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Income inequality and life expectancy

A study on inequality and its potential effect on longevity

by

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The potential effects of income inequality have received much attention from researcher and policy-makers in recent years. Income inequality is found by many researchers to have negative effect on health outcomes, crime rates and long-term economic growth. Previous studies have focused mainly on developed countries due to data availability. This study aims at further investigate the hypothesis of income inequality's effect on life expectancy by using a panel which also includes developing countries. The Palma ratio for measuring income inequality is used, which largely increase the number of countries and observations included in the analysis compared to previous studies. The ratio consists of the top 10 percent of the income share divided with the bottom 40 percent. The Palma ratio inequality measure is more sensitive to changes in income inequality compared to the Gini-coefficient and allows for more variation in the inequality measure, allowing for more statistical power with the use of a fixed effects model. The Palma ratio has to my knowledge not been used in studies looking at income inequality and life expectancy. The results of this study indicate that income inequality is strongly associated with life expectancy and finds a cut-off point for the effect of GDP per capita on longevity, supporting the previous findings of diminishing effect of GDP per capita on life expectancy.

Keywords*: income inequality, life expectancy, longevity, economic inequality*

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1 Introduction

The potential effects of economic inequality have interested many, and researchers disagree on whether increasing economic inequality is beneficial or detrimental. Some believe income inequalities in society reflect differences in work effort and other self-caused differences. Income inequality will therefore turn it into an engine for growth as individuals have incentives to work and perform. Others have found income inequality to be linked with higher crime rates, poorer population health and inequality in political power, which again could reduce long-term growth.

In the last decades, a global trend of rising economic inequality has been given large coverage in media and by researchers. The world has seen an increase in economic inequality the last decade, after a period of lower economic inequality. Following the Second World War, income inequality was lower, in many countries decreasing until 1980s and 1990s. This relative new trend of increasing income inequality is of great interest to both policy-makers and researcher, as policies and government interventions have a large impact on inequality. Even so, the recent discussion on inequality also has a more global dimension, as the world today allows people, labor and capital to move across countries and continents (Piketty & Goldhammer, 2014; Saez, 2014).

Findings suggest that economic inequality leads to other forms of inequality, such as inequality in health, education and opportunities. Studies have shown that societies with high economic inequality also have poorer health outcomes and lower life expectancy. The potential effects of income (and economic) inequality could be formative for policy-makers, giving indications on the optimal tax system, redistribution and other public goods and/or interventions. Public policy can potentially have a large impact on population and the economic growth of a country (Neumayer & Plümper, 2016).

Life expectancy in the world is far from converged, but a trend towards convergence can be observed. Many developing countries are rapidly catching up to the longevity of developed countries and life expectancy is increasing faster for developing countries than it did for developed countries, just as with many other factors of development. Even if development is faster today, there are still large differences in life expectancy in the world. In 2016, Japan had an average life expectancy of 83.7 years while an individual born in Sierra Leone could expect to live for 50.1 years. The highest to lowest life expectancy in 2016 had a difference of 33.6 years (United Nations, Department of Economic and Social Affairs, Population Division, 2017).

This study attempts to study the relationship between income inequality and life expectancy, to be able to identify potential effect of income inequality on population life expectancy. The research question is therefore:

- **To what extent does income inequality affect life expectancy?**

The aim of this study is to further develop research on life expectancy and income inequality and investigate how important income inequality is to longevity in the population. This is done through further developing the studies of other researchers, such as Babones (2008) and Neumayer and Plümper (2016). Both Babones and Neumayer and Plümper find correlations between income inequality and longevity. The study by Neumayer and Plümper is done using a fixed effects model on 28 developed countries over approx. 37 years (1974-2011). Babones uses a larger panel from 1970-1995, but as with most studies in inequality, data is scarce, especially for developing countries. These studies are here developed by including developing countries in the model, as these countries experience a more rapid increase in life expectancy than the western countries did. They also have larger variations in both life expectancy and income inequality than the OECD-countries included in the Neumayer and Plümper study. Data included will be a panel of all countries, similar to the data structure of Babones.

Research have looked into many different explanations for life expectancy, but no single variable is found to explain the differences between countries. Many factors seem to be relevant, stretching from economic development to nutrition and climate. Even so, research has pointed toward income inequality as an important explanatory variable in explaining population health outcomes, hereby also life expectancy(Wilkinson & Pickett, 2006).

Looking at economic development measured in GDP per capita and change in life expectancy, there does seem to be a strong correlation for developing countries. The correlation between the two variables is reduced the more developed the country becomes. For highly developed countries, the correlation between GDP per capita is smaller, and other explanations must be found to explain the differences in life expectancy. This could also indicate that GDP per capita might capture other explanatory variables (United Nations, Department of Economic and Social Affairs, Population Division, 2017).

An empirical example on the correlation made by Wilkinson (1992) is the development in GDP per capita compared to income inequality for the UK and Japan since the 1970s. At that point, their life expectancies were fairly similar, as was their level of economic development. Through the 1980s, income inequality increased substantially in Great Britain, while Japan's income inequality stayed relatively stable and this difference in income inequality between the countries has been consistent since. Today, Japan's life expectancy is almost 84 years, while for Great Britain close to 81.

Population health is of great interest to policy-makers. If a large portion of the population are healthy and in working age, there are more individuals contributing to the economy and the government. One important measure used in measuring health outcomes is life expectancy, as a low life expectancy indicate a young population and poor health situation for the population. This can be due to nutrition, diseases (for example HIV), poor health care or lack of such. Life expectancy gives indications of the development of a country and the health status of a population. For many of the less developed countries, infant and child mortality has a large impact on the life expectancy. When many children die in their first years of life, the average age of the cohort is largely reducing. A reduction in child mortality will therefore have a large effect on life expectancy in countries where child mortality is high (United Nations, Department of Economic and Social Affairs, Population Division, 2017; Wilkinson & Pickett, 2010).

Connected to this is the historical development of life expectancy. Reducing child mortality gives countries a large increase in life expectancy. For countries that have a low child mortality and access to health care (thus reducing death rates for treatable diseases), longevity is mainly increased due to individuals living longer. The trend in life expectancy is found to increase every year, but only marginally. This increase in life expectancy is substantially smaller than what can be observed by a reduction in child mortality. Developed countries will therefore be likely to have less of an effect by any variable compared to less developed countries, as the potential to increase is smaller.

The puzzle of income inequality and its potential effect on life expectancy lies in the complexity of explaining the differences in life expectancy between countries. Many factors have been found to have an effect, such as GDP per capita, access to health care, poverty, and disease prevention, but all are also found to have diminished explanatory power as countries develop and increase their life expectancy. Even so, large differences in longevity is found across developed countries. As an example - women in Singapore can expect to be 86.1 years old, while women in the US can expect to turn 81.6 years if born in 2016. That is a difference in life expectancy of 4.5 years between two countries both considered high-income countries by the World Bank. Further looking at variables that can explain the variation in life expectancy could give a larger insight into the driving forces behind health outcomes and policies that would benefit population health.

This study will include developed and less developed countries from 1990-2017, using newer data than previous researchers. This has several advantages. Firstly, the quality of data has much improved in this time span. Secondly, by using data from 1990 and forward, few countries are left out due to changes in country borders and other political changes. Different from Babones (2008), the main inequality measure used will be the Palma ratio. In this way, data is available, and interpolation and extrapolation can largely be avoided compared to previously used datasets, especially for developing countries. As the Palma ratio is more sensitive to changes in income inequality, there is also more variation in the data, as researchers previously has pointed out the low variation in changes in the Gini-coefficient, which has led to a further reduction in countries included in their studies (Cobham, Schlögl & Sumner, 2016). To my knowledge, the Palma ratio has not been used in studying income inequality and its effect on life expectancy.

This study is limited to income inequality and selected control variables due to data availability and comparability of available data across countries. Other measurements of economic inequality such as wealth or capital is outside the scope of this study. So is also other measurements of inequality, such as inequality in education or other health outcomes.

1.1 Outline of the Thesis

In the next chapter, theories on income inequality and life expectancy will follow and previous research on income inequality and health outcomes will be presented. A short discussion on life expectancy and its development follows before the method and model used in this study is presented. The data is then discussed before the results are presented. Further, a discussion of the results and their relation to previous findings and theories is presented followed by a conclusion.

2 Theory

A theoretical presentation on the relationship between income equality and life expectancy was presented by Rodgers (1979), which built the theory on income inequality and life expectancy based on empirical data. Rodgers found diminishing returns to life expectancy from income inequality. The higher the life expectancy, the less of an effect does a reduction in income inequality have. He emphasises that income inequality is important to increase life expectancy, but that the marginal effect is reduced with the increase of life expectancy. Though not stated in the article, is does seem as Rodgers do assume there is a limit to life expectancy, which in itself would explain the diminishing effect.

There are a number of theories explaining population health outcomes and income inequality. These all try to explain how the individual’s health is change by income inequality. I have identified five general theories on the effect of income inequality on life expectancy in the literature. These theories are not all mutual exclusive, giving that more than one can be explanatory (Rehbein & Guidetti, 2017).

The absolute-income hypothesis assumes that an increase in income at the individual level leads to an increase in individual health. The improvement in health is less than the increase in individual income. Average health will therefore improve if income increase and inequality of income decreases. If income increases for the individual, their health would improve. If income inequality is reducing, the number of individuals with the lowest incomes are reduced, and the average health will be improved according to this hypothesis.

The relative-income hypothesis assumes that on the individual level, health is dependent on the deviation if the individual’s income from the mean income of the population. An individual below the average would have poorer health than someone with an average income, while those with a better income than the average has better health. Higher income-inequality would indicate that more people have income below the average, and this hypothesis suggest that a high income-inequality will have negative effect on health.

The deprivation hypothesis is based on the effect of poverty on life expectancy. If an individual’s income or living standards is under a certain critical level, health status of the individual is reduced. This poverty line or threshold is usually based on level of income or on measurements on standard of living. The deprivation hypothesis suggests that there is a cut-off point for which income have an important explanatory power for the individual’s health outcomes.

The relative-position hypothesis includes not only income levels for the individuals, but also social status. This means that not only income but where an individual is place in the income distribution affects the health status. Thus, even if an individual has a good income, their health outcomes would be lowered if they are relatively poorer than the other members of the society. This hypothesis assumes that income inequality has a large explanatory power independent of economic development, as the relative social status is the important factor. This hypothesis assumes that income inequality will have an effect also for high-income countries (Wilkinson & Pickett, 2010).

The income inequality hypothesis assume that the individual's health is directly affected by income inequality. Income inequality in the country or community of the individual influence health status of the individual, with high income inequality having a negative effect on health outcomes (Rehbein & Guidetti, 2017).

2.1 Previous Research

In 1975, Samuel H. Preston presented a study demonstrating the correlation between GDP per capita and life expectancy known as the Preston curve. This correlation is found to have a curvilinear relationship between life expectancy at birth and national income per capita. When GDP per capita increases, the curve "jumps" to a new curve with higher life expectancy. A further finding of the study is that the data suggest that the within-country income distribution has an impact on life expectancy and that high-income inequality would have a negative effect on life expectancy. Preston's study also suggests that very low inequality, observed in former Soviet also would have a negative effect on life expectancy (Preston, 1975).

Researcher has later showed that there are diminishing returns to life expectancy as GDP per capita increases, suggesting that a certain level of income is important for a higher life expectancy. As countries and economies further develop, other factors become more important in explaining the continuous increase in longevity observed, and GDP per capita loses its explanatory power as countries are still found to have differences in life expectancy (Galbraith, 2016; Wilkinson & Pickett, 2010).

There exists a large body of studies on economic inequality and health outcomes, where life expectancy is one of the most common used variables. The vast majority of the studies are performed on developed countries and a group of OECD-countries in particular. This is mainly motivated by data availability, as data on income levels and distribution has been rather limited for developing countries (Wilkinson & Pickett, 2006).

Rodgers (1979) finds that income and income redistribution are highly significant with life expectancy at birth. The results indicate that more equal countries have higher life expectancy. The results from the study by Rodgers suggest that lower income inequality can increase the life expectancy by birth with five to ten years. Rodgers point out that economic inequality is probably correlated with other types of inequality, for example within education, health care, access to social security and other variables that in turn can affect life expectancy.

Wilkinson (1992) further develops the studies on inequality and longevity. Findings are mainly on developed countries. Wilkinson argues that increased income has diminishing positive effects on health outcomes. He therefore argues that increasing the income of the poor by slightly reducing the income of the rich will to a large degree improve the health of the poor but have little effect on those how are wealthy. Redistribution would therefore increase the average health status of the population.

He further discusses the potential issues of intervening variables, reversed causality and minority or ethnic communities affect the results as a consequence of discrimination, but reject the possibility of this being an issue.

Wilkinson argue that the income effect is based on relative income rather than absolute income. This due to exclusion, socially but also materially, those who are relatively poor in a society will also have poorer health.

Much research and literature from Wilkinson argues that income inequality has a large impact on health. He argues that it is the distribution of income and not the level of income that has the largest impact (over a certain level). A wide income distribution (and then also high-income inequality) generates social differences and the individuals at the bottom experience shame, distrust, lower social capital and other negative consequences which again leads to poorer health situation for the individuals as the bottom at the income distribution. Low social class and socioeconomic status is found by Wilkinson to decrease health status and lower social class and socioeconomic status is more present in a country with high economic inequality (Pickett & Wilkinson, 2015; Wilkinson, 1992; Wilkinson & Pickett, 2010, 2010).

Beckfield (2004) test the hypothesis by introducing a panel of all countries with available data using the Gini-coefficient. The data is an unbalanced panel with both developed and developing countries. Beckfield does not find any correlation between economic inequality and longevity and criticize the theories suggesting a relationship between population health and income inequality. Beckfield's methodology is later criticized, as well as the limited number of observations for each country included.

Babones (2008) concludes, with the use of a large panel including as many countries as data availability allows for in the time period 1970-1995 using the Gini-coefficient as the income inequality measure. He finds that there is a significant effect of inequality on life expectancy and infant mortality. The data used in Babones (2008) study is scarce, as much interpolation and extrapolation are done. This is both reducing the quality and variation in the data. The lack of data could also create large bias' in the results, as the problem of scarce data is found to be larger for less developed countries and countries with poor statistical services. Babones (2008) concludes in his study that there is a link between income inequality and life expectancy.

The findings of Babones (2008) is supported by Neumayer and Plümper (2016), with the addition of policy recommendations. Using data on 28 OECD-countries over a 37-year time period including the Gini-coefficient, life expectancy, GDP per capita and health/mortality related control variables. The conclusion of the fixed effects OLS-estimation leads the authors to conclude that longevity can be increased through public policy by reducing income inequality and increase redistribution from the relatively rich to the relatively poor.

A study that uses individual and multilevel data from Zambia on income levels and child nutrition health looks at the issue of income inequality and its effect on health. They find support for the absolute income-hypothesis. Thus, absolute income levels have an effect on health outcomes in Zambia, a less developed country. The study is performed on a developing country, and there could be suspected that absolute individual income does have diminishing effects on health outcomes, but that a certain level of income in necessary for the individual to uphold a certain level of health. This would mean that when the individual's income increases past a certain level, the effect of a higher individual income might be reduced. They do not find support for the income inequality hypothesis, but their findings do support Wilkinson in that income inequality gives different results for rich and poor as of population health. The authors also point out the gap in research on inequality and health outcomes for developing countries (Nilsson & Bergh, 2013).

A study on income inequality and life expectancy in the US, the authors use the differences between American states as an attempt to find a potential causal effect of income inequality on life expectancy. Kondo et.al. (2012) finds that there seems to be a threshold of a Gini-coefficient at 0.3. Only when having a Gini-coefficient that reaches below 0.3, income inequality contributes to increase longevity. Few countries today have such a low Gini-coefficient, especially among developing countries. The Nordic countries has a Gini around 0.3, as well as some former Soviet states.

Several comprehensive literature reviews exist covering studies on economic inequality and health outcomes. A literature review from 2006 studies 155 papers on income inequality and health. Findings from the large number of studies includes that many control variables are confounder such as education, class and individual income. The findings also include that economic inequality can give information on the importance of social class or socioeconomic status. Further does most studies agree that the relationship between GDP per capita and health outcomes becomes weaker as GDP per capita increases. Many of the studies find no relationship between life expectancy and GDP per capita among the richest countries (Pickett & Wilkinson, 2015; Wilkinson & Pickett, 2006).

There are also many region and country-specific studies done on inequality and health outcomes. Some examples are Latin-America (Biggs et al., 2010), Eastern Europe after Soviets fall (Bobak et al., 2000), while country-specific studies include among others Argentina (Maio et al., 2012), Brazil (Rasella, Aquino & Barreto, 2013), Canada (Daly, Wilson & Vasdev, 2001), China (Pei & Rodriguez, 2006), Finland (Aittomäki et al., 2014), India (Rajan, Kennedy & King, 2013) and Russia (Walberg et al., 1998).

Much research exists on the relationship between economic inequality and its effect on life expectancy and other health outcomes. Even so, few studies have been able to use a large panel including developing countries due to data availability. This gap in research is also pointed out by several researchers. By using newer data and a new inequality measure this study aims to overcome this issue and contribute to the existing research by looking at income inequality and life expectancy with a broad panel also including developing countries.

2.1.1 Life expectancy

Research on life expectancy has not concluded as of life expectancy and if we are reaching (or can reach) a maximum age. Researchers disagree, where some argue that we have not reached the maximum age yet, but that there is a limit to age. The argument used is the highest age ever reached. The oldest individuals recorded is at the same age as in the 1990's (Dong, Milholland & Vijg, 2016). The author therefore argue that the average age of death is increasing, but that none seem to pass the age limit of the oldest person alive. They therefore reason that more people will reach higher ages, but that there is a limit to human age.

Others uses historical data showing that the increase in life expectancy has increased linearly with approximately 3 months per year. They argue that all predictions on the development of life expectancy has assumed it will slow down, but that the data has proved these predictions wrong (Oeppen & Vaupel, 2002). With the development in life expectancy that has been constantly increasing, they argue there is no evidence that the maximum age will not continue, as the data show no reduction in the increase of life expectancy.

The discussion of life expectancy and the increase is relevant for this study as Rodgers (1975) suggest that the impact of income inequality on life expectancy will decrease. Diminishing returns of income inequality will be a given if there is a maximum limit of longevity, as there will be with all potential explanatory variables. If there is no maximum, the graph can still hold up, but then the diminishing effect of income inequality will be due to that the effect of inequality only has an effect on life expectancy up to a certain level of life expectancy. After this point, the effect is marginal and other factors will have a larger explanatory power.

3 Method

Studies analysing income inequality and longevity have used either quantitative or qualitative methods. Case studies on specific countries or communities have been done, as well as broad panel studies including as many countries as data availability would allow. Most studies would limit themselves to include only OECD-countries or be very restricted as of number of observations per country due to data availability (Pickett & Wilkinson, 2015).

To further develop the quantitative studies on income inequality and life expectancy, a fixed effects model is used, a common used method when studying income inequality and health outcomes. Using fixed effect, the aim is to be able to account for certain types of omitted variables bias. A fixed effects model allows to control for unobserved factors that are fixed over time. The idea is that observations might not be independent for one another so one could expect more similarity within a group than between them. In this study, this would be countries, and the model will therefore create 178 groups when all countries as included, and the unobserved effect is assumed to be a constant country-specific effect not captured in the control variables in the model. This also means that only within-country variation is tested in a fixed effects model, being dependent on within-country variation of the variables (Angrist & Pischke, 2009; Wooldridge, 2010, 2015).

Equation 1: Fixed effects equation.

$$y_{it} == x_{it}\,\beta + \; c_i + u_{it}$$

In a fixed effects model, if y and x are the dependent and independent variable, while c is the unobservable random variable, a fixed effects model attempt to keep c constant as a group-invariant omitted variable. This does not exclude the risk that there is a non-observed error term that varies over time. A fixed effects model controls for the time-invariant omitted variable bias, not the time-varying omitted variable bias, and so only a part of the potential omitted variable bias is removed using this model. There are three conditions for a fixed effect model. Firstly, an instrument- or proxy variable for c cannot be available. Secondly, the data must contain a time dimension (or other types of dimensions). Lastly, c is assumed to be constant (Angrist & Pischke, 2009).

A potential pitfall of using a fixed effects model is that because the model is restricted to within-variation, the fraction of the variation that might be measurement errors increase, making the model more vulnerable for error is the results due to measurement errors. A fixed effect model also restricts the type of variables that can be included as time-invariant variables will not have any variation. Using data on national level usually reduces this issue, as the aggregated level of variables that for an individual is time-invariant can change for a whole population. An example can be that the level of education and be assumed to be relative time-invariant for an adult, while the level of education in the population changes over time. Even so, the data included in the model must include variation, otherwise the variable will be equal to zero in the fixed effects model (Wooldridge, 2010).

To be able to identify the (diminishing) effect of GDP per capita on life expectancy, intervals of GDP per capita is tested in a simple OLS regression. The results will indicate the size of the effect of GDP per capita on life expectancy and whether this effect is significant. This is done to find a cut-off point for the effect of GDP per capita, as previous research suggest a diminishing effect of GDP per capita and to test the deprivation hypothesis presented in section 2.

3.1 Model

Equation 2 shows the model used in this study, where the Palma ratio is the main independent variable. Following the model of Neumayer and Plümper (2016), the control variables include GDP per capita, health expenditures as % of GDP and population size. Both health expenditure and GDP per capita is assumed to have a diminishing effect on life expectancy. These variables are therefore also included as squared. The dependent variable is not found to be autocorrelated in this study, and a lagged dependent variable is not included in the model, unlike Neumayer and Plümper. As this study includes all countries while Neumayer and Plümper only uses a selection of OECD-countries, the model in this study has fewer health controls due to data availability. They control for alcohol and cigarette consumption, as well as grouping the countries together based on health care systems. This data is unfortunately not available for the large panel used in this study.

Following Babones (2008), the fixed effects model is run dividing developed and developing countries in different regressions, with separate models are estimated for high- and low-income countries as well as for the four different income-groups given by the World Bank. This allows for studying the different effect of both income inequality and GDP per capita on developed and developing countries, to find if the effect of income inequality changes dependent on the economic development of a country. Even so, running the model on smaller samples of the dataset also makes the results more likely affected by outliers and can be affected by fewer observations. The model is therefore also run on the complete panel, including all countries with available data. The model is a fixed effects model on years with robust standard errors.

Equation 2: Model - Income inequality's effect on life expectancy, fixed effects model.

$$\begin{aligned} Life\ expectancy \\ &= Palma\ Ratio + log\ GDPperCapita + log\ GDPperCapita^2 \\ &+ log\ Health\ expenditure + log\ Health\ expenditure^2 + Populationsize + \varepsilon \end{aligned}$$

3.2 World Bank income groups

The definition of different categories of development for countries used in this paper is based on the World Bank income classification for countries based on level of GDP per capita. This paper will include all countries where data allows for it. Complete list over included countries and which income-group they belong to is found in the appendix. Countries missing much, or all data will be excluded from the analysis, while data for countries where a particular year are missing will be interpolated using the mean of the previous and following years.

The World Bank divides countries in four categories; low-income economies (995$ or less per capita), lower-middle income economies (996-3895$ per capita), upper-middle-income economies (3,896-12,055$) and high-income countries (12,056$ or more)[1] (World Bank Country and Lending Groups – World Bank Data, 2019).

In this study the two lowest and the two highest income groups are also merged to have a larger sample in the models, but separate regressions are run for each income group as well.

[1] Complete list of the different income-groups can be found in appendix A.

4 Data

This study use a dataset that consists of aggregated data from several sources such as UN, the World Bank and Gapminder (Gapminder, 2019; The World Bank - DataBank, 2019; United Nations Development Programme, 2019). The dataset covers the years 1990 to 2017 but is dependent on which variables are included as not all variables covers the whole time period. When including health expenditures per capita as a control variable, the dataset starts year 2000 due to data limitations. The dataset consists of 179 countries, where the vast majority of countries have data covering the whole time period. Exemptions include countries that did not exist in 1990 such as former Soviet states and countries in former Yugoslavia. A few countries have no or very little data available, such as Somalia, Cuba, North Korea and various smaller island states. They are therefore not included in this study. Certain less developed countries are missing data, but for those countries data is available for more recent years, usually from approximately year 2000. Selection bias and other limitations to the data will be further discussed in chapter 4.3.

The data used is on national level. One could argue for the use of aggregated data on lower level, such as states or regions. One argument by Wilkinson for choosing to use aggregated data on national level and not on smaller regions is the potential effect of segregation. Wilkinson argues that using data on income inequality on too small regions could give incorrect results as people with similar income levels chose to live in the same areas. Using too small levels of data would then lead to little variations in data and would appear as artificially low income inequality for the area studied (Pickett & Wilkinson, 2015; Wilkinson & Pickett, 2010).

Even so, adding data from smaller areas or preferably data on individual level could give deeper insight to what drives income inequality to potentially have an effect on life expectancy. This could potentially also make it possible to control for causes of death and other factors that affects the life expectancy measurement as well as individual income data. A further issue would be that most health data available on individual levels is self-reported. This data is also usually difficult to compare between countries, making the use of data on individual level difficult if wanting to have a global perspective in the research (Wilkinson & Pickett, 2010).

Beckfield (2004) finds no support for the hypothesis of an effect of income inequality on health (life expectancy) which can partly be explained by a large portion missing data. The dataset in this study can include 10 years more compared to Beckfield as well as a larger number of countries, but this study also uses the more recently introduced inequality measure of the Palma ratio which exists for most of the missing years of the Gini from 1990 (United Nations Development Programme, 2019).

4.1 Dependent variable

The data for life expectancy by birth is collected from a dataset by Gapminder, with the life expectancy data mostly collected from the World Bank and some estimations made by Gapminder based on historical data for years missing (Gapminder, 2019). Life expectancy is chosen as it is a variable that is comparable both over time and countries. There is also larger data availability for life expectancy by birth compared to most other health outcome variables. Many other health variables are based on self-reported information which can lead to selection bias or other issue with incorrect data. It can also be difficult to compare self-reported health variables across countries. The variation in the variable is large, with the minimum being 27.9 years and the maximum 84.1, as shown in figure 1. Figure 2 below show the development in life expectancy for the World Bank income groups. It is obvious that all groups have had an increase in life expectancy since 1990. The life expectancy is higher the higher the income group, and all groups show a positive trend from 1990 to 2017, with some countries having a less linear developement. The life expectancy measure is for the whole population and is not separated on gender, where women usually have a higher life expectancy than men.

	Mean	Std. Dev.	Min	Max
Life expectancy	68.09168	9.627221	27.6	84.1

Table 1 Descriptive statistics for life expectancy.

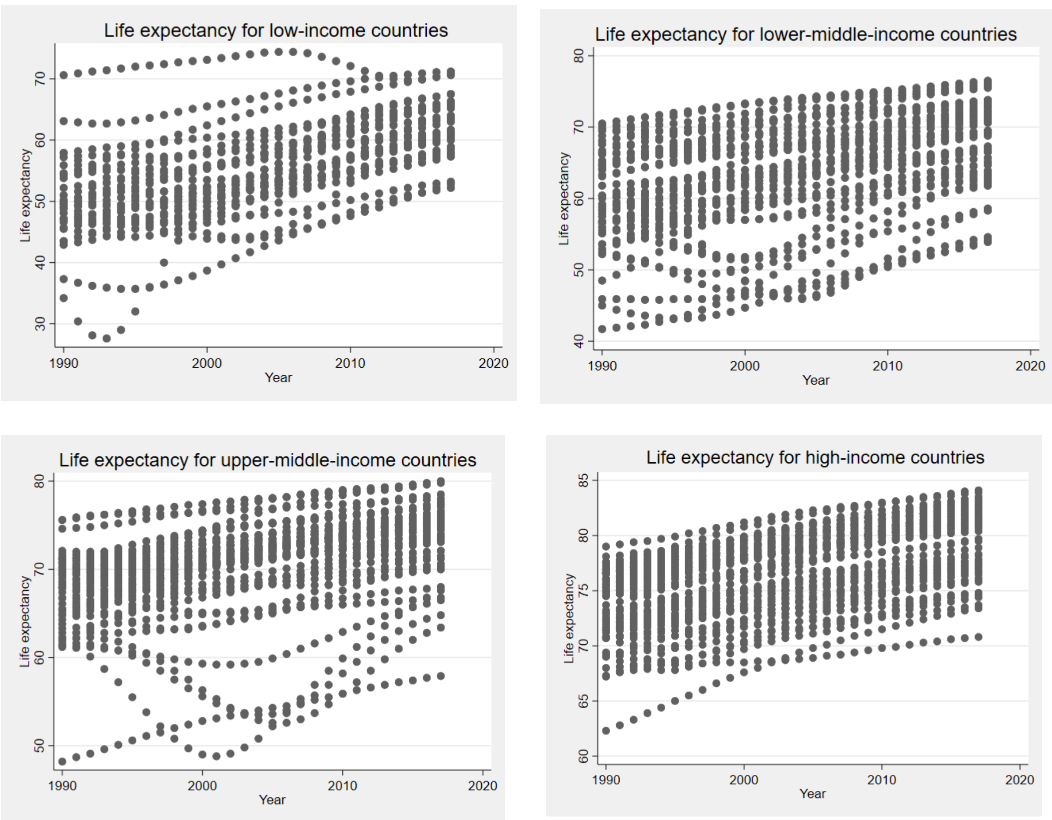

Figure 1 Life expectancy over year by income group.

4.2 Independent variables

The income inequality measure used is the Palma ratio. The Palma ratio data is collected from UN Development Program. The dataset stretches from 1990 to 2017, but for some countries data is only available for more recent years. This is due to survey or register income data is necessary for calculating the ratio, which are missing for certain countries or specific years (United Nations Development Programme, 2019).

The Palma ratio is a ratio that consists of the income share of the top decile to the bottom two quintile (top 10 percent divided by bottom 40 percent). The logic behind the Palma ratio is that the middle class hold a fairly stable income, so the real changes in inequality happens between the top and bottom income shares. As the middle class (middle 50 percent income share) holds a stable share of income, the changes in income inequality is argued to be in the tails, the income divided from the 10 percent richest and the 40 percent poorest in a country. By excluding the middle 50 percent, the measurement also becomes more sensitive to changes, as the stable middle class is not included in the ratio (Cobham, Schlögl & Sumner, 2016; Galbraith, 2016; Palma, 2014).

An advantage with the Palma ratio is that it is a simple and intuitive measure. The ratio is also more sensitive to changes in inequality compared to the Gini-coefficient. This allows for more variation in the data, which is a large advantage as the Gini has very low variation due to the calculation method. The difference in variation can be observed in figure 4, showing the large differences in variation between the Palma ratio and the Gini-coefficient. Further, the Palma ratio also has larger data availability compared to the Gini. This is partially due to the work of the creator of the Palma ratio, making a large effort to create a full dataset. It is also due to the

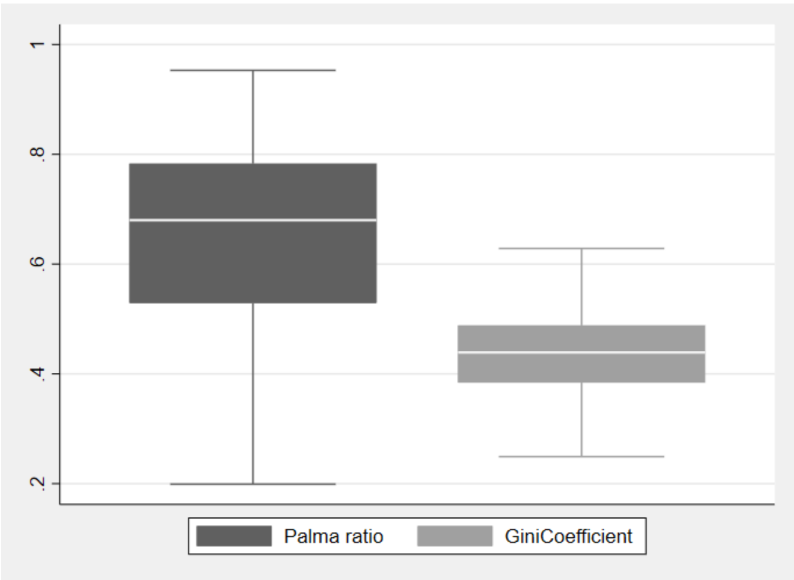

Figure 2 Variation in the Palma ration vs. the Gini-coefficient.

UN including the Palma ratio in their work with economic inequality. There does therefore exist an almost complete dataset of the Palma ratio from 1990 to 2017, with the exception of countries without available income data (Galbraith, 2016; United Nations Development Programme, 2019).

As with the Gini-coefficient, the Palma ratio requires income data from household level on micro-level. This is a disadvantage, just as with the Gini, as some countries does not have this type of data or survey availability, while for some economies, the surveys are of less-than-optimal quality, leading to the necessity to make estimations (Cobham, Schlögl & Sumner, 2016).

There are several reasons why the Palma ratio is used. First, the Gini-coefficient which is most often used is scarce as of data availability, and most so for developing countries. By using the Palma ratio, a larger dataset is available, and more countries is included, reducing the issue of selection bias in countries included. This allows for a full panel including almost all countries. It differs from Gini as the Palma also exist for developing countries. Secondly, the Palma ratio is more sensitive to changes in income inequality which improves the analysis compared to the use of the Gini-coefficient, as can be seen in figure 3. As the Gini-coefficient has had little observed variation for many countries, the dataset used in analysing income inequality has been further limited. This due to the most applicable model is a fixed effects model that only analyse within-variation for each country. Countries with little or no variation will in a fixed effects model be left out, reducing the degrees of freedom, which also reduces the estimation power(Babones, 2008; Beckfield, 2004; Cobham, Schlögl & Sumner, 2016).

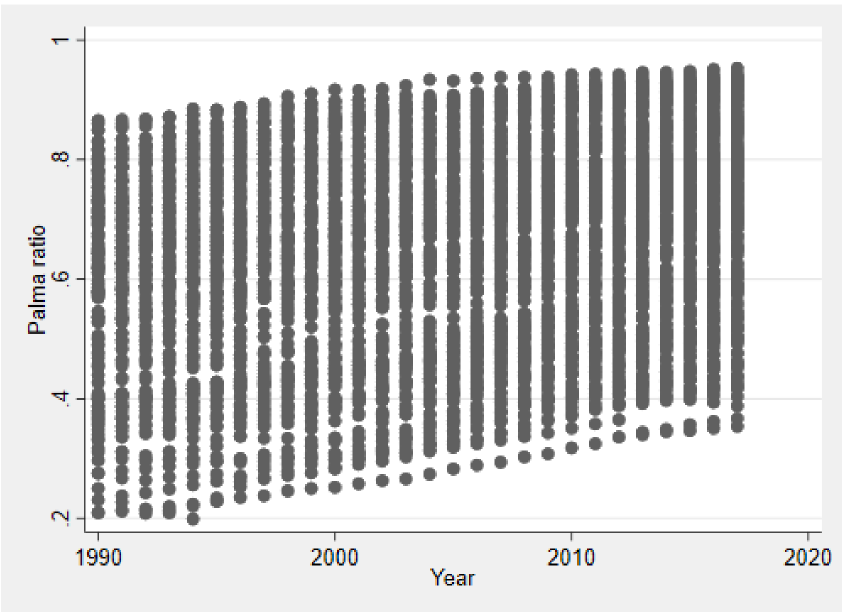

Figure 3 The Palma ratio from 1990 to 2017.

GDP per capita is collected from the World Bank and is measured in purchasing power parity US dollars. Previous research suggests a correlation between GDP per capita and life expectancy, but with diminishing effect. In line with the model used by Neumayer and

Plümper (2016), the logarithm of GDP per capita is therefore included as well as the logarithm of GDP per capita squared.

Health expenditures measured as percent of GDP is also included following the model of Neumayer and Plümper (2016). This data is only available from year 2000, and in five-year intervals until 2010. The missing years between 2000 and 2010 (total of 8 years missing) are therefore interpolated, to be able to include the variable. As can be seen in figure 5, it does appear to be a general trend of increasing health expenditures as percent of GDP, as an argument for the use of interpolation on the missing years between the given observations from UNDP.

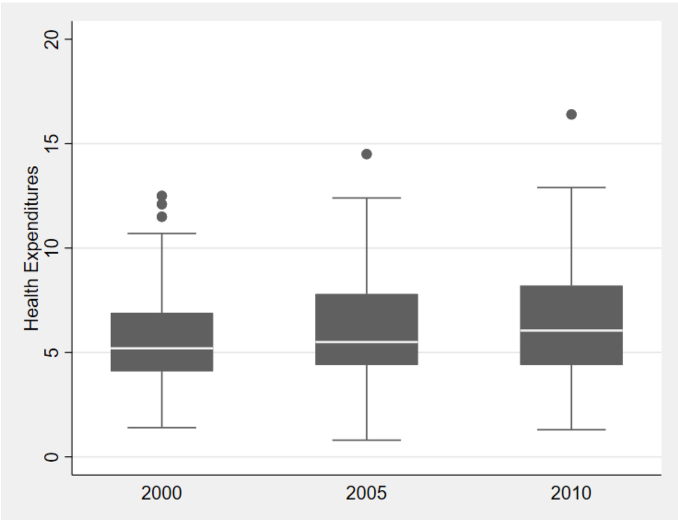

Figure 4 Health expenditure data points.

The logarithm of health expenditures is included in the model, as well as the variable squared. The same line of argument as for GDP per capita including both variables can be formulated. With health expenditure is can be assumed that spending on health can only help to a certain degree, so the model assumes diminishing returns of the variable.

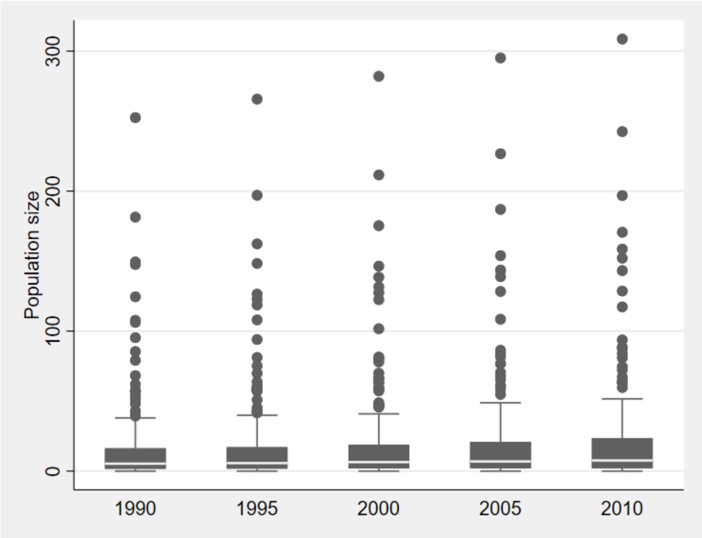

Figure 5 Population size data points.

Population size is also collected from UNDP, where long time-series are available. From 1990 to 2010, the data is only given in five-year intervals, and interpolation for the missing years between the observations is done. This is in total 16 observations. Looking at the mean and trend of the observations, there does seem to be a clear trend of an increasing population for most countries, which will reduce the error in the estimations of population size in the missing years.

Table 2 Independent variables descriptive statistics.

	No. Of observations	Mean	Std. Dev.	Min	Max
Palma ratio	4,756	65.50561	16.57501	19.9	95.3
Log GDP per capita	4,811	8.958469	1.231622	5.8701	11.77028
Log GDP per capita squared	4,811	81.77075	22.0097	34.45	138.5394
Log health expenditures	2,888	1.731021	0.431867	-.2231	2.980619
Log health expenditures squared	2,888	3.182877	1.414417	0.0038	8.884088
Population size	5,236	34.06203	129.3217	0.1	1409.5

4.3 Data limitations

The most obvious limitation in the data used in this study is the years and countries missing from the dataset. The countries missing and specific years missing from included countries can both be creating a selection bias in the results. Countries that is typically missing years are Former Yugoslavian and Soviet countries and the poorest African countries. Some countries have no available data (or so few observations that they cannot be included). Examples are Cuba, Somalia, North Korea and most small island states among others.

Included in the dataset is 30 of 34 low-income countries, 45 of 47 lower-middle income countries, 47 of 56 upper-middle income countries and 54 out of 81 high-income countries. There are more countries from the higher income groups missing than from the lower. This could partly be explained by the missing data from smaller island states and small countries missing such as Luxembourg, San Marino and large part of the island states in the Caribbean and the Pacific. The smaller countries and certain regions are therefore underrepresented in the dataset. Even so, the number of included countries and observations is much improved compared to previous studies. This could potentially affect the results in several ways, as will be discussed in section 5.

A further limitation in this dataset is the potential risk of measurement errors. As this study is dependent on data calculated using household and micro surveys, there is a risk for measurement errors. This risk is higher in less developed countries as this is often correlated with poor national statistical services. As several of the included variables in this study is based on estimations from surveys or historical estimations, that is also a possible source of measurement errors. The risk of measurement errors is also increased by the use of interpolation for health expenditure and population size in the dataset.

Using the Palma ratio increases the number of included observations in the time period of the study compared to previous studies. Even so, using the Palma ratio limits the study to a time period of 1990 to 2017 due to data availability. For high-income countries, the association between income inequality and life expectancy would be better described if more historical data was included.

5 Empirical analysis

5.1 Descriptive results

The descriptive results suggest that GDP per capita has diminishing effect on life expectancy, thus an increase in GDP per capita has a larger effect for low-income countries, as can be seen in figure 7. Testing the significance of different intervals of GDP per capita, there does seem to be a cut-off point for the impact of GDP per capita on life expectancy for a GDP per capita around the interval between 8000-10,000 US dollars per year. This finding indicates that GDP per capita is important for countries in the three lower income groups, while high-income countries seem to not have an effect of increased GDP per capita on longevity

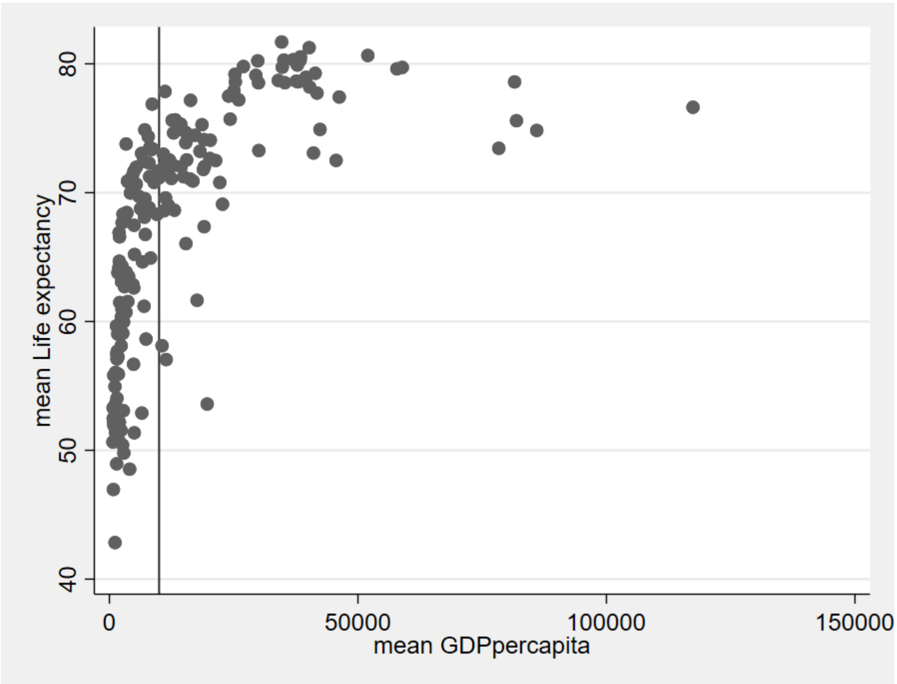

Figure 6 Life expectancy and GDP per capita with cut-off point.

As figure 8 shows, the correlation between life expectancy and the Palma ratio suggest a near linear relationship compared to GDP per capita. There is no obvious diminishing effect of the Palma ratio (thus, income inequality) on life expectancy, which could suggest that income inequality can to some degree be associated with increases in life expectancy for both low- and high-income countries.

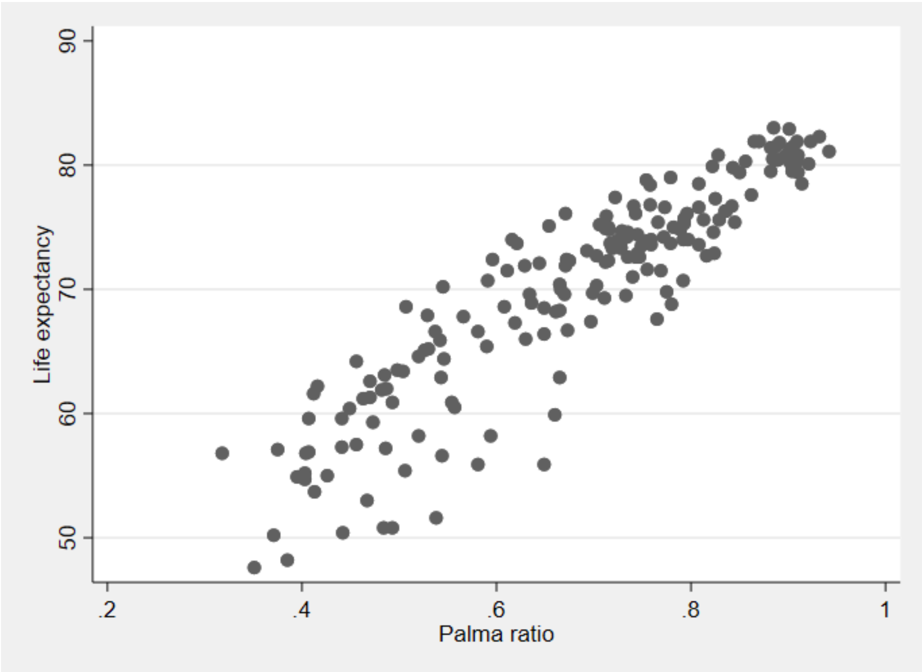

Figure 7 Life expectancy and the Palma ratio.

There is less of an observed relationship between life expectancy and health expenditure, as can be seen in figure 9. The correlation is found to be 0.27, suggesting a low and positive relationship between the two variables. This does suggest that health expenditures do not necessarily increase the health of the population, and that longevity and health outcomes are results of other variables than the spending on health care. Health expenditure is measured as percent of GDP per capita, which means that for high-income countries, the actual spending on health can be higher than for a low-income country while the percent in the data is lower.

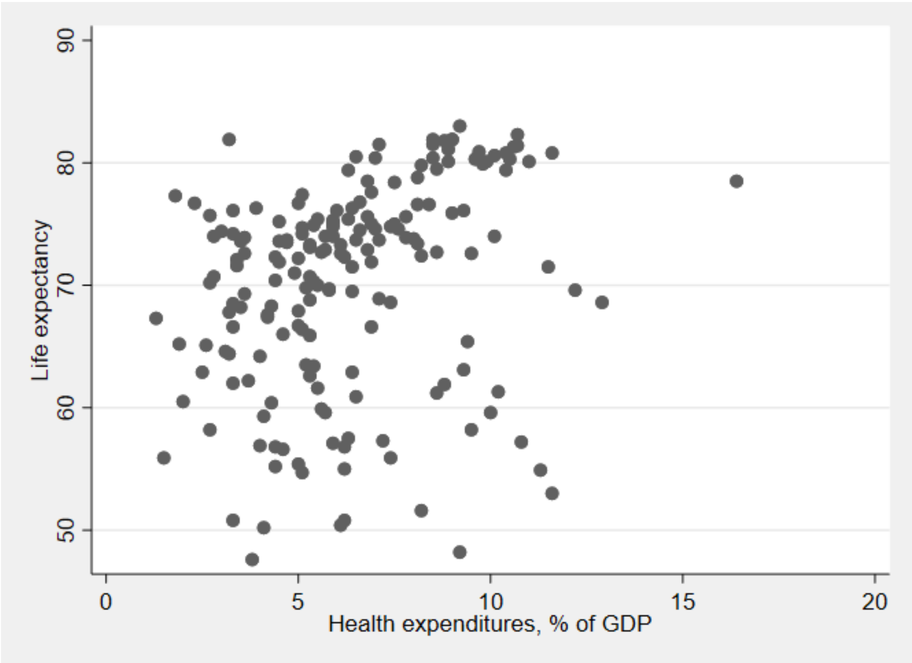

Figure 8 Life expectancy and health expenditure.

5.2 Results from the model

Table 3 Results from the model with all countries and the countries divided into two income groups.

	All countries	Lower-income countries	Higher-income countries
Log GDP per Capita	8.991**	18.53***	-4.758
	(4.154)	(6.025)	(4.943)
Log GDP per Capita squared	-0.672***	-1.431***	0.158
	(0.223)	(0.349)	(0.254)
Palma Ratio	0.731***	0.868***	0.588***
	(0.0534)	(0.0701)	(0.0788)
Log Health expenditures (% of GDP)	-1.116	-1.681	-0.0980
	(1.007)	(1.509)	(1.097)
Log Health expenditures (% of GDP) squared	0.381	0.653	-0.0203
	(0.379)	(0.547)	(0.410)
Population size	-0.0119**	-0.00664*	-0.0185*
	(0.00468)	(0.00340)	(0.0105)
Constant	-3.709	-38.24	61.29***
	(18.36)	(24.63)	(23.31)
Fixed effects	Yes	Yes	Yes
Observations	2,701	1,124	1,577
R-squared	0.812	0.865	0.768
Number of countries	176	75	101

Robust standard errors in parentheses

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

The Palma ratio is significant in all three models. For lower-income countries, a one unit increase in the Palma ratio (scaled 0-100), life expectancy increases with 0.868. This would mean that a one unit increase in the Palma ratio leads to 10.5 month increase in life expectancy. This is calculated by multiplying the coefficient with 365 (days in a year). This number is then divided by 30, finding the number of months a one unit change in the Palma ratio has on life expectancy. This would seem as a large effect, but one must keep in mind that countries does not commonly have large changes in the Palma ratio, where within-country variation over long time-periods is less than 10 units. Short-term one could therefore not expect a country to change their income inequality (measured in the Palma ratio) by more than a few units, leading to only a few years improvement in life expectancy for lower-income countries.

For high-income countries, the effect of low income inequality is lower than for lower-income countries, but with a substantial effect nonetheless. A one unit increase in the Palma ratio would according to the model in table 1 increase life expectancy with 7 months.

The results in table 2 also suggest that GDP per capita has a large effect on lower-income countries, and that this large effect impacts the model including all countries, as GDP per capita in the model only including higher-income countries is not significant. Interpreting the coefficients, a 1 percent increase in GDP per capita leads to a 0.18 increase in life expectancy, which is equal to approximately two months. In other terms, a six percent increase in GDP per capita in lower-income countries would increase life expectancy with a year. The coefficient is calculated by the formula $\beta/100$, as the coefficient is the logarithm of GDP per capita (Wooldridge, 2015).

Further is also the GDP per capita squared significant with a negative coefficient for lower-income countries, further confirming the findings from the descriptive results indicating a diminishing effect of GDP per capita on longevity.

The variable of population size is significant at ten percent level for the two income groups, but significant at five percent level for the total sample. The coefficient indicates that a one unit increase in population (millions), would have a very small, but negative effect on life expectancy. This is in accordance with previous research, where a larger population is assumed to be more heterogeneous or have the possibility of having larger differences and higher inequality.

Neither of the variables for health expenditures are significant in any of the models, leading to the conclusion that health expenditure as a % of GDP might not have an effect on life expectancy. Higher GDP per capita would also allow for the actual sum behind the % of GDP per capita to be higher, which might explain the lack of results for these variables. The results from table 2 suggests that it is more meaningful to interpret this variable in the models where the model is run on more specific income-groups, thus has more similar GDPs per capita.

The results are found to be robust, with little changes in the results when adding the control variables[2]. The results for the Palma ratio and GDP per capita also remain unchanged when health expenditure is removed from the model, adding another 10 years to the dataset used. Tests for normality in the residuals can be found in appendix B.

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[2] Table of these regressions can be found in appendix B

In Table 3 the model is tested on each of the income-groups given by the World Bank. This gives a more nuanced picture of the effects of the different variables. Unfortunately, the number of included countries is very much reduced. For the low-income countries, this also reduces the number of observations drastically, as this groups are missing the most variables. Low-income countries have approximately half of the observations the high-income groups has. It also has the fewest countries included in the sample.

The Palma ratio-coefficient if found very significant for all four income-groups with the highest coefficient is found for low-middle income countries suggesting a one unit increase in Palma would give almost eleven months increase in life expectancy. The lowest coefficient for the Palma ratio is found for the high-income countries implying that a one unit increase in the Palma ratio would give five months increase in life expectancy. The Palma ratio is the only variable in the model that is significant for all income-groups. While this is not possible to see in figure 8, the decrease in the Palma ratio-coefficient can possibly suggest that also income inequality might have a diminishing effect on life expectancy.

The results of GDP per capita when the model is run on the different income-groups does seem somewhat different than the previous results. It is not significant for low- and high-income countries, while it is strongly significant with a large effect for low-middle income countries. For upper-middle income countries the coefficient is negative. Looking at the figures in section 5.1, there is reason to suspect that there might be some disturbances in the data, potential outliers or other issues that are affecting the results in these models. Especially for low-income countries, with so few countries, a large outlier could potentially have a large effect on the results.

Table 4 Model run on the World Bank income groups.

	Low-income	Low-middle income	Upper-middle income	High-income
Log GDP per capita	5.208	18.81***	-9.630**	-0.866
	(8.138)	(3.608)	(3.755)	(2.730)
Log GDP per capita squared	-0.469	-1.438***	0.344*	0.0193
	(0.569)	(0.216)	(0.204)	(0.133)
Palma ratio	0.780***	0.867***	0.706***	0.429***
	(0.0280)	(0.0216)	(0.0217)	(0.0125)
Log Health expenditures (% of GDP)	-2.697**	-0.314	1.012	-2.780***
	(1.247)	(0.785)	(0.768)	(0.664)
Log Health expenditures (% of GDP)	1.283***	-0.121	-0.706***	1.260***
squared	(0.343)	(0.251)	(0.237)	(0.187)
Population size	0.0717***	-0.00544**	-0.00246	-0.00805
	(0.0208)	(0.00232)	(0.00264)	(0.00493)
Constant	10.48	-40.46***	81.54***	49.08***
	(29.04)	(14.94)	(17.29)	(13.65)
Fixed effects	Yes	Yes	Yes	Yes
Observations	427	697	721	856
Number of countries	30	45	47	54

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

5.3 Discussion

The results of this study points towards GDP per capita having an effect for lower-income countries life expectancy. The large effect of GDP per capita might be explained by being correlated with more and/or better health care for children, as infant and child mortality has a large impact on life expectancy in developing countries. A reduction in infant mortality largely increases life expectancy at birth, and if GDP per capita is correlated, this might be a logical explanation for the finding of the cut-off point at approximately 8000-10,000 USD per capita.

The results of the GDP per capita-coefficient do support the absolute-income hypothesis to a certain degree, as GDP per capita does seem to be largely important for developing countries. Even so, the results are clear that in increase in income (here GDP per capita) does not always increase health status. The hypothesis is therefore only found true for countries below the identified cut-off point in this study.

Further, the findings on the GDP per capita-coefficients does give support for the deprivation hypothesis, that income (in this study, only GDP per capita is available) has a large effect on life expectancy under a critical threshold. This cut-off point if found to be somewhere in the interval of 8000-10,000 US dollars per capita. Up until this threshold, an increase in GDP per capita has a strong, positive effect, supporting the deprivation hypothesis of a critical level. The Preston curve does therefore seem to hold, but only for countries under the threshold. Countries above the threshold does not fit with the Preston curve. The finding of a cut-off point for the effect of GDP per capita on longevity is in line with previous empirical studies, as these has also observed that GDP per capita loses its explanatory power for higher income countries (Wilkinson & Pickett, 2006).

There are too few countries with very low income inequality to empirically test the statement of Preston (1975) that also very low income inequality having a negative effect on life expectancy. A possible country that potentially could shed some light on Preston's hypothesis of very low income inequality having a negative effect on life expectancy is Cuba, which unfortunately is not included in this study as data availability is limited.

It must be mentioned that as this study uses macro data, there is no possibility to study the increase or decrease of individual's incomes. The measurement available is GDP per capita, giving an indication of the economic development and status of the country as a whole. What effect changes have on individuals cannot be tested in this study, only changes on population level.

As for income inequality, the findings in this study does suggest that low income inequality improves life expectancy in line with the relative-income hypothesis. This study is not able to address whether high income inequality affects all individuals in a country negatively or if the negative effect on health from high income inequality only applies to individuals below the average income level.

This argument is extended to the relative-position hypothesis, which states that it is not the relative low income itself that has a negative effect on the individual's health, but the social status that follows. As this study does not include and data on individual level, nor any variable on social status, the potential impact of this theory cannot be analyzed. The income inequality measure is found to be positively correlated with life expectancy, but a different methodology and data must be used to find if income inequality picks up the effect of social status in a society.

It is worth keeping in mind the theories of Wilkinson, suggesting that income inequality having an effect besides the economic differences within a society. The difference in economic difference can also create differences in access to education, health or political power (Wilkinson & Pickett, 2010). Income inequality could, if following Wilkinson's theories, affect society far beyond the economic perspective.

The income inequality hypothesis assume that the individual's health is directly affected by income inequality, where a high income inequality would affect longevity negatively. This hypothesis is confirmed in this study, but as there are only a limited number of control variables included and no data on individual level, it is difficult to confirm the direct effect of income inequality. There is a possibility that income inequality catches the effect of other factors that affect life expectancy such as differences in education, health care, crime rates or other variables that might be a consequence of high inequality.

The large positive association found between income inequality and life expectancy in this thesis supports the findings of the large body on income inequality and health research. By having a more complete dataset, this study finds the opposite of Beckfield (2004), giving support to the criticism of his study that uses an unbalanced panel with large shortcomings in observations, especially for developing countries.

The coefficient on income inequality is lower for the high-income countries when running the model on the four different income groups provided by the World Bank. This could indicate that also income inequality has a diminishing effect on life expectancy, but at a later point the GDP per capita. Going back to the discussion on life expectancy and its potential limits, there would be a diminishing effect of any variable if there is a limit to life expectancy.

5.3.1 Limitations

There are several limitations to the results of this study. The methodology can only give us correlations and does not find causal effects. Further studies with larger dataset and potentially data on individual level would be necessary to be able to make use of methods allowing for causal relationships.

The study is also limited as some data is lacking and there are incomplete data on countries, this can lead to bias in the data as the problem of missing data is larger for lower-income countries, which eliminated the selection of countries missing/having a reduced number of observations being random. Calculations for the data are made for certain years for certain countries, estimating health expenditures and population size. These are only estimations and could potentially be an issue.

An important point in the inequality discussion is the way of measuring economic inequality. This study only looks at income inequality, but more recent discussions on inequality has also included wealth and wealth inequality, which is proving to be rising factor of inequality. It could be that large wealth-inequalities also have an effect on health outcomes. It could also possible enhance the effect of the income inequality if one assumes that those with a high income also have the most capital/wealth.

The study is further not able to identify potential effect that different levels of income inequality has, such as social status that Wilkinson points towards. The importance of education and health interventions was not included in this study, as it is not possible to include health inequality and education as controls in the model used in this study.

The choice of using the Palma ratio in this study aimed at reducing the issue of using a fixed effects model in previous studies. This as the Palma has larger variation than the Gini-coefficient, and as a fixed effects model only uses within-country variation in its estimations, models looking at inequality and longevity is dependent on countries having changes in their income inequality.

As discussed in section 3, there is a risk of potential violation of the strict exogeneity assumption (for example shocks). The model used cannot control for the influence of unobserved factors that are time-variant such as inventions, new research or knowledge. Wilkinson (1992) argues that this is not an issue for when studying income inequality and longevity. I would rather argue that it might potentially affect the results, but knowledge and research in particular would likely affect everyone and might even lower the effect of income inequality, as it could be findings making health care more cost efficient or better treatment for diseases. This does naturally depend. The same is for advances in research and technology. For example, if the new technology is expensive and not covered by some form of welfare, the effect of income inequality might be increased. If the new findings are a way of reducing the cost or for example making treatments less costly, then this might cause a downward bias in the results.

6 Conclusion

The aim of this thesis was to study to what extent income inequality has on life expectancy. The results of this study imply that income inequality is strongly associated with life expectancy independent of the economic development of the country. There is a small indication that the effect is somewhat smaller for high-income countries. GDP per capita is found to be an important explanatory for developing countries, but no association is found between GDP per capita and life expectancy for high-income countries.

This study finds several associations supporting findings in previous research. The data indicate that GDP per capita is very important for low-income economies, but the effect of GDP per capita has diminishing returns, with a cut-off point in the interval of 8000-10,000 US dollars per capita. The fixed effect model supports these findings, as GDP per capita is strong associated with life expectancy for lower-income countries, with a one percent increase in GDP per capita leads to two months increase in life expectancy. The model finds no effect of GDP per capita on the higher-income countries.

The Palma ratio is found to be strongly associated with life expectancy throughout all models, with a slightly lower coefficient for high-income countries. The further discussion is what this association implies. Wilkinson believes that high income inequality has social consequences that affect the health of those in the lower distribution of income, while the income inequality hypothesis suggests a direct effect on income inequality on longevity. This study cannot give an answer to the potential causes behind the effect of income inequality but should be a concern for further research.

As the Palma ratio, thus income inequality is found to be strongly associated with longevity, the policy recommendation for better health outcomes does seem to point towards lower income inequality. The policy implications of the findings of this study is in line with Neumayer and Plümper (2016), pointing towards policies reducing income inequality to improve public health through for example income redistribution. This could include the government spending more on infrastructure, education, health care, or through direct transfers or tax policies. The result of this study and previous research does indicate that government intervention in form of income redistribution would benefit health outcomes for the population.

There are several issues that should be considered in further research. Including wealth and wealth inequality would give a broader picture of economic inequality and the potential outcomes of rising inequality. Studying economic inequality and health using individual data on a global level would potentially open up for causal methods and being able to include more control variables giving more precis results. Further, improvements in data for the least developed countries are necessary for more advanced studies including developing countries.

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Appendix A

Table 5 World Bank income groups.

LOW-INCOME ECONOMIES ($995 OR LESS)

Afghanistan	Guinea-Bissau	Sierra Leone
Benin	Haiti	Somalia
Burkina Faso	Korea, Dem. People's Rep.	South Sudan
Burundi	Liberia	Syrian Arab Republic
Central African Republic	Madagascar	Tajikistan
Chad	Malawi	Tanzania
Comoros	Mali	Togo
Congo, Dem. Rep	Mozambique	Uganda
Eritrea	Nepal	Yemen, Rep.
Ethiopia	Niger	Zimbabwe
Gambia, The	Rwanda	
Guinea	Senegal	

LOWER-MIDDLE-INCOME ECONOMIES ($996 TO $3,895)

Angola	Indonesia	Papua New Guinea
Bangladesh	Kenya	Philippines
Bhutan	Kiribati	São Tomé and Principe
Bolivia	Kosovo	Solomon Islands
Cabo Verde	Kyrgyz Republic	Sri Lanka
Cambodia	Lao PDR	Sudan
Cameroon	Lesotho	Swaziland
Congo, Rep.	Mauritania	Timor-Leste
Côte d'Ivoire	Micronesia, Fed. Sts.	Tunisia
Djibouti	Moldova	Ukraine
Egypt, Arab Rep.	Mongolia	Uzbekistan
El Salvador	Morocco	Vanuatu
Georgia	Myanmar	Vietnam
Ghana	Nicaragua	West Bank and Gaza
Honduras	Nigeria	Zambia
India	Pakistan	

UPPER-MIDDLE-INCOME ECONOMIES ($3,896 TO $12,055)

Albania	Fiji	Namibia
Algeria	Gabon	Nauru
American Samoa	Grenada	Paraguay
Armenia	Guatemala	Peru
Azerbaijan	Guyana	Romania
Belarus	Iran, Islamic Rep.	Russian Federation
Belize	Iraq	Samoa
Bosnia and Herzegovina	Jamaica	Serbia
Botswana	Jordan	South Africa
Brazil	Kazakhstan	St. Lucia
Bulgaria	Lebanon	St. Vincent and the Grenadines
China	Libya	Suriname
Colombia	Macedonia, FYR	Thailand
Costa Rica	Malaysia	Tonga
Cuba	Maldives	Turkey
Dominica	Marshall Islands	Turkmenistan
Dominican Republic	Mauritius	Tuvalu
Equatorial Guinea	Mexico	Venezuela, RB
Ecuador	Montenegro	

HIGH-INCOME ECONOMIES ($12,056 OR MORE)		
Andorra	Germany	Oman
Antigua and Barbuda	Gibraltar	Palau
Argentina	Greece	Panama
Aruba	Greenland	Poland
Australia	Guam	Portugal
Austria	Hong Kong SAR, China	Puerto Rico
Bahamas, The	Hungary	Qatar
Bahrain	Iceland	San Marino
Barbados	Ireland	Saudi Arabia
Belgium	Isle of Man	Seychelles
Bermuda	Israel	Singapore
British Virgin Islands	Italy	Sint Maarten (Dutch part)
Brunei Darussalam	Japan	Slovak Republic
Canada	Korea, Rep.	Slovenia
Cayman Islands	Kuwait	Spain
Channel Islands	Latvia	St. Kitts and Nevis
Chile	Liechtenstein	St. Martin (French part)
Croatia	Lithuania	Sweden
Curaçao	Luxembourg	Switzerland
Cyprus	Macao SAR, China	Taiwan, China
Czech Republic	Malta	Trinidad and Tobago
Denmark	Monaco	Turks and Caicos Islands
Estonia	Netherlands	United Arab Emirates
Faroe Islands	New Caledonia	United Kingdom
Finland	New Zealand	United States
France	Northern Mariana Islands	Uruguay
French Polynesia	Norway	Virgin Islands (U.S.)

Appendix B

Table 6 Model including all countries - robustness.

	Model 1	Model 2	Model 3
Log GDP per capita	8.083**	8.286**	8.991**
	(3.326)	(4.088)	(4.154)
Log GDP per capita squared	-0.693***	-0.640***	-0.672***
	(0.209)	(0.221)	(0.223)
Palma ratio	0.745***	0.727***	0.731***
	(0.0538)	(0.0531)	(0.0534)
Log Health expenditures (% of GDP)		-1.205	-1.116
		(0.997)	(1.007)
Log Health expenditures (% of GDP)		0.420	0.381
squared		(0.376)	(0.379)
Population size			-0.0119**
			(0.00468)
Constant	4.237	-0.224	-3.709
	(14.90)	(17.97)	(18.36)
Fixed effects	Yes	Yes	Yes
Observations	4,467	2,717	2,701
R-squared	0.806	0.810	0.812
Number of country1	178	177	176

Robust standard errors in parentheses

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

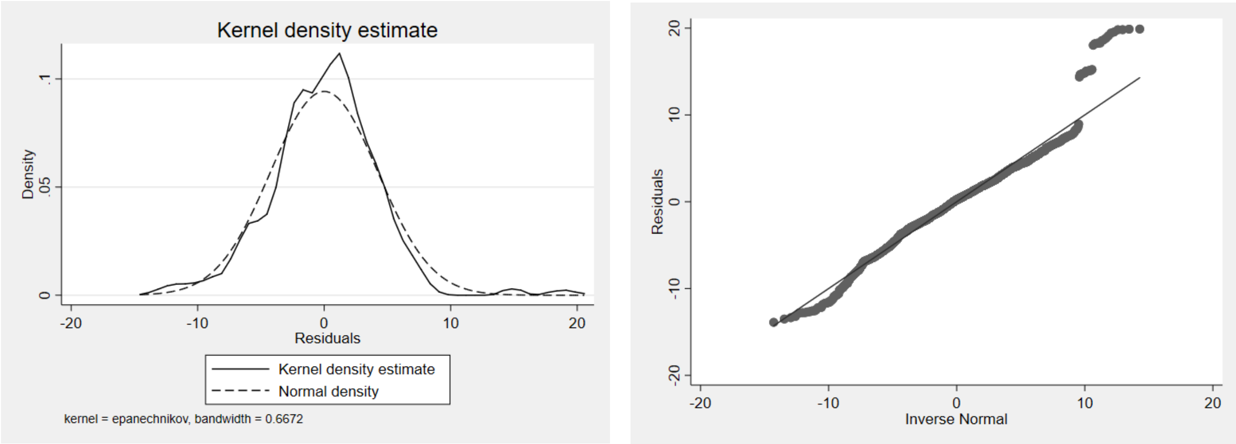

Figure 11 Normality in the residuals. Table 3, all countries.

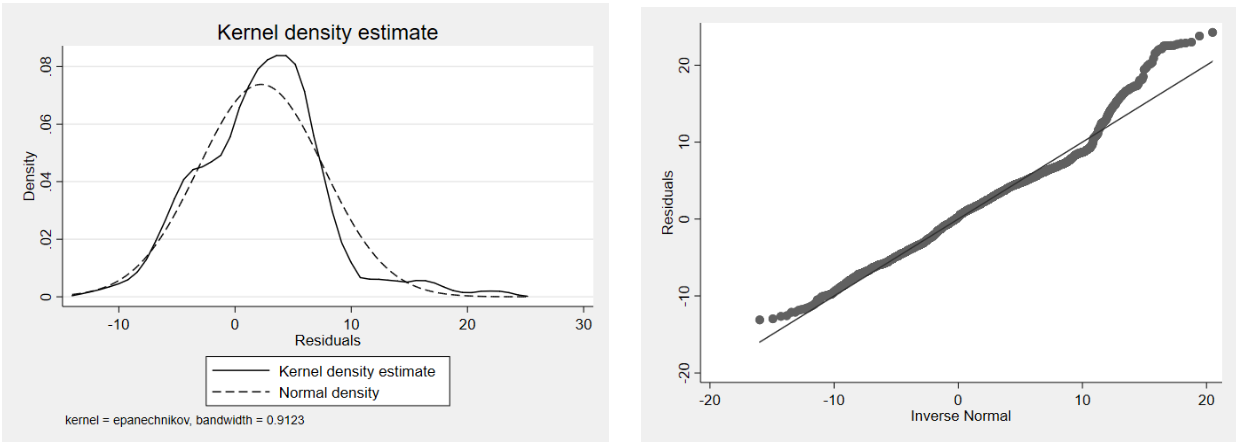

Figure 10 Normality in the residuals. Table 3, lower-income countries.

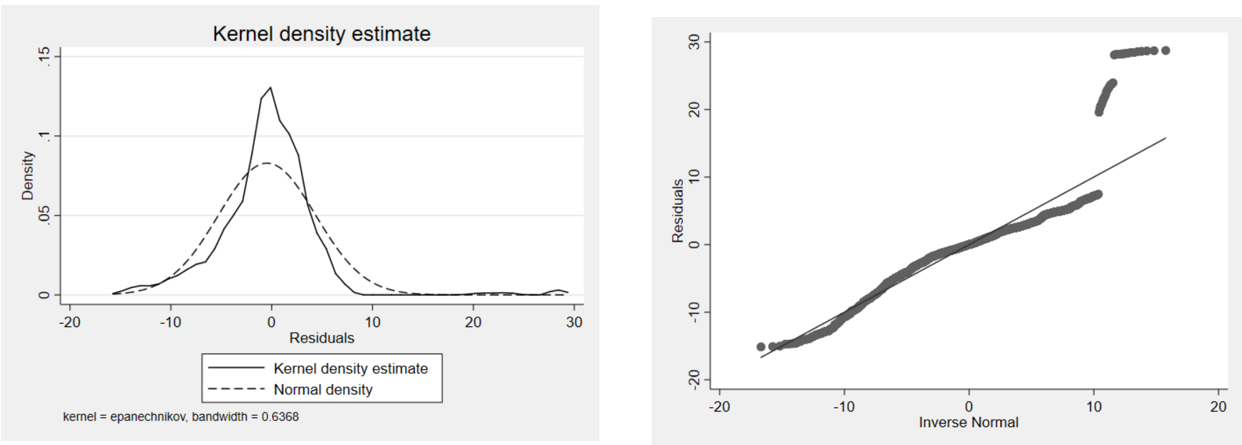

Figure 9 Normality in the residuals. Table 3, higher-income countries..