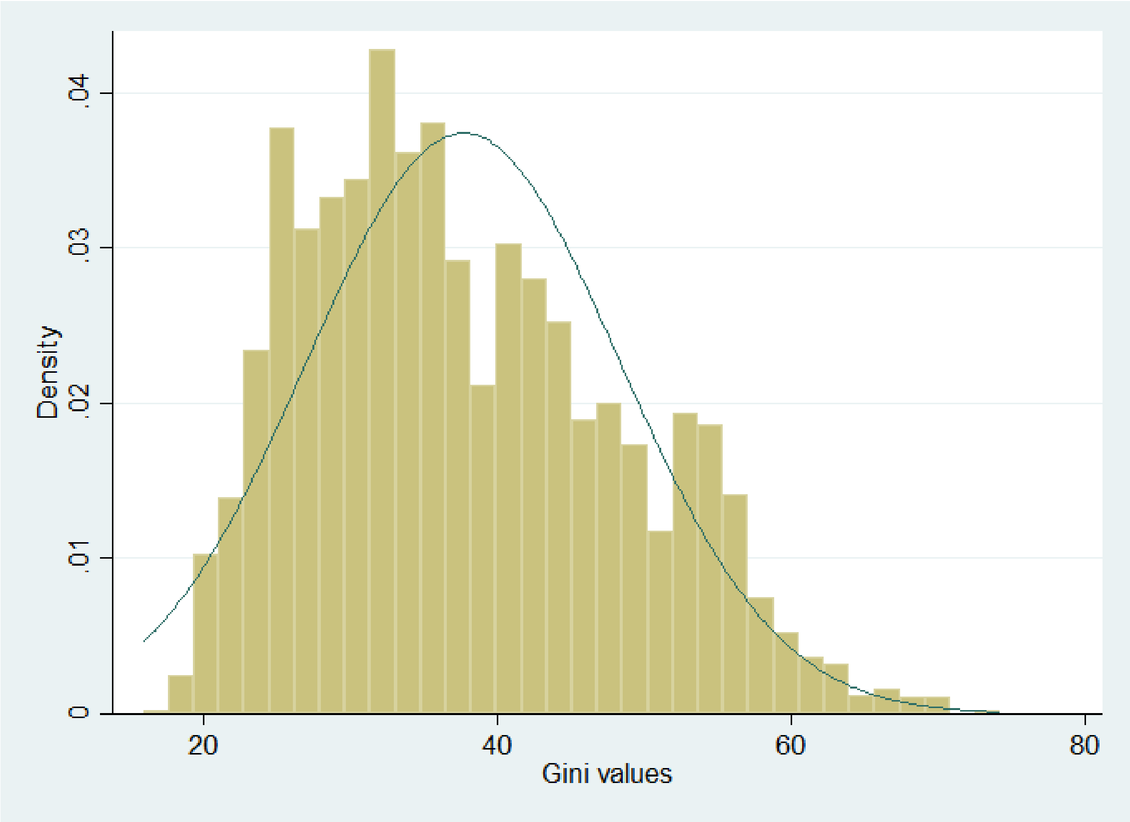

Figure 8 Region Mean of Gini-index

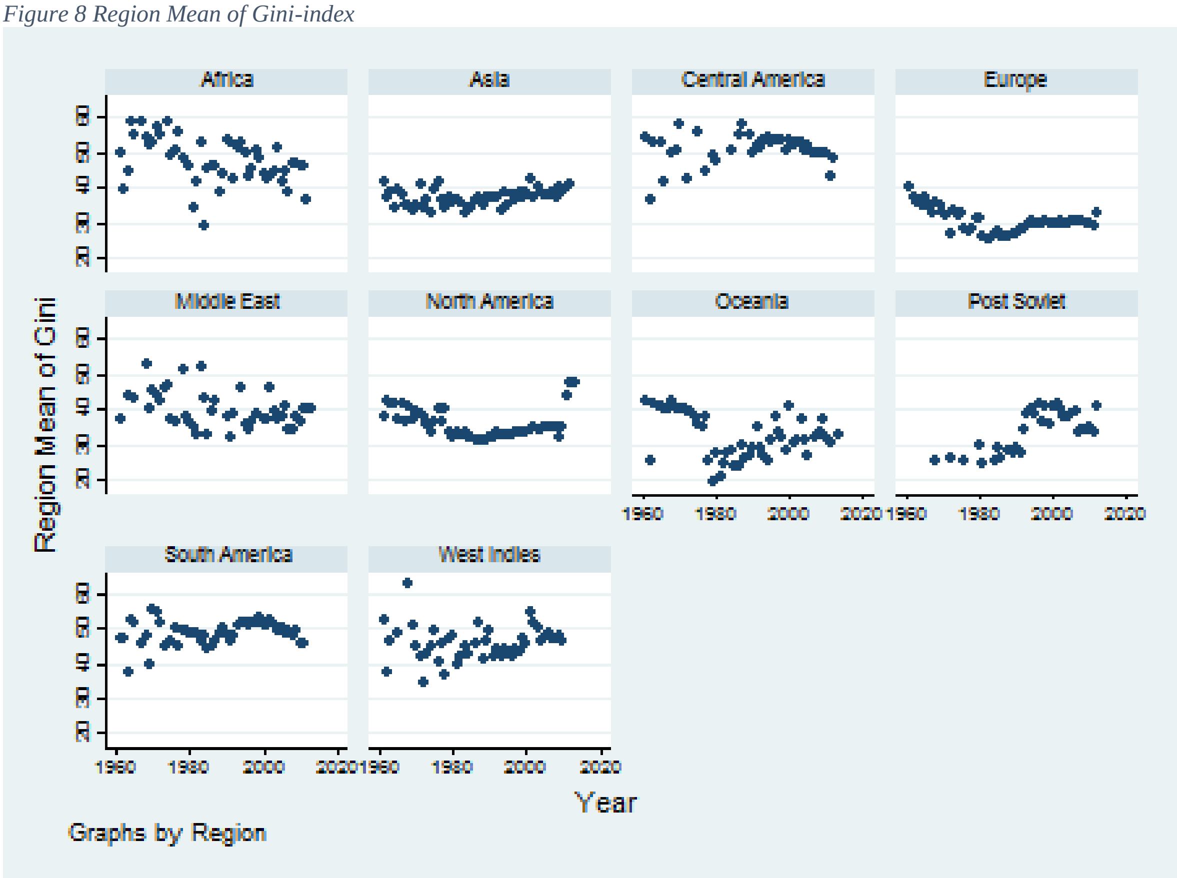

Figure 9 Income Group Mean of Gini-index

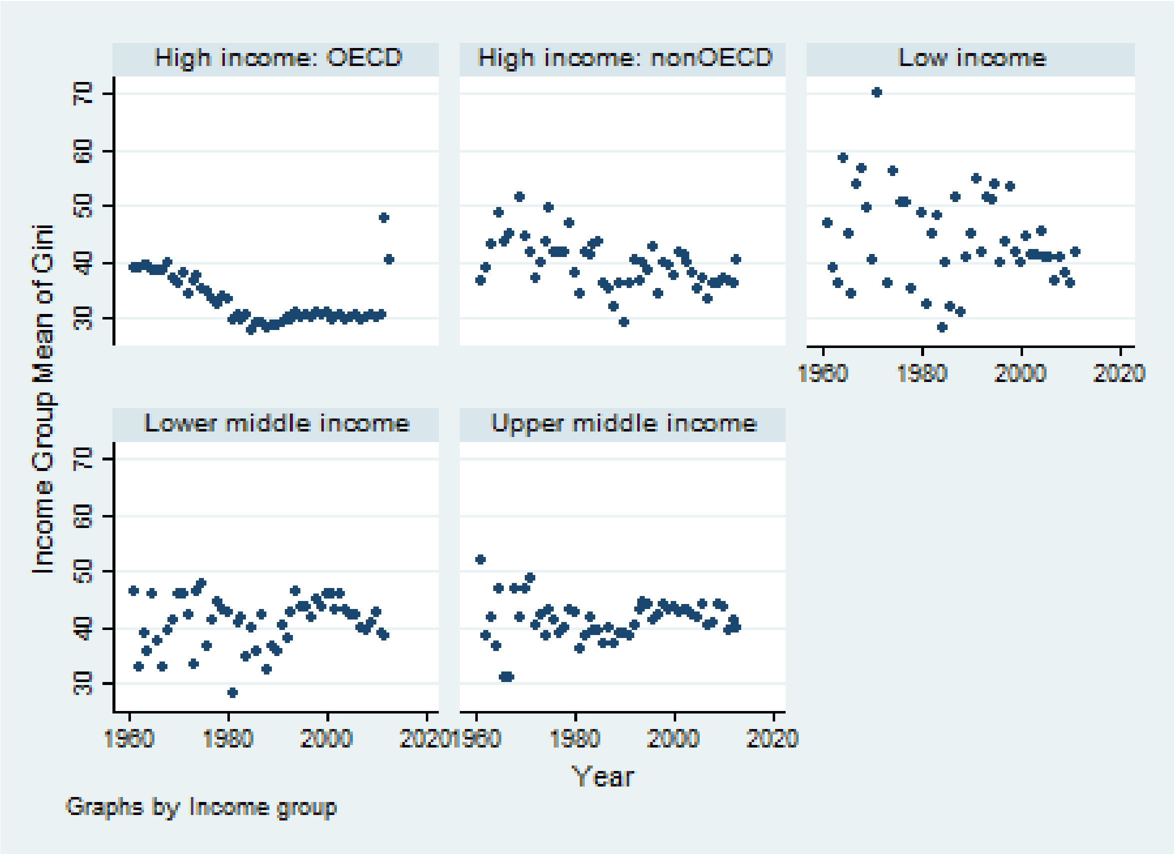

Figure 10 GDP Per Capita

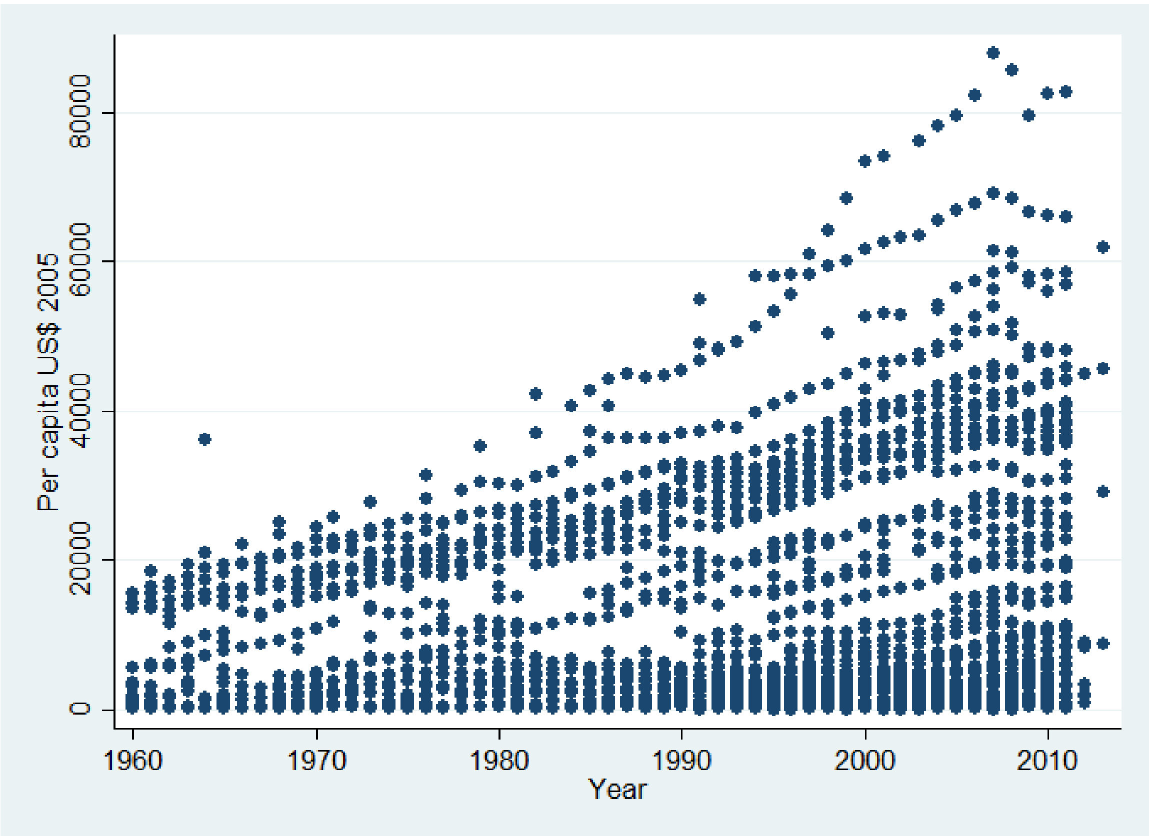

Figure 11 Measles Immunization Rate

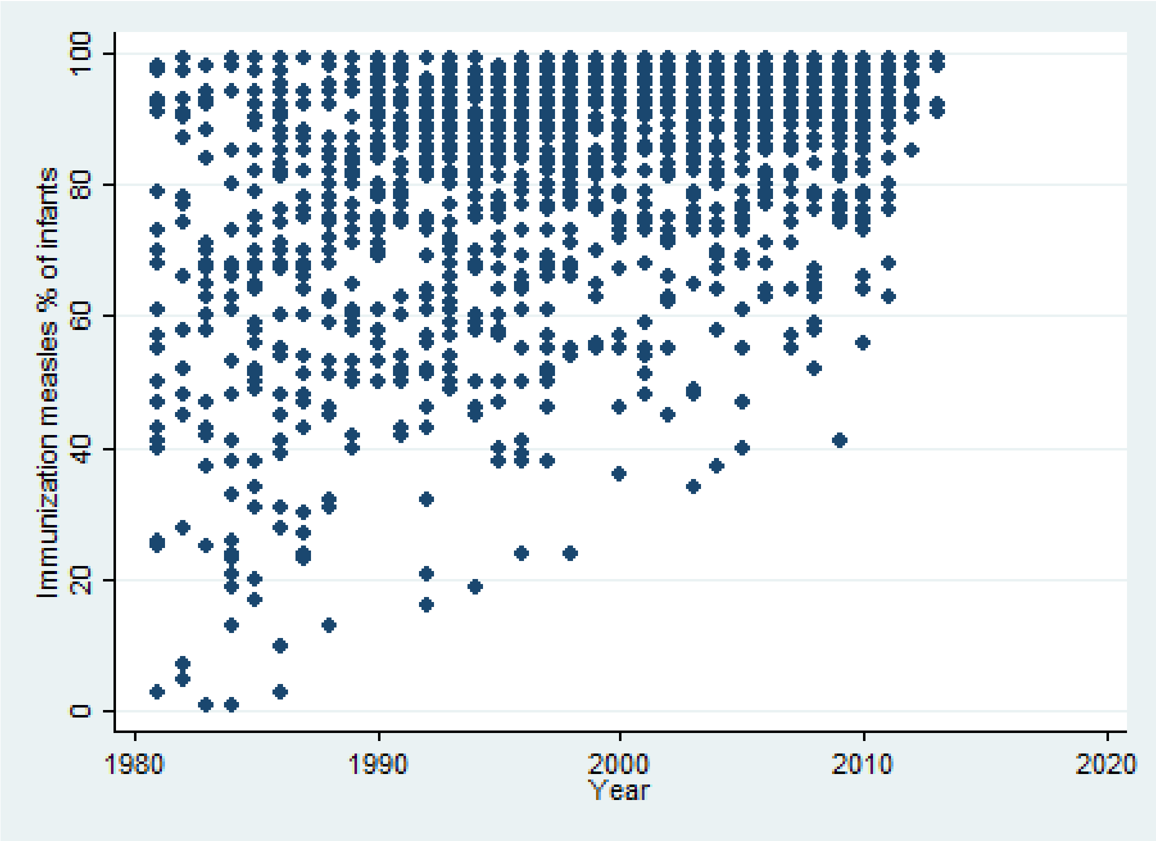

Figure 12 Measles Immunization by Income Group

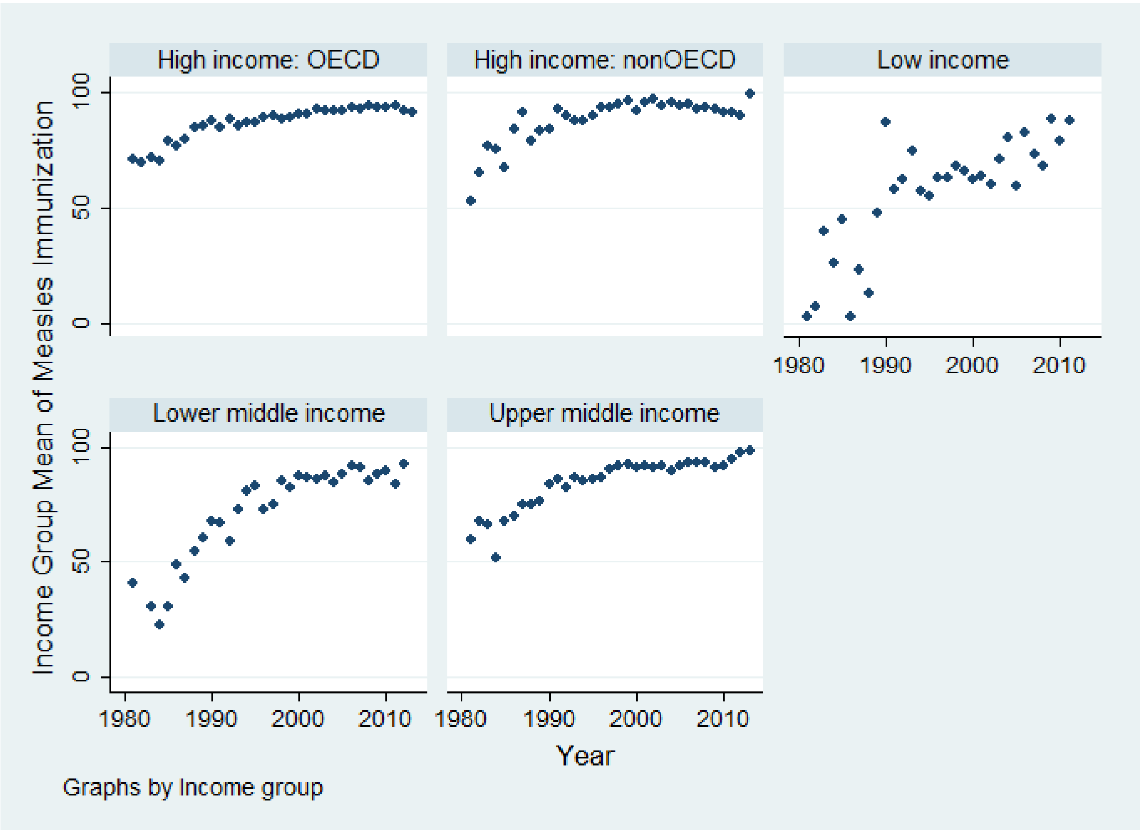

Figure 13 Measles Immunization by Region

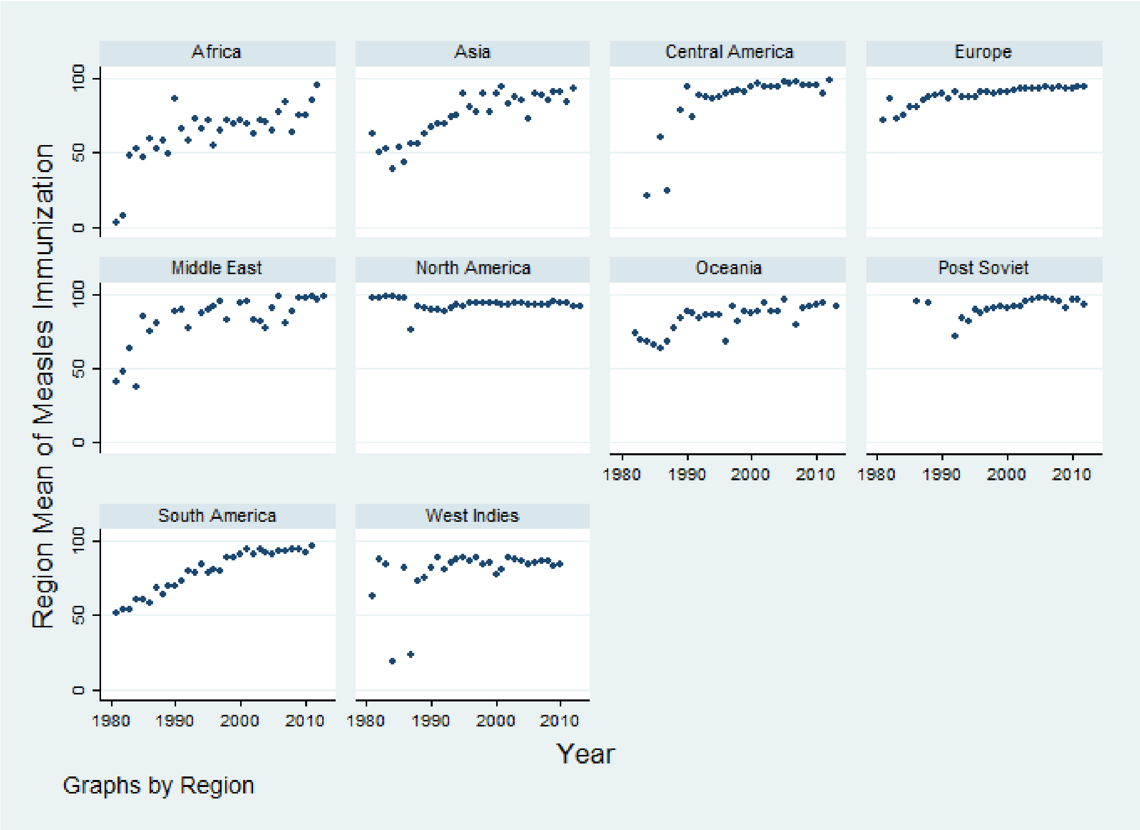

Figure 14 Enrollment Rate Primary and Secondary School

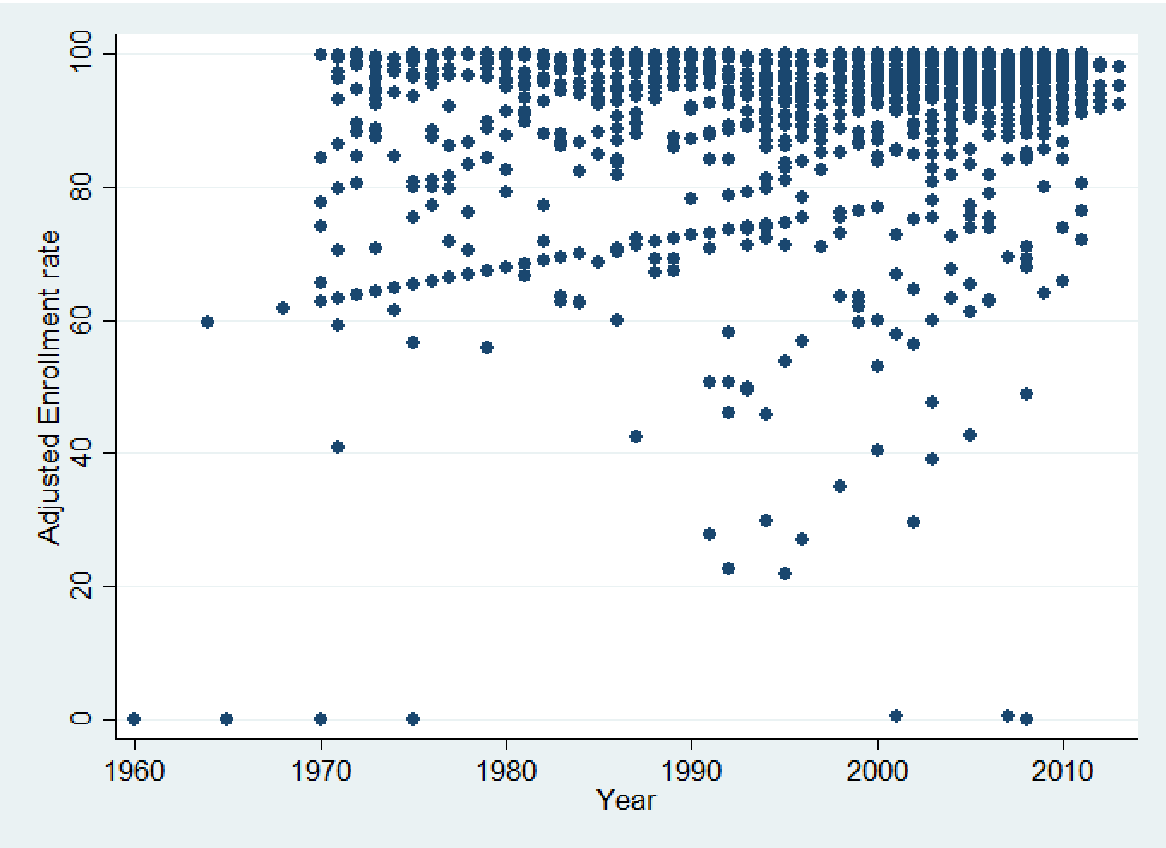

Figure 15 Measles Immunization Africa

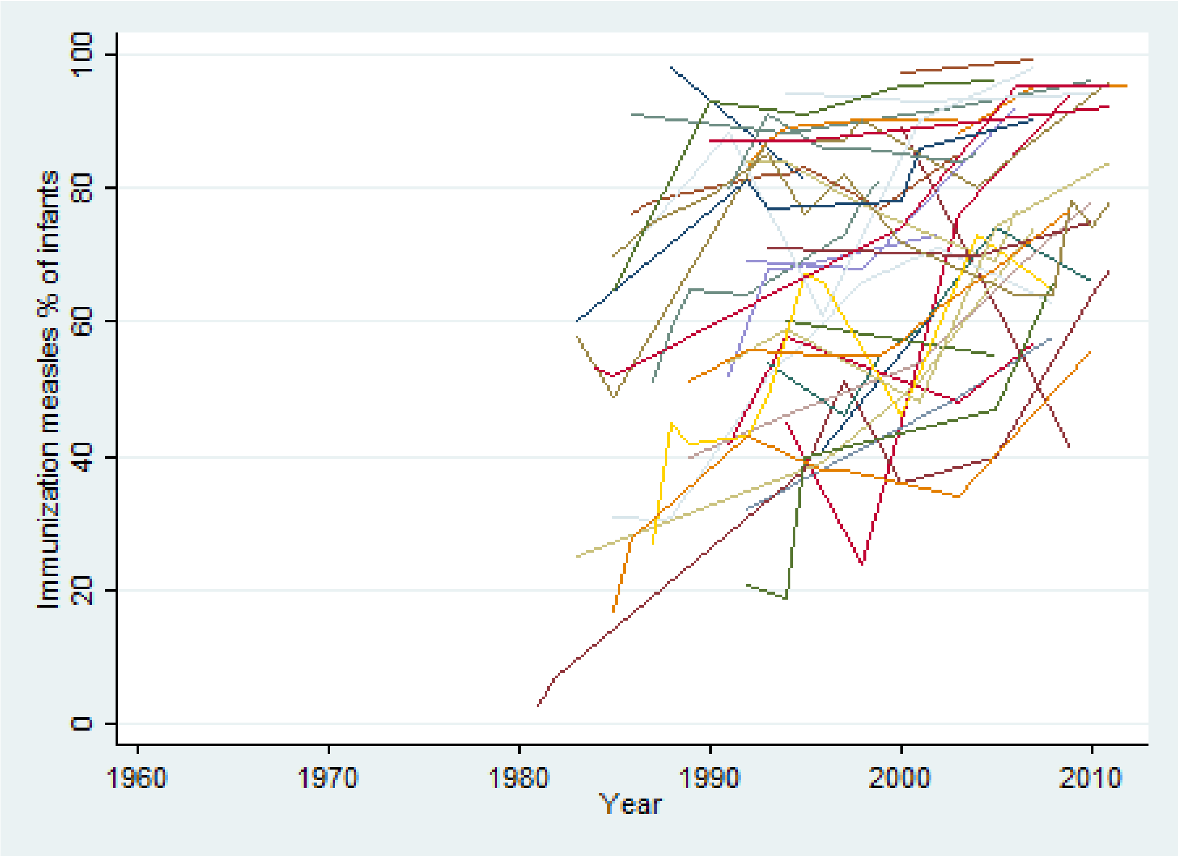

Figure 16 Enrollment Rate Asia

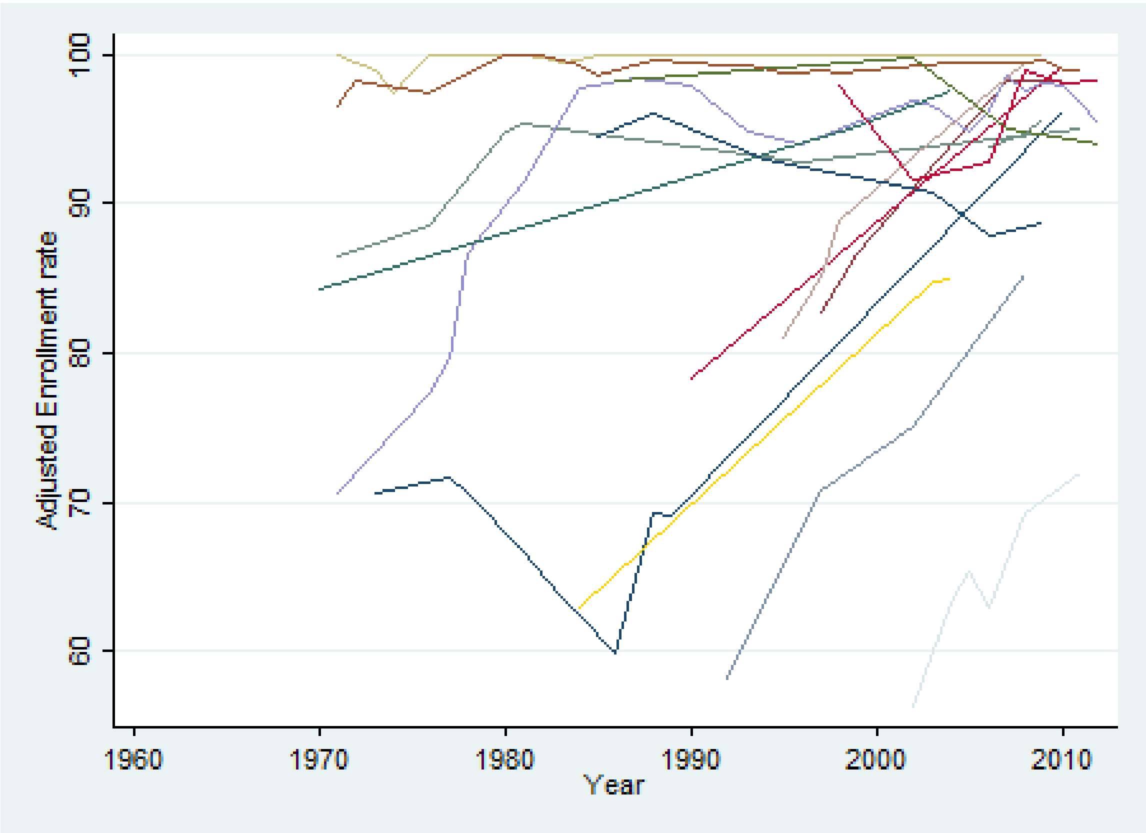

Figure 17 Gini-index & Life Expectancy

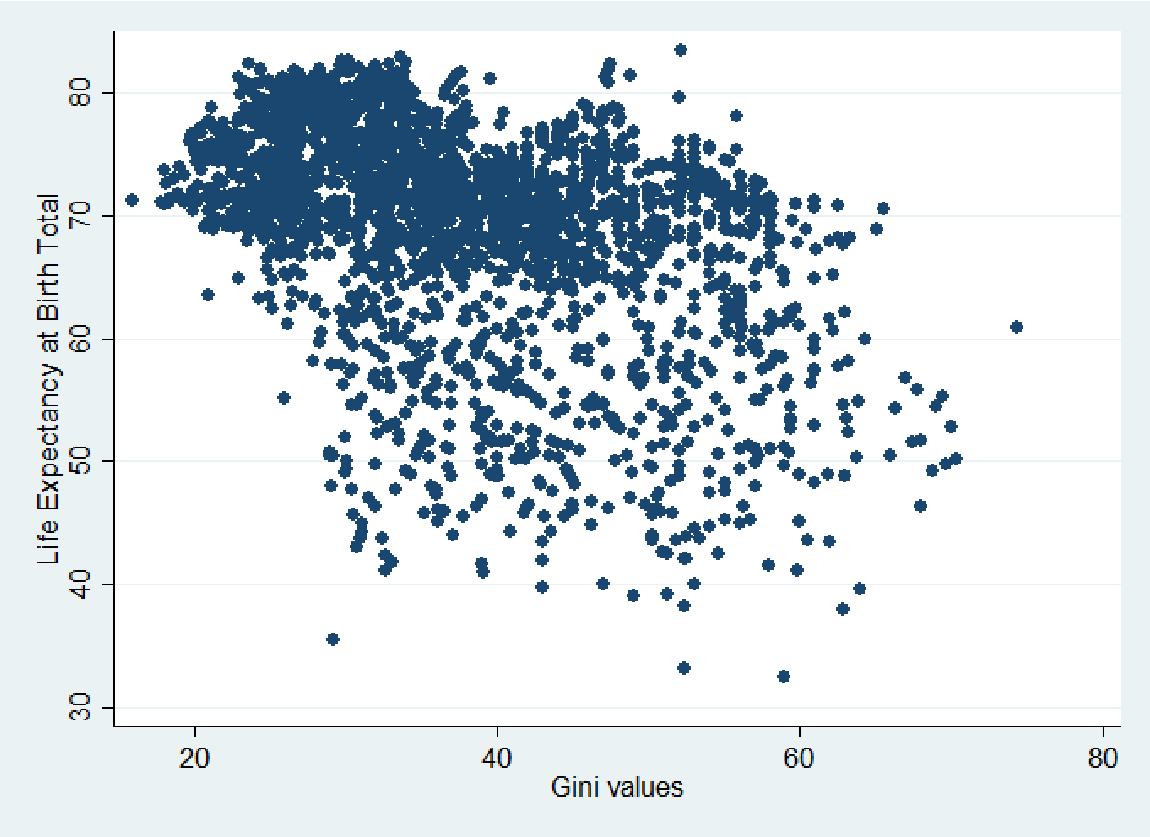

Figure 18 Log (GDP/Capita) & Life Expectancy

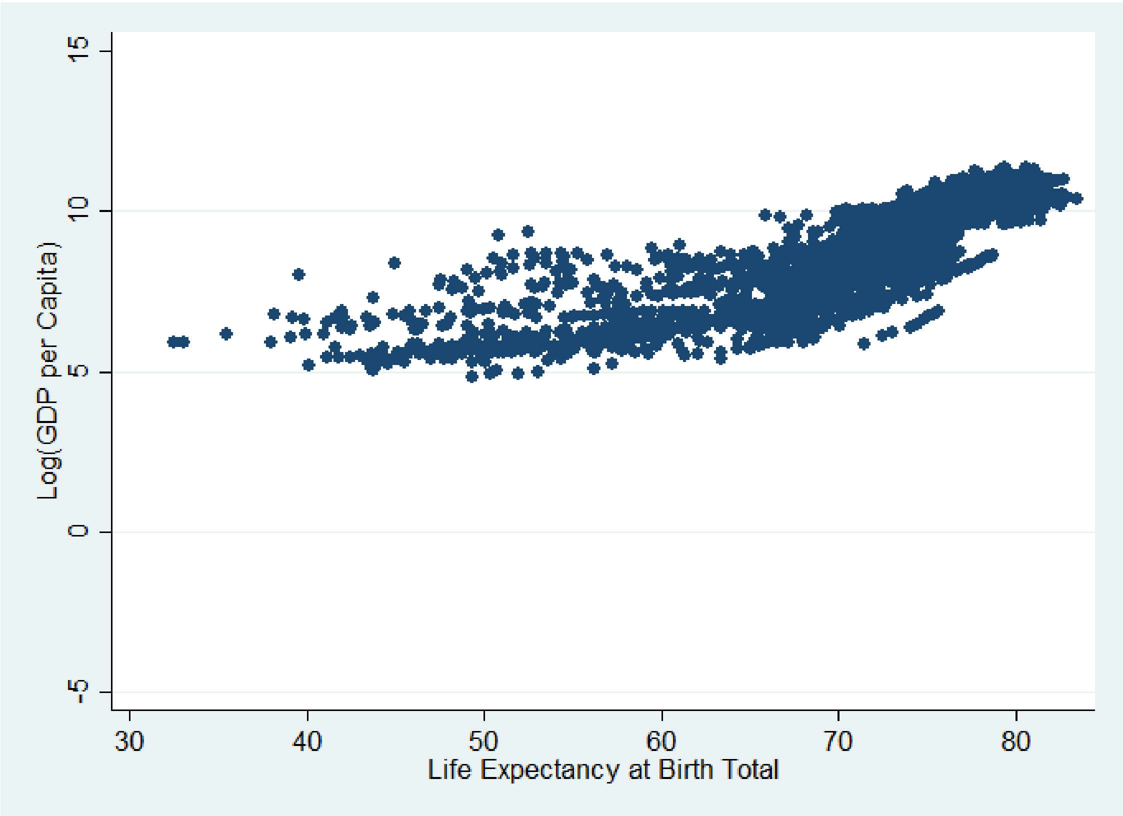

Figure 19 Measles Immunization and Life Expectancy at Birth

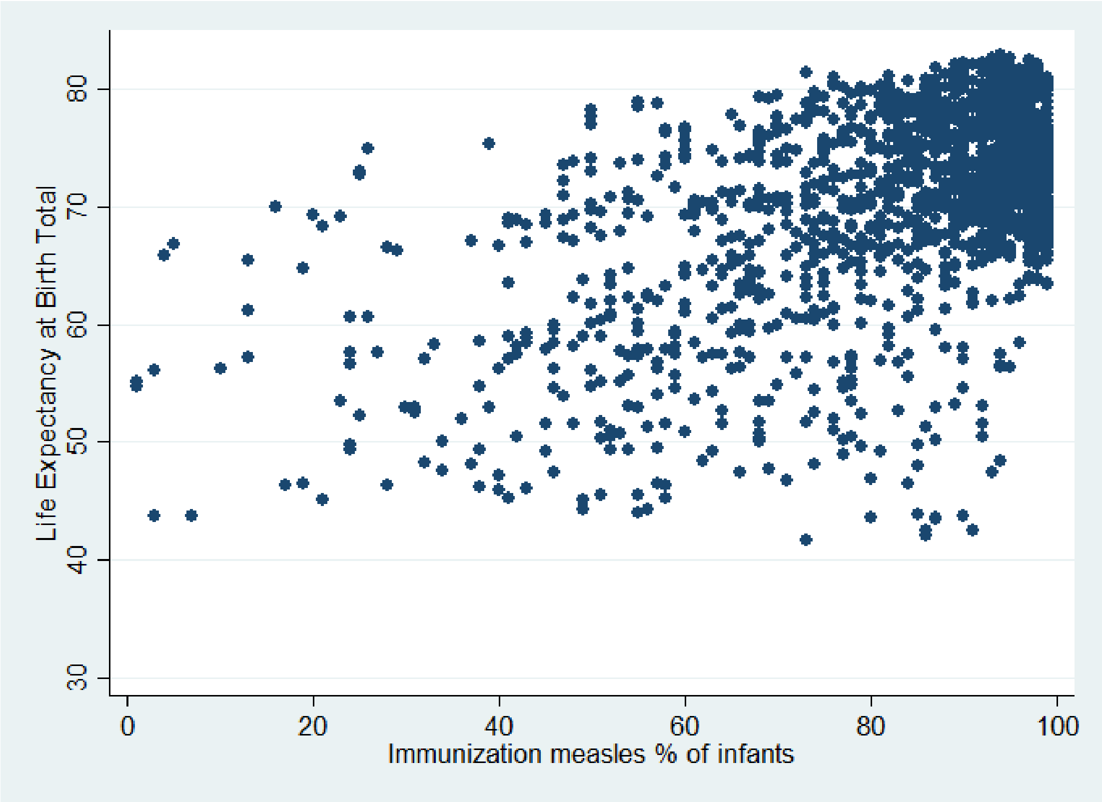

Figure 20 Enrollment Rate and Life Expectancy at Birth

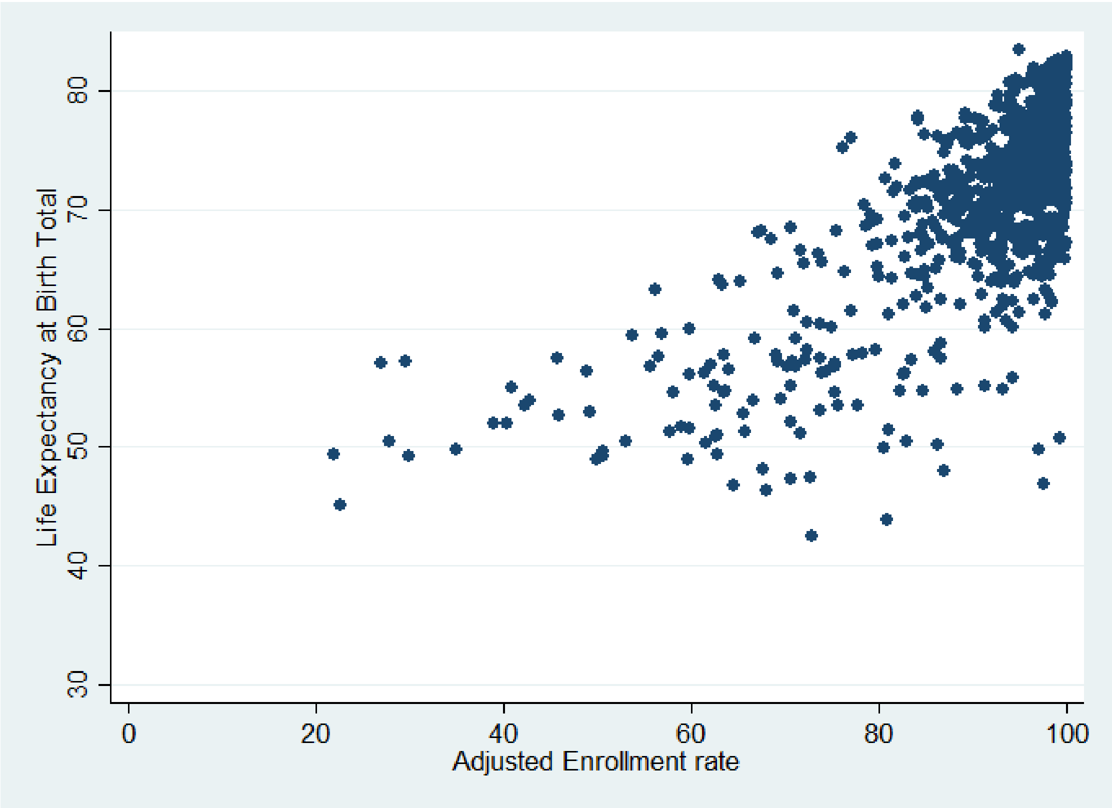

Table 10 OLS Results of the Effects of Inequality on Total Life Expectancy

	Total Life Expectancy from Birth					
VARIABLES	LEBTot	LEBTot	LEBTot	LEBTot	LEBTot	LEBTot
Gini	-0.101***	-0.0210*	-0.0173	-0.101**	-0.0210	-0.0173
	(0.0118)	(0.0122)	(0.0122)	(0.0392)	(0.0323)	(0.0326)
Log(GDP/Capita)	4.331***	2.830***	2.878***	4.331***	2.830***	2.878***
	(0.0788)	(0.0885)	(0.0897)	(0.279)	(0.221)	(0.224)
Enrollment Rate		0.205***	0.205***		0.205***	0.205***
		(0.0120)	(0.0125)		(0.0285)	(0.0282)
Measles Immunization Rate		0.0605***	0.0419***		0.0605***	0.0419**
		(0.00761)	(0.00945)		(0.0138)	(0.0190)
Constant	36.46***	24.02***	23.60***	36.46***	24.02***	23.60***
	(0.964)	(1.172)	(1.657)	(3.418)	(2.572)	(2.549)
Observations	2,344	1,075	1,075	2,344	1,075	1,075
R-squared	0.649	0.810	0.822	0.649	0.810	0.822
Year Dummies			X			X
Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11 Fixed Effects Results of the Effects of Inequality on Total Life Expectancy

	Total Life Expectancy from Birth					
VARIABLES	LEBTot	LEBTot	LEBTot	LEBTot	LEBTot	LEBTot
Gini	-0.0219*	0.0120	-0.00411	-0.0219	0.0120	-0.00411
	(0.0123)	(0.0120)	(0.0107)	(0.0253)	(0.0209)	(0.0193)
Log(GDP/Capita)	8.035***	5.271***	1.067***	8.035***	5.271***	1.067
	(0.189)	(0.246)	(0.322)	(0.599)	(0.572)	(0.902)
Enrollment Rate		0.0891***	0.0647***		0.0891***	0.0647***
		(0.0106)	(0.00944)		(0.0162)	(0.0176)
Measles Immunization Rate		0.0716***	0.0502***		0.0716***	0.0502***
		(0.00490)	(0.00504)		(0.0117)	(0.00948)
Constant	1.903	11.01***	49.70***	1.903	11.01**	49.70***
	(1.757)	(2.089)	(2.922)	(5.178)	(4.411)	(7.399)
Observations	2,344	1,075	1,075	2,344	1,075	1,075
R-squared	0.467	0.662	0.769	0.467	0.662	0.769
Number of Countries	158	125	125	158	125	125
Year Fixed Effects			X			X
Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12 OLS Results of the Effects of Inequality on Female Life Expectancy

	Life Expectancy from Birth Female					
VARIABLES	LEBFem	LEBFem	LEBFem	LEBFem	LEBFem	LEBFem
Gini	-0.109***	-0.0325**	-0.0289**	-0.109**	-0.0325	-0.0289
	(0.0130)	(0.0127)	(0.0128)	(0.0438)	(0.0363)	(0.0367)
Log(GDP/Capita)	4.573***	2.687***	2.708***	4.573***	2.687***	2.708***
	(0.0863)	(0.0925)	(0.0945)	(0.344)	(0.256)	(0.256)
Enrollment Rate		0.240***	0.239***		0.240***	0.239***
		(0.0126)	(0.0132)		(0.0329)	(0.0336)
Measles Immunization Rate		0.0803***	0.0722***		0.0803***	0.0722***
		(0.00795)	(0.00995)		(0.0138)	(0.0207)
Constant	37.63***	23.79***	23.55***	37.63***	23.79***	23.55***
	(1.056)	(1.224)	(1.745)	(4.187)	(2.693)	(2.762)
Observations	2,344	1,075	1,075	2,344	1,075	1,075
R-squared	0.633	0.812	0.821	0.633	0.812	0.821
Year Dummies			X			X
Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13 Fixed Effects Results of the Effects of Inequality on Female Life Expectancy

	Life Expectancy from Birth Female					
VARIABLES	LEBFem	LEBFem	LEBFem	LEBFem	LEBFem	LEBFem
Gini	-0.0220*	0.0171	0.00710	-0.0220	0.0171	0.00710
	(0.0131)	(0.0116)	(0.0108)	(0.0269)	(0.0203)	(0.0198)
Log(GDP/Capita)	8.080***	4.702***	1.251***	8.080***	4.702***	1.251
	(0.200)	(0.239)	(0.326)	(0.655)	(0.514)	(0.778)
Enrollment Rate		0.0886***	0.0731***		0.0886***	0.0731***
		(0.0103)	(0.00954)		(0.0161)	(0.0175)
Measles Immunization Rate		0.0720***	0.0558***		0.0720***	0.0558***
		(0.00475)	(0.00509)		(0.0106)	(0.00975)
Constant	4.445**	18.98***	49.92***	4.445	18.98***	49.92***
	(1.860)	(2.026)	(2.951)	(5.736)	(4.133)	(6.536)
Observations	2,344	1,075	1,075	2,344	1,075	1,075
R-squared	0.442	0.650	0.740	0.442	0.650	0.740
Number of Countries	158	125	125	158	125	125
Year Fixed Effects			X			X
Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14 OLS Results of the Effects of Inequality on Male Life Expectancy

	Life Expectancy from Birth Male					
VARIABLES	LEBMale	LEBMale	LEBMale	LEBMale	LEBMale	LEBMale
Gini	-0.0935***	-0.0101	-0.00616	-0.0935**	-0.0101	-0.00616
	(0.0112)	(0.0129)	(0.0128)	(0.0367)	(0.0322)	(0.0325)
Log(GDP/Capita)	4.101***	2.966***	3.040***	4.101***	2.966***	3.040***
	(0.0747)	(0.0939)	(0.0945)	(0.229)	(0.213)	(0.216)
Enrollment Rate		0.171***	0.172***		0.171***	0.172***
		(0.0128)	(0.0132)		(0.0263)	(0.0251)
Measles Immunization Rate		0.0416***	0.0131		0.0416**	0.0131
		(0.00807)	(0.00995)		(0.0163)	(0.0198)
Constant	35.35***	24.24***	23.65***	35.35***	24.24***	23.65***
	(0.914)	(1.243)	(1.745)	(2.861)	(2.684)	(2.629)
Observations	2,344	1,075	1,075	2,344	1,075	1,075
R-squared	0.648	0.777	0.794	0.648	0.777	0.794
Year Dummies			X			X
Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15 Fixed Effects Results of the Effects of Inequality on Male Life Expectancy

	Life Expectancy from Birth Male					
VARIABLES	LEBMale	LEBMale	LEBMale	LEBMale	LEBMale	LEBMale
Gini	-0.0219*	0.00733	-0.0147	-0.0219	0.00733	-0.0147
	(0.0119)	(0.0130)	(0.0113)	(0.0244)	(0.0227)	(0.0201)
Log(GDP/Capita)	7.992***	5.810***	0.888***	7.992***	5.810***	0.888
	(0.182)	(0.267)	(0.341)	(0.559)	(0.662)	(1.049)
Enrollment Rate		0.0896***	0.0567***		0.0896***	0.0567***
		(0.0115)	(0.00998)		(0.0176)	(0.0189)
Measles Immunization Rate		0.0713***	0.0448***		0.0713***	0.0448***
		(0.00531)	(0.00533)		(0.0136)	(0.0103)
Constant	-0.517	3.427	49.51***	-0.517	3.427	49.51***
	(1.697)	(2.262)	(3.088)	(4.786)	(4.982)	(8.529)
Observations	2,344	1,075	1,075	2,344	1,075	1,075
R-squared	0.482	0.650	0.772	0.482	0.650	0.772
Number of Countries	158	125	125	158	125	125
Year Fixed Effects			X			X
Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16 OLS Results of the Effects of Inequality on Male Mortality Rate

	Mortality Rate Male					
VARIABLES	MortMale	MortMale	MortMale	MortMale	MortMale	MortMale
Gini	1.230***	0.239	0.186	1.230**	0.239	0.186
	(0.156)	(0.253)	(0.256)	(0.566)	(0.658)	(0.655)
Log(GDP/Capita)	-40.82***	-38.24***	-39.26***	-40.82***	-38.24***	-39.26***
	(1.043)	(1.848)	(1.899)	(3.438)	(4.261)	(4.149)
Enrollment Rate		-1.552***	-1.635***		-1.552***	-1.635***
		(0.248)	(0.261)		(0.511)	(0.499)
Measles Immunization Rate		0.671***	1.080***		0.671*	1.080**
		(0.157)	(0.197)		(0.391)	(0.426)
Constant	520.3***	609.9***	643.8***	520.3***	609.9***	643.8***
	(12.68)	(24.18)	(34.54)	(45.87)	(56.07)	(58.02)
Observations	2,297	1,045	1,045	2,297	1,045	1,045
R-squared	0.499	0.534	0.552	0.499	0.534	0.552
Year Dummies			X			X
Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17 Fixed Effects Results of the Effects of Inequality on Male Mortality Rate

	Mortality Rate Male					
VARIABLES	MortMale	MortMale	MortMale	MortMale	MortMale	MortMale
Gini	0.0210	-0.0925	-0.0123	0.0210	-0.0925	-0.0123
	(0.137)	(0.218)	(0.223)	(0.261)	(0.327)	(0.377)
Log(GDP/Capita)	-74.78***	-58.53***	-24.89***	-74.78***	-58.53***	-24.89
	(2.106)	(4.454)	(6.716)	(6.444)	(12.59)	(19.72)
Enrollment Rate		-0.602***	-0.377*		-0.602**	-0.377
		(0.190)	(0.194)		(0.280)	(0.301)
Measles Immunization Rate		-0.621***	-0.453***		-0.621***	-0.453**
		(0.0879)	(0.104)		(0.182)	(0.201)
Constant	854.6***	824.4***	517.3***	854.6***	824.4***	517.3***
	(19.55)	(37.65)	(60.73)	(56.63)	(90.29)	(158.5)
Observations	2,297	1,045	1,045	2,297	1,045	1,045
R-squared	0.380	0.375	0.434	0.380	0.375	0.434
Number of Countries	158	125	125	158	125	125
Year Fixed Effects			X			X
Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18 OLS Results of the Effects of Inequality on Female Mortality Rate

			Mortality Rate Female			
VARIABLES	MortFem	MortFem	MortFem	MortFem	MortFem	MortFem
Gini	1.522***	0.911***	0.878***	1.522***	0.911	0.878
	(0.147)	(0.194)	(0.198)	(0.554)	(0.564)	(0.564)
Log(GDP/Capita)	-38.99***	-20.73***	-20.67***	-38.99***	-20.73***	-20.67***
	(0.985)	(1.419)	(1.467)	(3.735)	(3.458)	(3.391)
Enrollment Rate		-2.702***	-2.738***		-2.702***	-2.738***
		(0.190)	(0.202)		(0.544)	(0.564)
Measles Immunization Rate		-0.270**	-0.240		-0.270	-0.240
		(0.120)	(0.152)		(0.225)	(0.308)
Constant	411.1***	536.5***	548.2***	411.1***	536.5***	548.2***
	(11.98)	(18.57)	(26.68)	(46.83)	(45.70)	(47.05)
Observations	2,297	1,045	1,045	2,297	1,045	1,045
R-squared	0.521	0.608	0.619	0.521	0.608	0.619
Year Dummies			X			X
Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19 Fixed Effects Results of the Effects of Inequality on Female Mortality Rate

			Mortality Rate Female			
VARIABLES	MortFem	MortFem	MortFem	MortFem	MortFem	MortFem
Gini	-0.185	-0.396**	-0.463**	-0.185	-0.396	-0.463
	(0.142)	(0.190)	(0.196)	(0.285)	(0.281)	(0.329)
Log(GDP/Capita)	-62.06***	-25.56***	-12.70**	-62.06***	-25.56***	-12.70
	(2.189)	(3.871)	(5.881)	(7.213)	(8.235)	(10.24)
Enrollment Rate		-0.524***	-0.575***		-0.524***	-0.575***
		(0.165)	(0.170)		(0.193)	(0.210)
Measles Immunization Rate		-0.551***	-0.553***		-0.551***	-0.553***
		(0.0764)	(0.0912)		(0.0893)	(0.147)
Constant	671.9***	448.3***	355.2***	671.9***	448.3***	355.2***
	(20.32)	(32.72)	(53.19)	(65.48)	(62.42)	(84.63)
Observations	2,297	1,045	1,045	2,297	1,045	1,045
R-squared	0.278	0.233	0.295	0.278	0.233	0.295
Number of Countries	158	125	125	158	125	125
Year Fixed Effects			X			X
Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20 OLS Results of the Effects of Inequality on Infant Mortality Rate

			Mortality Rate Infant			
VARIABLES	MortInf	MortInf	MortInf	MortInf	MortInf	MortInf
Gini	0.332***	0.124***	0.121***	0.332**	0.124	0.121
	(0.0518)	(0.0359)	(0.0362)	(0.161)	(0.108)	(0.106)
Log(GDP/Capita)	-15.73***	-7.171***	-7.184***	-15.73***	-7.171***	-7.184***
	(0.349)	(0.262)	(0.267)	(1.524)	(0.740)	(0.712)
Enrollment Rate		-0.813***	-0.770***		-0.813***	-0.770***
		(0.0355)	(0.0371)		(0.101)	(0.101)
Measles Immunization Rate		-0.378***	-0.433***		-0.378***	-0.433***
		(0.0224)	(0.0280)		(0.0736)	(0.0769)
Constant	153.0***	187.8***	178.1***	153.0***	187.8***	178.1***
	(4.300)	(3.464)	(4.914)	(18.49)	(9.657)	(10.24)
Observations	2,281	1,073	1,073	2,281	1,073	1,073
R-squared	0.569	0.842	0.850	0.569	0.842	0.850
Year Dummies			X			X
Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 21 Fixed Effects Results of the Effects of Inequality on Infant Mortality Rate

			Mortality Rate Infant			
VARIABLES	MortInf	MortInf	MortInf	MortInf	MortInf	MortInf
Gini	0.174***	0.0196	0.0289	0.174	0.0196	0.0289
	(0.0612)	(0.0444)	(0.0453)	(0.135)	(0.102)	(0.0930)
Log(GDP/Capita)	-25.97***	-8.661***	-2.379*	-25.97***	-8.661***	-2.379
	(0.946)	(0.914)	(1.376)	(3.367)	(2.542)	(4.550)
Enroll		-0.574***	-0.530***		-0.574***	-0.530***
		(0.0394)	(0.0403)		(0.136)	(0.126)
ImmuMeas		-0.259***	-0.264***		-0.259***	-0.264***
		(0.0181)	(0.0214)		(0.0602)	(0.0635)
Constant	246.6***	172.1***	111.8***	246.6***	172.1***	111.8***
	(8.882)	(7.794)	(12.53)	(29.21)	(21.10)	(41.32)
Observations	2,281	1,073	1,073	2,281	1,073	1,073
R-squared	0.281	0.561	0.605	0.281	0.561	0.605
Number of cntry	155	124	124	155	124	124
Year Fixed Effects			X			X
Cluster-robust Standard Errors				X	X	X

Table 22 OLS Results of the Effects of Inequality on Life Expectancy from Birth by Region

		LEBTot	LEBTot	LEBTot	LEBTot	LEBTot	LEBTot
Africa	Gini	-0.217***	-0.246***	-0.262***	-0.217***	-0.246***	-0.262***
		(0.0434)	(0.0597)	(0.0714)	(0.0771)	(0.0864)	(0.0842)
	Observations	252	83	83	252	83	83
	R-squared	0.253	0.527	0.702	0.253	0.527	0.702
Asia	Gini	0.105**	0.0612	0.0197	0.105	0.0612	0.0197
		(0.0430)	(0.0674)	(0.0786)	(0.0712)	(0.112)	(0.115)
	Observations	321	105	105	321	105	105
	R-squared	0.749	0.878	0.918	0.749	0.878	0.918
Central America	Gini	0.250**	0.109	0.369***	0.250	0.109	0.369**
		(0.102)	(0.0677)	(0.0954)	(0.179)	(0.111)	(0.0983)
	Observations	109	53	53	109	53	53
	R-squared	0.227	0.675	0.826	0.227	0.675	0.826
Europe	Gini	-0.0626***	0.0856***	0.0359*	-0.0626**	0.0856	0.0359
		(0.0137)	(0.0212)	(0.0194)	(0.0287)	(0.0568)	(0.0618)
	Observations	816	471	471	816	471	471
	R-squared	0.545	0.701	0.790	0.545	0.701	0.790
Middle East	Gini	-0.844***	-0.507***	-0.546***	-0.844***	-0.507***	-0.546**
		(0.0953)	(0.0792)	(0.116)	(0.156)	(0.0685)	(0.216)
	Observations	92	44	44	92	44	44
	R-squared	0.639	0.900	0.967	0.639	0.900	0.967
North America	Gini	-0.264***	0.0138	-0.0217	-0.264	0.0138	-0.0217***
		(0.0303)	(0.0805)	(0.0648)	(0.0787)	(0.0498)	(4.91e-08)
	Observations	95	35	35	95	35	35
	R-squared	0.811	0.229	0.998	0.811	0.229	0.998
Oceania	Gini	0.0538	0.0499	-0.111***	0.0538*	0.0499**	-0.111***
		(0.0429)	(0.0483)	(0.0267)	(0.0196)	(0.0108)	(0.000738)
	Observations	86	52	52	86	52	52
	R-squared	0.679	0.871	0.994	0.679	0.871	0.994
Post-Soviet	Gini	0.0190	-0.0164	0.0176	0.0190	-0.0164	0.0176
		(0.0243)	(0.0409)	(0.0406)	(0.0690)	(0.0510)	(0.0548)
	Observations	202	84	84	202	84	84
	R-squared	0.041	0.125	0.486	0.041	0.125	0.486
South America	Gini	-0.111**	-0.0978**	-0.0473	-0.111	-0.0978*	-0.0473
		(0.0449)	(0.0378)	(0.0524)	(0.113)	(0.0480)	(0.0606)
	Observations	264	110	110	264	110	110
	R-squared	0.349	0.696	0.780	0.349	0.696	0.780
West Indies	Gini	-0.0978	-0.129**	-0.136	-0.0978	-0.129	-0.136
		(0.0624)	(0.0608)	(0.101)	(0.0821)	(0.0971)	(0.126)
	Observations	107	38	38	107	38	38
	R-squared	0.089	0.385	0.786	0.089	0.385	0.786
Explanatory Variables			X	X		X	X
Year Dummies				X			X
Cluster-robust Standard Errors					X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 23 OLS Results of the Effects of Inequality on Life Expectancy from Birth by Income Group

		LEBTot	LEBTot	LEBTot	LEBTot	LEBTot	LEBTot
Low Income	Gini	-0.235***	-0.0804	-0.155	-0.235***	-0.0804	-0.155
		(0.0482)	(0.0733)	(0.133)	(0.0719)	(0.0950)	(0.181)
	Observations	160	55	55	160	55	55
	R-squared	0.220	0.512	0.634	0.220	0.512	0.634
Low Middle	Gini	-0.196***	-0.182***	-0.169***	-0.196**	-0.182**	-0.169*
		(0.0372)	(0.0366)	(0.0442)	(0.0832)	(0.0796)	(0.0987)
	Observations	462	181	181	462	181	181
	R-squared	0.292	0.557	0.605	0.292	0.557	0.605
Upper Middle	Gini	-0.204***	0.0131	0.0136	-0.204***	0.0131	0.0136
		(0.0213)	(0.0206)	(0.0210)	(0.0592)	(0.0433)	(0.0422)
	Observations	636	283	283	636	283	283
	R-squared	0.212	0.301	0.401	0.212	0.301	0.401
High Income OECD	Gini	-0.0388***	0.0701***	0.0242	-0.0388	0.0701	0.0242
		(0.0133)	(0.0186)	(0.0172)	(0.0422)	(0.0598)	(0.0637)
	Observations	885	485	485	885	485	485
	R-squared	0.585	0.560	0.705	0.585	0.560	0.705
High Income Non-OECD	Gini	-0.117***	-0.104*	-0.150*	-0.117	-0.104	-0.150
		(0.0297)	(0.0614)	(0.0866)	(0.0816)	(0.132)	(0.154)
	Observations	196	70	70	196	70	70
	R-squared	0.500	0.475	0.742	0.500	0.475	0.742
Explanatory Variables			X	X		X	X
Year Dummies				X			X
Cluster-robust Standard Errors					X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 24 OLS Results of the Effects of Inequality on Infant Mortality by Region

		MortInf	MortInf	MortInf	MortInf	MortInf	MortInf
Africa	Gini	0.647***	0.473***	0.459**	0.647**	0.473**	0.459*
		(0.197)	(0.156)	(0.198)	(0.297)	(0.196)	(0.260)
	Observations	244	83	83	244	83	83
	R-squared	0.297	0.721	0.803	0.297	0.721	0.803
Asia	Gini	-0.949***	-0.988***	-0.825***	-0.949*	-0.988***	-0.825**
		(0.261)	(0.232)	(0.267)	(0.518)	(0.310)	(0.285)
	Observations	278	103	103	278	103	103
	R-squared	0.648	0.925	0.951	0.648	0.925	0.951
Central America	Gini	-0.795*	0.642***	0.292	-0.795	0.642	0.292
		(0.468)	(0.204)	(0.255)	(0.952)	(0.379)	(0.188)
	Observations	109	53	53	109	53	53
	R-squared	0.103	0.628	0.843	0.103	0.628	0.843
Europe	Gini	0.315***	-0.0791**	-0.00602	0.315*	-0.0791	-0.00602
		(0.0345)	(0.0319)	(0.0312)	(0.158)	(0.0738)	(0.0735)
	Observations	820	471	471	820	471	471
	R-squared	0.403	0.643	0.713	0.403	0.643	0.713
Middle East	Gini	3.650***	1.281***	1.285***	3.650***	1.281***	1.285**
		(0.498)	(0.254)	(0.297)	(0.616)	(0.191)	(0.527)
	Observations	87	44	44	87	44	44
	R-squared	0.546	0.857	0.970	0.546	0.857	0.970
North America	Gini	0.563***	0.0442	0.182	0.563	0.0442	0.182***
		(0.0373)	(0.0816)	(0.0951)	(0.103)	(0.0615)	(2.09e-07)
	Observations	95	35	35	95	35	35
	R-squared	0.929	0.254	0.996	0.929	0.254	0.996
Oceania	Gini	0.0363	-0.0149	0.156***	0.0363	-0.0149	0.156***
		(0.0760)	(0.0423)	(0.0280)	(0.0811)	(0.0258)	(0.000700)
	Observations	86	52	52	86	52	52
	R-squared	0.765	0.927	0.995	0.765	0.927	0.995
Post-Soviet	Gini	-0.303*	0.263	0.205	-0.303	0.263	0.205
		(0.156)	(0.181)	(0.214)	(0.416)	(0.196)	(0.275)
	Observations	202	84	84	202	84	84
	R-squared	0.301	0.713	0.763	0.301	0.713	0.763
South America	Gini	0.511**	0.341***	0.0829	0.511	0.341	0.0829
		(0.218)	(0.129)	(0.155)	(0.564)	(0.262)	(0.226)
	Observations	261	110	110	261	110	110
	R-squared	0.265	0.684	0.828	0.265	0.684	0.828
West Indies	Gini	0.546***	0.376**	0.320	0.546**	0.376	0.320
		(0.204)	(0.165)	(0.290)	(0.196)	(0.365)	(0.327)
	Observations	99	38	38	99	38	38
	R-squared	0.288	0.402	0.768	0.288	0.402	0.768
	Explanatory Variables		X	X		X	X
	Year Dummies			X			X
	Cluster-robust Standard Errors				X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 25 OLS Results of the Effects of Inequality on Infant Mortality by Income Group

		MortInf	MortInf	MortInf	MortInf	MortInf	MortInf
Low Income	Gini	0.574**	-0.280	-0.418	0.574	-0.280	-0.418
		(0.261)	(0.226)	(0.325)	(0.393)	(0.235)	(0.506)
	Observations	157	55	55	157	55	55
	R-squared	0.120	0.733	0.874	0.120	0.733	0.874
Low Middle	Gini	0.585***	0.560***	0.588***	0.585*	0.560***	0.588**
		(0.165)	(0.101)	(0.118)	(0.336)	(0.197)	(0.222)
	Observations	431	179	179	431	179	179
	R-squared	0.287	0.759	0.797	0.287	0.759	0.797
Upper Middle	Gini	0.900***	0.319***	0.302***	0.900***	0.319**	0.302**
		(0.0822)	(0.0550)	(0.0544)	(0.192)	(0.129)	(0.119)
	Observations	624	283	283	624	283	283
	R-squared	0.312	0.612	0.689	0.312	0.612	0.689
High Income OECD	Gini	0.305***	0.0361**	0.112***	0.305**	0.0361	0.112**
		(0.0332)	(0.0177)	(0.0136)	(0.126)	(0.0468)	(0.0416)
	Observations	883	485	485	883	485	485
	R-squared	0.466	0.515	0.773	0.466	0.515	0.773
High Income Non-OECD	Gini	0.449***	0.423***	0.375***	0.449*	0.423***	0.375***
		(0.0848)	(0.0542)	(0.0513)	(0.208)	(0.0841)	(0.0524)
	Observations	177	70	70	177	70	70
	R-squared	0.390	0.893	0.976	0.390	0.893	0.976
Explanatory Variables			X	X		X	X
Year Dummies				X			X
Cluster-robust Standard Errors					X	X	X

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1