Inequality and Life Expectancy in Africa and Asia, 1820-2000

Lisa Martin* Joerg Baten**

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**Abstract**

Previous research into the relationship between income inequality and life expectancy has almost entirely focused on developed countries. If developing countries were included, these previous studies could only study the last decades. We assess the association between income inequality and life expectancy in Africa and Asia during the period from 1820 to 2000. We use anthropometric techniques, namely employing human stature and the coefficient of variation thereof as indicators, to extend the database by approximating values for life expectancy and inequality. We observe a statistically significant, negative correlation between life expectancy and income inequality over time and across countries, even controlling for income or poverty and other factors. Potential mechanisms could be the provision of public goods such as health care, or psychosocial mechanisms that compromise health in more unequal societies.

*University of Oxford **University of Tübingen, CESifo, CEPR and Academia Europaea, (corresponding author, address: Melanchthonstr. 30, 72074 Tübingen, joerg.baten@uni-tuebingen.de)

## 1. Introduction

Many of the richer societies of the world today are rapidly ageing, partly as a result of increasing life expectancies over the past two centuries. While ageing poses some challenges of financing the rents of the elderly and caring for their health in these societies, this study takes a long-run view and explores the underlying determinants of higher or lower life expectancy and the role of inequality in this process.

The relationship between income inequality and life expectancy has sparked a productive controversy in research over the past decades which generated a better understanding of the health production process. Wilkinson and Pickett (2006) and others found supportive evidence of a significant impact of inequality on health (other examples: Babones 2008, Detollenaere et al. 2018). In contrast, Judge et al. (1997), provided the result of no significant inequality effect (see also: Mayrhofer and Schmitz 2014).

The controversy is not confined to analyses of the mere correlation between inequality and life expectancy, but also discusses potential mechanisms through which the effect of inequality on life expectancy might operate. Wilkinson (2000) suggested psychosocial factors like chronic social stress due to a lack of cohesion and trust as the most plausible candidate for the mechanism, especially for the health effect of income inequality in rich countries. Elgar (2010) viewed difficulties in the provision of public goods in unequal societies as a main mechanism. In contrast, taking a skeptical view towards a potential role of inequality on life expectancy, Deaton (2001a) argued that for a poor population group with low life expectancy, their own poverty matters, while it is unimportant for them whether another, richer and healthier population group in the same country has the double or triple income, compared to their own income.

In this study we examine the correlation between inequality and life expectancy for Africa and Asia – and, for the first time, we take a long-term perspective over two centuries. As income inequality is usually relatively stable in the short run, a long timeframe is a strong advantage to capture sufficient variation. The setting of Africa and Asia provides a substantial variability of inequality and life expectancy. For example, life expectancy at birth in our sample ranges from 20.1 in Pakistan in the 1920s to 82.2 in Singapore in the 2000s. Income inequality values in our sample were among the lowest and the highest that were ever observed in worldwide inequality history, ranging from 25.3 to 73.7 Gini index values.

The low amount of long-run studies on developing countries in general and Africa and Asia in particular is mostly a result of low data availability. Hence this study uses anthropometric techniques to enhance the existing data on life expectancy and inequality, in order to cover countries and time periods for which direct observations were lacking until now. This is achieved by exploiting the correlation between (i) life expectancy and human height on the one hand and (ii) the coefficient of variation of height and income inequality on the other hand. The coefficient of variation of height is converted into a “height Gini” measure in order to make it more easily comparable with income Gini coefficients.

This effort of creating a new data set allows us to study the following two hypotheses:

(1) inequality reduces life expectancy in Africa and Asia in long-term perspective, even if income and health infrastructure are controlled for.

(2) inequality is uncorrelated with life expectancy, especially if other factors are taken into consideration.

Our study contributes to the literature about the relationship between income inequality and life expectancy. Following Preston (1975) and his famous income-longevity curves with declining marginal income effects at higher income levels, Rodgers (1979) was the first who studied an international cross-sectional data set and found that higher inequality was associated with lower life expectancy. Wilkinson (1992) supported that view by arguing that especially the relative income distribution matters for health. However, skepticism about the effect of inequality grew after Judge et al. (1997) used data from the Luxembourg Income Study (LIS), at this time the highest-quality data available to show the opposite: In their analysis of 15 developed countries they found no significant effect of income inequality on health outcomes such as life expectancy. Deaton (2001b) discussed their study as "final" evidence that should settle the controversy on the issue, arguing that it was "surely time to agree that there is currently no evidence that income inequality drives life expectancy and general adult mortality within the industrialized countries" (Deaton, 2001b, p. 43), but leaving it open whether this was possibly just the result of still insufficient data quality.

Research on the topic, however, did not cease and came to very different results than Judge et al. (1997). Pickett and Wilkinson (2015) published a comprehensive causal review on the effect of inequality on health. They point out that data quality is not the only pitfall in the analysis of this effect, but that empirical strategy also plays an important role. They emphasize the importance of the choice of geographical scale for the analysis, as studies that employ large geographical units, like countries, tend to find supportive evidence of the effect, while studies of smaller units such as neighborhoods more often yield unsupportive results. The reason is that when taking neighborhoods (or districts, counties etc.) as the unit of analysis, inequality may generally be low due to residential segregation of rich and poor. In that case, no significant effect of inequality on health can be detected, while median income appears to account for differences in average health between neighborhoods. Pickett and Wilkinson (2015) argue, however, that poor health in low-income neighborhoods is not due to inequality within that neighborhood but that it is rather determined by the degree of deprivation vis-à-vis the rest of society. What is actually important is not inequality *within* these very small geographical units, but the inequality *between* them.[1] At the country level, however, income inequality is an indicator of the degree of social stratification and reflects how hierarchically a society is structured (Wilkinson and Pickett, 2006).

Other methodological issues include the choice of estimation method and the appropriate inclusion of controls. Pickett and Wilkinson (2015) argue that the inclusion of controls which mediate the effect of inequality on health, such as average income or education, can bias the results, leading to an underestimation of the effect of inequality. In the language of Angrist and Pischke (2009), these would be "bad controls", as they can be interpreted as being endogenous – average income depends on health and life expectancy as does education.

Wilkinson and Pickett (2006, 2009) also experimented with alternative outcome variables to extend the hypothesized effect of inequality on mental health, in addition to physical health. In order to do so they construct an index of health and social problems which proves to be strongly positively correlated with income inequality (Pickett & Wilkinson, 2015). They conclude that health outcomes show a social gradient, i.e. phenomena more frequent in certain social strata such as obesity, are more sensitive to socioeconomic status differentiation and social hierarchy and are therefore intensified if inequality increases.

[1] For a recent study of within and between regional health inequality (and how it is affected by tax decentralization), see di Novi et al. (2019).

So far, the literature has, with few exceptions, focused largely on developed countries. This has primarily been driven by the higher data quality and availability in richer countries. Much of the controversy in fact stems from discussions about data quality and methodology. Particularly the USA have been assessed frequently (Kaplan et al., 1996, Kennedy et al., 1996), where data is more widely available and higher quality (Pickett and Wilkinson, 2015, p.319). However, there are some studies which do take developing countries into consideration as well. For example, Babones (2008) has used two cross-sectional data sets (from 1970 and 1995) of over one hundred countries, including both developed and developing ones. His results show a strong and statistically significant correlation between national income inequality and population health (as measured by life expectancy and infant mortality) in developing countries. Babones does not claim to show a causal relationship. Marmot and Bobak (2000) conducted a study on Eastern European countries, finding a correlation coefficient between income inequality and life expectancy of -0.63.

In the following section, we provide a discussion of the data is provided (section 2). We describe anthropometric techniques to estimate life expectancy and inequality in section 3, before we present the econometric model and the results in section 4. We perform an IV analysis in section 5 to take care of potential endogeneity, allowing us to conclude that the impact of inequality on longevity is causal, rather than just correlational. We provide robustness tests in the same section. Section 6 discusses potential mechanisms. Section 7 points out potential limitations of the study, and section 9 concludes.

## 2. Data

The majority of the data used in our analysis is based on the Clio Infra project (Height and Height Inequality: Baten and Blum 2012, 2014; see on all sources Appendix B). We will briefly discuss this project and the new evidence that it provided.

The Clio Infra project aimed at collecting a large number of economic indicators for ideally all countries of the world between 1800 and 2000, sometimes going back to 1500.[2] The main data collection, evaluation, counterchecking and interpretation work was carried out in the late 2000s and the early 2010s. Since then, modest improvements in some series have been undertaken. Several indicators of the global country panel could obviously rely on earlier data collection effort, such as the GDP per capita project in the Groningen Growth and Development Center and other data bases on population, conflict data, life expectancy, income inequality and other indicators. Many of these series have been expanded dramatically by Clio Infra in terms of temporal and geographic inclusiveness.

Indicators collected for the first time at the global level include height and height inequality, therefore we discuss them in more detail here, as they will be the basis for the new life expectancy and inequality estimates. Historical studies on human stature using substantial samples started in the 1970s when the later Nobel Prize winner Robert F. Fogel searched for a welfare indicator to countercheck debatable estimates of GDP, real wages and life expectancies during early developments (Fogel 2004).[3] Komlos (1985) and Steckel (1995) expanded this anthropometric work by emphasizing the health indicator function of heights.[4] Since then,

[2] They included countries with 500,000 and more inhabitants in 1990.

[3] Building on even earlier studies by Le Roy Ladurie (1969).

[4] Komlos coined the term “biological standard of living”.

almost all countries in the world have been studied (for an overview see Baten and Blum 2014). Baten and Blum (2014) studied the heterogeneous nature of the underlying sources and many of the potential biases in a systematic comparison study. In this data collection, all heights were aggregated by birth decades, because the first two to three years after birth are the most influential on final adult height (with a modest additional contribution during the teenage years).

Bodenhorn et al. (2017) stated that the collection of height data was probably the largest data input work in economic history, although they had severe doubts about labor market selectivities (Komlos and A'Hearn 2019; Zimran 2019 contradicted their view for the U.S.).

What are the most relevant potential biases of anthropometric sources? Firstly, genetic height maxima at the population level could be such a bias. After all, East Asians have a reputation for being short and Northern Europeans for being tall, for example. Are all height differences caused by income variation? Baten and Blum (2014) argued that while income plays a very strong role, a number of other factors also needs to be taken into account. For example, income inequality, nutritional preferences (especially at very high-income levels, such as for the industrial countries of the last few decades) and in particular agricultural specialization are also important. The latter factor is highly relevant, because easily digestible high-quality protein was scarce in most historical economies and remains so in many developing countries until today. Milk and to a lesser extent meat represented high-quality protein sources for early societies and today's poor economies (Baten and Blum 2014). Hence, the availability of milk and meat determined height, sometimes in spite of a low GDP. The American Prairie Indians, for example, were among the tallest populations in the world in the 19$^{th}$ century, although their GDP per capita was not high (Steckel and Prince 2001). By contrast, the (rich) Dutch were among the shorter populations of mid-19$^{th}$ century Europe, as their highly urbanized society suffered terribly during the "hungry 40s". The mid-19$^{th}$ century crisis was visible both in declining heights and in declining life expectancy (Haines 1998). In general, all world regions had quite similar heights in the 19th century, which indicates that genetic height potentials were probably not very influential (Appendix Figure C.1).[5]

Other biases that were studied in the Clio Infra project were source-related. In the early 19th century, many countries in the world had introduced conscription-based armies following the model of the Napoleonic military system. The lot decided among the young male population who had to serve in the army and who did not. Already before this selection, their height was measured (usually with very few exceptions in the two to three percent range). Similarly, anthropological mass measurements of the late 19th, 20th and the early 21st centuries were generally free of social, regional and labor market related biases. These two sources, conscript army records and anthropological surveys, formed the backbone of the Clio Infra height project. However, in order to fill some important gaps, evidence on volunteer armies and prisoners was also considered, although these two groups have obvious potential for bias and, even more severe for the interpretation of trends, for changing selectivity over time. In other words, the selection measured relative to the underlying population might change over time, for example in periods of booming labor markets. During these periods, less well-nourished, unhealthier and shorter people joined the army, unless the army salaries were raised as quickly as the general salaries. A different selectivity in army recruitment emerged when the risk of battle death during conflicts (or perceived likelihood of conflict) increased.

5 Taking the view of a world leading anthropologist, Bogin (1988) argued against genetic height potentials.

For these source-related biases, a large number of counter-checking strategies has been developed in the Clio Infra project. In cases where multiple sources from different institutional background were available for the same geographic and temporal unit, the comparison of these allowed the investigation of potential selectivities of different institutions such as prisons, volunteer army institutions and other contexts. After adjusting for the effects of the minimum height requirement, Baten and Blum (2014) find that levels were not very different between volunteer armies, prison as well as migrant samples and similar sources.[6]

The dataset on height inequality needs to be even more restrictive in some respect, as evidence based on population subgroups or different age groups cannot be used to calculate height inequality values in a sensible way. Nevertheless, the availability of both height and height inequality is surprisingly large for Africa and Asia over the two centuries, and it can fill many white spots on the health and inequality map of the last two centuries that otherwise could not be studied. We have complemented the Clio Infra sample by data taken from anthropological studies. In particular, we could add some critical cases and periods such as Gambia for the birth decades of the 1910s to 1950s, Nigeria, Benin and Ghana in the 1900s, and Egypt in the 1870s. These observations yielded both average height and height inequality values (Table 1). In conclusion, the height and height inequality datasets of Clio Infra – as well as our own additions – have been carefully assessed for potential biases and selectivities. They are suitable for serving the present study as a basis for health and inequality estimates.

[6] Another strategy to mitigate or eradicate the effect of labor market selectivity was to use a short period of large-scale recruitment that included various age groups and then to trace the evolution of height based on the different birth decades. In addition, comparison with secondary characteristics such as the literacy and numeracy of army recruits proved to be an important tool for assessing changing selectivities. Zimran (2019) suggested a selectivity model to estimate changes taking into account potential selectivity.

The data used in our present study contains observations on 57 African and 51 Asian countries throughout the period from 1820 until 2000. The variables included in our panel data set are life expectancy at birth, the Gini coefficient of income, height (average male stature), and the height Gini (a transformation of the coefficient of variation of height). The key variables of interest are life expectancy and income Gini. Anthropometric variables (height and height Gini) are used to estimate these two primary variables to replace missing values. Other variables are included as controls. In Table 2, we provide some descriptive statistics for the observations that are used in the following regressions (such as in Table 4, Column 1). Mean life expectancy was around 44 years across the whole period, but the variation was substantial, ranging from 20.1 years to 82.2 years. Hence, we can study a range of life expectancies that is 62 years between minimum and maximum. Similarly, the income inequality range is very wide and covers the whole spectrum of income inequalities that we can observe nowadays. We have nowadays typically low income inequalities in the upper 20s for Scandinavian countries and income inequalities in the 60s for high inequality countries such as Brazil, South Africa and Nigeria (Babones 2008). We discuss the control variables (malaria, health insurance, pandemics, war) and the instrumental variable (wheat sugar ratio) below after explaining them.

The dataset is unbalanced, as not for all countries values are available for each decade. Especially for the earlier decades, not all countries can be documented with inequality and life expectancy values. However, Baten and Blum (2014) report that for the early 20$^{th}$ century – a period that was complete terra incognita until now – 77% of the African population can be covered, as well as 71 to 98% of the various Asian regions.

Wherever observations of a variable are reported on an annual basis (e.g. life expectancy), observations are averaged in our study by decade, as this is necessary for the consistency with the Clio Infra project data. Moreover, this reduces short-term fluctuations in some of the variables that sometimes are more related to a measurement error than to true short-term variation, especially for the height variables (Baten and Blum, 2014).

A small amount of interpolation was conducted for the two main variables of interest, i.e. life expectancy and income inequality, and for height and height Gini. This can be justified by the fact that in most situations, these variables are relatively stable in the short run. Linear interpolation is used to fill gaps in the data between decades within the same country (for example, life expectancy at birth ($e^0$) in Ghana in 1850 might be interpolated as $egh1850 = egh1840 + (egh1860 - egh1840)/2$). Only 1.2% of the life expectancy values are based on interpolation, and 8.6% of the income inequality data.

## 3. Anthropometric strategies to estimate life expectancy and inequality

In this study, we expand the dataset by approximating life expectancy and income inequality using height inequality and average height. In the following we will describe the methods and their limitations. Anthropometric studies (i.e. studies based on human stature) have already contributed much to the general understanding of economic issues in historical contexts (Komlos 1985, Komlos and Baten 1998, Steckel 1995). Data on anthropometric indicators such as human height are more widely available than data on complex health measures such as life expectancy (van Zanden et al. 2014). This is especially true for earlier periods and for low-income countries which do not have a comprehensive statistical apparatus (Zijdeman & de Silva 2014, p.104). Anthropometric data can enhance the data base for the analysis of Africa and Asia by exploiting the correlation between (i) life expectancy and average height on the one hand and (ii) the Gini coefficient of income and the coefficient of variation of height on the other hand.

### 3.1 Approximation of life expectancy using height

The correlation between a population's life expectancy and average height was first explicitly investigated by Baten and Komlos (1998) in a review article of Steckel and Floud's *Health and Welfare during Industrialization* (1997), in a chapter of which Costa and Steckel experimented with the substitution of height for life expectancy. In their review article, Baten and Komlos reported a strongly positive correlation coefficient (0.71) of life expectancy and height, although the sample was small (three cross-sections for 1860, 1900, 1950 with n=16, 17 and 17 countries, respectively).

Baten and Komlos (1998) emphasize that the relationship between life expectancy and height is to be treated as time-variant, because innovative and rapid medical advancements during the 20th century had a much larger effect on life expectancy than on height.[7] Baten and Komlos show that, when estimating the relationship separately for earlier and later time periods, this medical progress is reflected in a higher constant in later periods. Thus, we also divide our data set into two separate time periods (1820-1959 and 1960-2000) for the estimation. In addition, the choice of the year 1960 dividing the two periods is justified by the fact that we had a strong break in statistical reporting in 1960. After 1960, the density of statistical evidence is much higher compared to the period before, which is also reflected by the fact that for example the Penn World Tables of income estimates and many social and economic variables begin only in the 1960s.

In Figure 1 we see the relationship between height and life expectancy. In general, the regression line is upward sloping and there is a group of countries with tall heights and high

[7] Hence, an average height of for example 180 cm is associated with higher life expectancy in 1950 than in 1900.

life expectancy in the upper right corner such as Singapore in the 2000s, South Korea in the 1980s and Japan in the 1980s. On the other hand, several countries had low height values and low life expectancy and are correspondingly situated in the lower left corner, such as the extreme case of Sierra Leone in the 1960s, a country that was characterised by many conflicts during the 20$^{th}$ century arising from the distribution of revenues of diamond mining. Other countries in the lower left corner are Korea in the 1900s, not yet separated into North and South Korea, with a very low life expectancy and low height values of around 160 cm; Myanmar in the 1920s (all of South Asia had very low life expectancies in this period), and interestingly Japan in the 1880s. This is perhaps surprising because Japan has a reputation for high life expectancy. However, during the first phase of its modern development the country was characterised by low life expectancy and low height values. This changed up to the 1970s when Japan is one of the slightly outlying regions to the upper left, representing higher life expectancy – using, for example, modern hygienic and medical techniques – but still having a lower milk consumption than Western countries and other parts of Asia with a different nutritional style. However, Japan converged to the high-life-expectancy, high-height group already during the 1980s. On the other side of the lower right deviations, we observe many Sahel zone countries such as Mali in the 1950s, having a high number of cattle per capita and correspondingly tall heights. However, given that the educational sector in the Sahel zone was extremely underdeveloped, problematic health-related behaviour implied that life expectancies were lower. This also applies to Pakistan in the 1920s. Another interesting case is North Korea in the 1980s, because the communist government claimed a very high life expectancy while this is not supported by the height values that were more average during the 1980s.

The results of OLS regressions of life expectancy on height, including regional fixed effects, are presented in Table 3. Using the deviation of height from a high value[8] rather than absolute height as the explanatory variable has the advantage that the interpretation of the constant is more straightforward (Baten and Komlos, 1998): At 180 cm height, life expectancy is estimated to be ca. 52 years in the pre-1960 period and 71 years in the later period. With each centimeter that height is lower, life expectancy decreases by 0.975 years for the early period, and by 0.809 years for the period after the 1960s. Figure 2 shows the correlation between actual observations of life expectancy and the values estimated based on height. With the inclusion of world region dummies and the division into earlier and later time periods, the observations are evenly scattered around the 45-degree line, with over- and underestimations mostly balancing out.

Without a doubt there are limitations to the predictability of life expectancy based on height. Despite the strong correlation, there are idiosyncratic parts to both life expectancy and human stature. Although both life expectancy and height are indicators of well-being, it should also be noted that height is only to a very limited degree valuable in and of itself and can rather be seen as a proxy for other health measures. Individuals usually do not seek to maximize their height, while they do often aim to maximize longevity.

### 3.2 Approximation of income inequality using the coefficient of variation of height

A similarly strong relationship exists between the Gini coefficient of income and the coefficient of variation of height (height CV). Hence, several studies have suggested using the variation of height as a proxy for income inequality (Moradi and Baten, 2005, Pradhan et al.,

[8] The "high" value used in the regression is 180cm, corresponding with the Dutch male height equivalent from 1990.

2003, Guntupalli and Baten, 2006). More affluent individuals can afford better nutrition and shelter and are less exposed to disease, thus resulting in higher average height while the opposite is true for less affluent individuals.[9]

The variance of the distribution of height within a population is for the most part determined by the genetic potential of individuals in the population, i.e. there is a basic *biological variance*. However, the allocation of nutritional resources is independent of the biological variance. Moradi and Baten (2005) argue that, because of this independent allocation, the "input-induced variance is to be added to the biological variance" (Moradi and Baten, 2005, p.5). The variance (or standard deviation) alone, however, is not an appropriate measure to compare populations in terms of inequality, as the *biological* variance tends to increase with the average height of a population (Schmitt and Harrison, 1988). The coefficient of variation (CV) of height takes this into account by incorporating both the variance and the mean of the distribution

$$CV_{it} = \frac{\sigma_{it}}{\mu_{it}} * 100 \qquad (1)$$

Baten (2000) compared different measures of height inequality, including the coefficient of variation, the standard deviation and centimeter deviations between occupational groups. The different measures are strongly positively correlated, and the height CV appropriately reflects inequality between income groups without relying on assumptions

[9] It is important to note that stature is primarily determined during early childhood, which justifies the birth cohort approach taken in this study. The height inequality observed in a particular birth cohort is therefore an adequate indicator of the corresponding income inequality prevailing during the respective birth decade (van Zanden et al., 2014).

about occupational or social classifications (Moradi and Baten, 2005, p. 1237). Moradi and Baten (2005) discuss in detail both the advantages as well as the limitations of estimating income inequality from height.

All studies which have tested the relationship so far have found a positive correlation[10] between height inequality (as measured by the CV of height) and income inequality (as measured by the Gini coefficient of income) (Baten and Fraunholz, 2004, Moradi and Baten 2005, Van Zanden et al., 2014, Moatsos et al. 2014, Baten and Mumme 2014, for example). Of course, the height CV, as a measure of health inequality, is not perfectly correlated with income inequality. Moradi and Baten (2005) point out that the correlation becomes weaker if the poorer strata of the income distribution have access to public health care, food aid, or other non-market public goods that impact health outcomes. This is quite intuitive, as for example the provision of food aid to the poor effectively implies a nutritional redistribution, thus decreasing nutritional inequality while leaving income inequality unchanged. The correlation between the two inequalities may be weakened in the short run because height inequality is in general smoother and less volatile than income inequality. This is in part due to consumption smoothing, i.e. nutritional intake can be maintained in harder times by reducing savings to hold consumption at the same level, offsetting any effect of a decrease in income (Moradi and Baten, 2005). While height inequality and income inequality may not always be strongly correlated, height inequality can also be thought of as the more adequate measure in some contexts. Deaton (2001a) and Pradhan et al. (2003) have laid out the

[10] In the data set underlying this study the correlation coefficient between height inequality and income inequality is 0.48 (N=220). Note that this is only a pooled subsample including countries and periods for which observations on both variables are available.

convincing argument that health inequality in and of itself may be a more important concern than income inequality. One aspect of this argument is that health is "*intrinsically important*" to human well-being, while income is only "*instrumentally significant*" (Pradhan et al., 2003, p.274). Height has proven to be an appropriate indicator of the biological standard of living in many contexts (Komlos, 1985, Steckel, 1995, Komlos and Baten, 1998), thus making *height inequality* an adequate indicator of *health inequality*. Baten and Fraunholz (2004, p.49) explicitly emphasize the advantages that the height CV has as a measure of inequality, in addition to higher data availability. Height CVs incorporate the effect of public goods such as health care and education, which income inequality does not. In addition, height CVs, unlike income Ginis, do not only include the part of the population that earns wages, but also unemployed, self-employed, and those who earn their wage in the informal sector. In this study the formula brought forth by Moradi and Baten (2005),

$$\textit{height gini} = -33.5 + 20.5 \cdot CV \qquad (2)$$

is used to approximate Gini coefficients of income. Other studies have observed very similar relationships (Van Zanden et al. 2014, Radatz and Baten, 2021). Figure 3 plots the correlation of observed income Gini coefficients and values estimated based on height CVs. We observe high income inequality and height inequality in Botswana and Iraq during the 1990s, while Taiwan and Korea in the 1970s had low inequalities on both accounts. One outlying observation was Sudan, for example. While deviations and noise exist, the general correlation holds, also for the overlapping cases for which we have both height and income inequality estimates for Asia and Africa.

## 4. Econometric Model and Analysis

We start our analysis looking descriptively at the relationship between inequality and life expectancy (Figure 4). We study this relationship separately for two periods, the 1820s-1950s and the 1960s-2000s. The scatter plots show a negative correlation for both time periods, i.e. higher inequality is associated with lower life expectancy, although the slope of the regression line is smaller in the early period (Figure 4). The correlation can again be explained by looking at some country-birth-decade observations as examples. For the early period, the territory of what is today the Democratic Republic of Congo in 1880 as well as Angola in 1940 and Egypt in 1950 were very unequal societies with low life expectancy, whereas Japan and Korea in the 1950s were relatively equal and could achieve a relatively high life expectancy. The same is true for Korea in the 2000s and Georgia in the 1990s, whereas in the later period Iraq, South Africa, Gabun and Sierra Leone were high-inequality, low-life-expectancy cases. The outliers are slightly more frequent in the early periods with Turkey on the higher inequality and life expectancy side and Pakistan in the 1920s on the opposite side. Chad 1960 and Mali 1960 were relatively equal societies with low life expectancies. However, in general the negative association between income inequality and life expectancy becomes quite clear even for the early period where the correlation is less strong. All observations are averaged by decade (and country) in order to reduce noise caused by short-term fluctuations and measurement error.

As we want to take into account several control variables, we now turn to multiple regression analyses of the relationship between inequality and life expectancy. Life expectancy$_{itr}$ is the dependent variable, and it is specific to decade t, country i within world region r. It is regressed on the income Gini$_{itr}$ and a vector of controls X:

$$life\ expectancy_{itr} = \alpha + \beta_1 \cdot income\ gini_{itr} + \beta' X + m_t + n_r + e_{itr} \qquad (3)$$

We also include decade-specific time fixed effects $m_t$, and world region specific fixed effects $n_r$. The vector of controls X consists of a number of control variables, keeping an eye on whether they can be observed for the two centuries under study (Table 4). Our control variables are: (1) existence of a health insurance system, (2) wars, (3) the pandemic decade of the 1910s – flu, (4) malaria-intensive countries:

(1) One variable that could be related to life expectancies is the existence of a health insurance system. This system was initiated originally in Germany by the right-conservative chancellor von Bismarck in 1882. He was concerned about the election successes of the (at this time) left-extreme social democratic party. He aimed at removing the electoral support for the left extreme by initiating a strong health support system for industrial workers. This new system has recently been shown to dramatically decrease the mortality records using natural-experiment-type data (Bauernschuster et al. 2020). In many Asian and African countries, the health insurance systems were introduced following similar political economy considerations during the Cold War competition between communism and market-economy systems. Hence this variable is arguably quite exogenous. (2) Another variable that might have an impact on life expectancies are major wars. We adopt the definition and compilation of major wars of the Clio Infra database. We code this variable as the share of years in a decade characterised by war.

(3) Pandemics can obviously also have an influence on life expectancies. We consider in particular the decade of the 1910s that included the “Spanish Flu” influenza pandemic of 1918 which was responsible for the largest number of infection-related deaths during the last two centuries. Victim estimates are covering a quite wide range, but some estimates arrive at 50 million victims and more (Gallardo-Albarrán and de Zwart 2021). Unfortunately, for very few countries in Africa and Asia, country-specific estimates exist. Nevertheless, given the

nature of the pandemic, in each country during the 1910s life expectancy can be expected to be substantially reduced, hence controlling for cross-country variation might be less important than to control for the "pandemic decade" of the 1910s. Therefore, we focus on the whole decade of the 1910s in order to control for this pandemic (see also Appendix D).

(4) Finally, malaria is probably the most-studied disease in economics. However, Malaria is traditionally very difficult to measure, because the malaria measurement depends on persons who are willing to go to hospitals in which the medical assessment of this disease is mostly done. But in the most malaria-intensive regions of central and western Africa, hospitals are far away from many villages, as the hospital network is not densely woven.[11] Hence to control for the most extreme cases of malaria, we coded an indicator variable that is based on the top 10 countries in terms of malaria deaths per population (in 1990). We are well aware that this is only a very rough approximation, and that the disease burden from this particular disease also changed over time.

The malaria top 10 countries represent 11% of all observations and the health insurance availability is given for 31% of our observations (Table 2). Health insurance was only available for 549 observations. 11% of the countries were affected by war during the period of observation and 7% of observations fall into the pandemic decade of the 1910s that was characterized by the Spanish flu influenza. Three of the explanatory variables are indicator variables taking the values of 0 or 1. War is defined as the fraction of years covered by a war.

[11] One option would be to include the climatic and soil suitability of Malaria, but this variable naturally does not include the real death burden of Malaria, as in many countries the counter-measures were quite successful and helped to remove the effect on life expectancies substantially (Small et al. 2003).

These four variables are arguably quite exogenous to life expectancy. In addition, we add some variables that can be interpreted as “bad controls” using the definition of Angrist and Pischke (2009), namely GDP per capita and numeracy (see Appendix A).

Turning to the results, the first specification is a simple univariate regression, including only the income Gini as an explanatory variable and time fixed effects (Table 5). The coefficient of inequality is estimated at approximately -0.23 and statistically significant. It implies that an increase in the Gini coefficient by one index point translates approximately into a two and a half month decrease in estimated life expectancy. In specification 2 we include world region fixed effects; the size of the coefficient of inequality declines as part of the between-region effect is removed. Though the effect is smaller, it is still significant and represents about one month of life expectancy.

In columns (3) and (4) we include the other potential determinants of life expectancy. Prominently, we observe that introducing a health insurance system corresponds with 4.8 additional years of life expectancy. Although one could imagine that health insurance systems might be introduced at higher income levels, we would argue that at least a part of this effect is exogenous. In the early phase, not the richest nations were the first to introduce health insurance systems. For example, South Africa introduced a health insurance already during the 1940s, while much richer oil states such as Kuwait or Qatar did not introduce such a system until the 1990s, when they had a multiple of the South African GDP per capita level of the 1940s already (see Appendix B and C for sources).

We also control for war events in the countries under study. Not only the deaths in the military combat mattered for this variable, but also the health challenges of large numbers of soldiers being clustered together and potentially infecting each other, as well as deaths following from the destruction of infrastructure and productive assets. However, during the

$20^{th}$ century we do not observe a significant effect for Africa and Asia – the coefficient is unexpectedly positive, though insignificant.

We include an indicator variable for the pandemic of 1918, based on the decade in which this pandemic took place. The constant represents the two surrounding decades, the 1900s and the 1920s. The 1910 dummy does not only include the 1918 pandemic effects proper, but also WWI and other potential unhealthy events during this decade. We observe a negative, but insignificant coefficient (on alternative measure concepts, see Appendix C).

Finally, we include an indicator variable for the ten countries that are suffering from the highest number of Malaria deaths in the late $20^{th}$ century (in 1990). These ten countries had life expectancy values that were 7.3 to 7.4 years lower. Not the whole effect can be attributed to Malaria, as these countries also suffered from other tropical diseases and from poverty, but Malaria probably had a substantial share. Perhaps the most important result of these two specifications (3) and (4) for our study is the fact we again observe a statistically significant negative coefficient for income inequality, though it is smaller than the significant estimates in (1). Even including the "bad controls" income and education, we observe a significant additional effect of inequality (results in Appendix A).

## 5. Instrumental Variable Models and Robustness Tests

We also need to consider endogeneity. Although the existing literature widely agrees that this is not the case, one could imagine that the results of the ordinary least square regressions could be affected by reverse causality (moreover, omitted variables or measurement error could imply endogeneity). Instrumental variable estimation allows us to circumvent these issues of endogeneity. Moreover, our instrumental variable approach helps to cope with measurement error which is obviously an issue as we discuss in this article, as well as omitted variable bias. We base our first stage of the two stage-least-square estimate on the following equation:

$$Ineq_i = \beta_1 + \beta_2\ Sugar/wheat_i + \beta' X + \varepsilon_i \qquad (4)$$

where *sugar/wheat* is an Easterly-type instrumental variable of relative soil suitability that varies by country i, and *X* is a vector of other exogenous variables. Easterly (2007) advocated for the use of climatic, geological and similar variables that allow types of agriculture that correlate either with higher or lower efficient sizes of scale. A sugar plantation is a clear example of an agricultural production type of large-scale economies (on this and the following, see also Baten and Juif 2014). On the other hand, wheat production is already highly productive on much smaller farm units, as has been amply demonstrated in the agricultural economics literature. The specialization of a country on the cultivation of large-scale cash crops is positively associated with inequality, whereas food crops such as wheat are not scale-intensive and were historically planted in smallholdings. Both sugar and wheat production methods require relatively clear-cut climatic and soil characteristics. Based on this premise, the UN- Food and Agriculture Organization quantified the share of a country's area that is suitable for the production of each of those crops. In the spirit of Easterly (2007) we use the ratio of the share of the land suitable for the cultivation of the "inequality crop" (sugar) to the share of the land suitable for the cultivation of the "equality crop" (wheat). The advantage of the ratio between the climatic and geological suitability ratio of sugar and wheat is its intrinsically exogenous nature, whereas actual crop use could be influenced by other economic variables. The wheat sugar ratio is unfortunately not available for all countries under study because soil productivity values were not recorded for these countries (Table 2). Hence, the number of observations for this variable is only 463.

The results of the two-stage-least-squares regressions confirm that the variable fulfils the necessary requirements to be a good instrument for inequality: First, it correlates with inequality, as is documented by the “first stage” section (Table 6). The F-Test is always above 10, meaning that the instrument has substantial strength (see Stock and Yogo 2005). Second, we would argue that the instrument influences the dependent variable only through the potentially endogenous variable, inequality. As a result, the significant impact of inequality remains a consistent determinant of life expectancy. In column (5), we include the additional controls of our earlier OLS estimation. In the TSLS estimation, the “pandemic” indicator variable becomes statistically significant and negative, the other results are similar to the OLS results. Although the war variable remains insignificant, its negative coefficient is considerably larger than in the OLS specification. The health insurance coefficient also becomes larger (on the positive side). In Appendix A we also report results for GDP per capita and education, well aware that these can be interpreted as bad controls. However, they give a hint that also the causal relationship between inequality and life expectancy is not “just a side-product” of education or poverty reduction.

Moreover, we perform a number of robustness tests. In column (2) of Table 6, we include only Asia and the Middle East in the estimation, dropping Sub-Saharan Africa, in order to assess whether the results are only driven by the specific combination of the two world regions. We find that the coefficient of inequality is smaller, but remains substantial, if Sub-Saharan Africa is not included. For a further robustness test, in column (3) of Table 6, we restrict our measurement concept to only those observations for which life expectancy is not estimated using anthropometric techniques, and in column (4), we do the same for noninterpolated observations. These two data-specific robustness tests indicate that the relationship between inequality and life expectancy is quite robust for Africa and Asia during the past two centuries. In sum, when using an established instrument for inequality, TSLS regression results are robust and indicate that we observe a causal relationship here.

One of the biggest challenges in any instrumental variable approach is the requirement of the exclusion restriction, which implies that the instrumental variables do not have a direct influence on the ultimate dependent variable except via the instrumented variable. It is probably the case, that a critical reader can always think of a potential violation of this condition. In his seminal paper, Easterly (2007) studied the applicability of the exclusion restriction of relative soil and climatic suitability by using both theoretical reasoning and econometric tests. One possibility for such a direct causal channel is the possibility that wheat/rice and sugar have different effects on the wealth of the local population. This wealth difference could be a potential direct causal influence on life expectancies because those might depend on different health investment possibilities. On the other hand, Easterly argues convincingly that the difference in the wealth effects of those agricultural goods are quite limited compared to all of the other goods that countries are producing.

Another potential violation of the exclusion restriction could stem from the widely discussed concept of the “natural resource curse” (Easterly 2007). Exceptionally high incomes from raw material exports might generate rents that in turn could lead to political economy problems (Sachs und Warner 1995, see also the review by Frankel 2010). Sugar cane is a primary product that might produce such high windfall profits, for example. Isham et al. (2005) have developed a theory of “point-source” agricultural exports. Typical cases are exports such as sugar cane. The idea is that the “point-source” export revenues can more easily be captured by ruling elites than “diffuse” exports such as wheat and rice. Easterly

(2007) argues that if these “resource curse” effects operate via inequality, the exclusion restriction is of course not violated. Most of the studies discussing these issues emphasize that the behavior of rich elites and their interactions with the institutional environment is the main issue, which is consistent with the inequality story (Isham et al. 2005).

Nevertheless, one can still imagine that the resource curse works through other channels. Baten and Juif (2014) addressed these issues head-on by including additional controls for a resource-oriented export structure and determine whether inequality, instrumented with the sugar/wheat-rice suitability variable, turns insignificant. They constructed a variable of the share of raw material and mining exports relative to the country’s total exports. The “resource curse” variable was insignificant for those cases that could be included and did not affect the significance of inequality instrumented by the suitability variable. We build on their results here.

In sum, although the exclusion restriction is always a challenge when applying instrumental variable techniques, this potential issue does not invalidate our results that inequality reduced life expectancy in Africa and Asia over the last two centuries in a causal way. Moreover, the instrumental variable strategy circumvents not only potentially issues of reverse causality, but also measurement error and omitted variable challenges to a certain extent.

**6. Discussion of Potential Mechanisms**

We observed in the previous sections that inequality has a negative effect on life expectancy. We now discuss these results in the context of potential causal pathways. These include (a) the provision of public goods such as education and health care, (b) psychosocial mechanisms that compromise health, which are strongly affected by inequality, and (c) a direct effect of income (or its inverse, poverty).

Alesina et al. (1999) provide a theoretical discussion of the relationship between inequality and the provision of public goods which influence population health, such as education, water supply and public health care. More unequal societies face greater difficulties in deciding on the provision of public goods. This is due to the fact that individual preferences are more heterogeneous in unequal societies, decreasing the average value of public goods to the society and thus lowering the incentives for their provision. In line with Sen (1999), political inequality may be the underlying reason, hence reducing political inequality may lead to lower inequality also in other respects (e.g. health inequality, income inequality) through the provision of effective public goods (review: Deaton 2001b). However, studies which have explicitly tested this relationship in developed countries (Elgar, 2010, Elgar and Aitken, 2011, Layte, 2012) conclude that material factors (as opposed to psychological ones) play only a negligible role. Nevertheless, in our analysis of developing countries in Africa and Asia the relevance of public goods is highly plausible.

However, we also found that even after controlling for health insurance systems that reflect many of the public goods investments, a separate effect of inequality was visible. Pickett and Wilkinson (2015) support these findings and attribute a much stronger effect to psychosocial mechanisms than to material factors like welfare regimes or investment in human capital.

Wilkinson differentiates between societies that “are structured by low-stress affiliative strategies which foster social solidarity” and societies that exhibit “much more stressful strategies of dominance, conflict and submission. Which social strategy predominates is mainly determined by how equal or unequal a society is” (Wilkinson, 2000, p.4). The story outlined by Wilkinson (1997) is that of relative deprivation. This hypothesis implies that it is *relative*, and not *absolute income*. An individual deprived by a low position in an unequal society treats the own body and health (and the ones of other family members, including children) often with less care and respect. Another (though related) mechanism may be that more affluent people have more control over their lives e.g., in the workplace. Kawachi et al. (1999) see an even more fundamental role for inequality in determining health, referring to the lack of social cohesion, trust and protective friendships in unequal societies. Finally, income and education can play a role, even though these variables might be endogenous (themselves being influenced by health and longevity). However, we observe in a "bad control" regression in Appendix A that while these variables might be also correlated with life expectancy, the effect of inequality does not disappear, but remains substantial and significant.

We conclude that all these factors were at work for our sample of Africa and Asia in the last two centuries – a public goods effect that we can separate out with the health insurance system variable, a correlation with income (or poverty) and a psychosocial effect of less healthy behavior in more unequal societies.

**7. Potential limitations of this strategy**

Although our analysis provides new – and as we discussed, quite reliable – evidence for Africa and Asia, we need to discuss one potential caveat, namely survivor bias. The birth cohort approach of height inequality causes the indicator to be subject to survivor bias. Adult heights are used in a backward projection to estimate inequality during the corresponding birth decade. This implies that only survivors enter the measure. Individuals that died during childhood are naturally not included in the average adult height of the birth decade. Moradi and Baten (2005) argue that this bias possibly leads to a potential overestimation of adult height and underestimation of inequality, as individuals on the left tail of the true height distribution would likely be underrepresented. They test for the effect of infant mortality and find in fact a correlation. However, only a very small fraction of the height CV's variance could be explained by differences in mortality across countries. In other words, while survivor bias exists, its magnitude is so small that it is not substantial. And van Zanden et al. (2014) point out that in fact all inequality measures are subject to survivor bias, because for example the income Gini, too, only includes those individuals that "survived" and reached the wage-earning age.

## 8. Conclusion

This study has yielded new insights regarding the association of inequality and development in Africa and Asia. The relationship between income inequality and life expectancy, a prominent indicator of human development, has been investigated in a historical time frame ranging from 1820 to 2000. The lack of data on these two indicators has in the past impaired research for the said continents and time frame. In this study, we used anthropometric techniques to enhance the available data. Life expectancy was estimated using average height, while income inequality was estimated using the coefficient of variation of height.

The subsequent econometric analysis yielded significant results which are generally supportive of a negative correlation between inequality and life expectancy in the countries and time periods under study. Instrumental variable techniques helped to cope with the endogeneity of the relationship we were interested in. As instrument, we used the well-established soil suitability ratio of sugar and wheat.

Even for low-income countries, the evidence found in this study suggests that inequality and life expectancy are significantly negatively correlated. This finding is not implausible, though no evidence existed before, hence the value-added of this study is substantial. The psychosocial pathways described by Wilkinson (2000) certainly played a role. High inequality can lead to social unrest and distrust, not only in developed countries. Pickett and Wilkinson (2015) have described how chronic social stress can decrease life expectancy. In contrast, a higher degree of cohesion and trust of more equal societies can increase life expectancies.

This research about the long-term development of inequality and its negative impact on life expectancy also has important policy implications for the still young populations of many African and Asian countries. In many industrialized countries, increases in life expectancy and declining fertility have resulted in significant population ageing. By contrast, most of the developing countries in our sample are still a long way from the issue of an 'ageing population' that industrialized countries face.[12] As policy makers in these countries aim to improve population health and increase longevity, policies aimed at lowering inequality could play an important part in supporting this trajectory toward higher life expectancy. High or increasing inequality, on the other hand, could potentially exacerbate the many challenges that developing countries face as they aim to improve population health.

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[12] A notable exception in our sample of African and Asian countries is of course Japan.

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Table 1: Other sources on height and height inequality, not included in Clio Infra

| Country | Decade | Height | Height CV | N | Source |
|---|---|---|---|---|---|
| Egypt | 1870 | 165.82 | 3.58 | 802 | Orensteen 1915 |
| Ghana | 1900 | 165.29 | 3.67 | 77 | Herskovits 1937 |
| Benin | 1900 | 168.57 | 3.77 | 93 | Herskovits 1937 |
| Nigeria | 1900 | 167.12 | 3.86 | 100 | Herskovits 1937 |
| Gambia | 1910 | 167.80 | 3.99 | 153 | Billewicz 1981 |
| Gambia | 1920 | 167.50 | 4.36 | 89 | Billewicz 1981 |
| Gambia | 1930 | 167.50 | 3.70 | 130 | Billewicz 1981 |
| Gambia | 1940 | 169.30 | 3.72 | 113 | Billewicz 1981 |

Note: When the birth decade was not given in the source, it was estimated by subtracting 30 years (the estimated average age of individuals in the sample) from the year of measurement. If the year of measurement was not given, the year of publication was used. Only samples that were marked as "male" and "adult" were used.

Table 2: Descriptive statistics of key variables and controls

| Variable | N | Mean | Std. Dev. | Min | Max | Unit of analysis |
|---|---|---|---|---|---|---|
| Life Expectancy | 618 | 44.129 | 13.174 | 20.132 | 82.187 | years (at birth) |
| Income Inequality | 618 | 43.486 | 7.711 | 25.261 | 81.604 | gini coeff. |
| Malaria | 618 | 0.112 | 0.315 | 0 | 1 | 1/0 |
| Health insurance | 549 | 0.308 | 0.462 | 0 | 1 | 1/0 |
| War | 596 | 0.105 | 0.219 | 0 | 1 | Fraction |
| Pandemic | 618 | 0.071 | 0.257 | 0 | 1 | 1/0 |
| Wheat-sugar ratio (ln) | 463 | 0.035 | 0.107 | -0.205 | 0.385 | Log ratio |

Note: The numbers of observations refer to those reported in table 5, column 1. Statistics for life expectancy and income inequality are based on Clio Infra data: clio-infra.eu. Statistics for height and height Gini also include other sources (details in Table 4 and Appendix B), but no interpolations.

Table 3: OLS regression of life expectancy on height deviation including world region dummies

| Life expectancy | 1820-1959 | 1960-2000 |
|---|---|---|
| Constant | 51.698*** | 71.235*** |
| | (5.268) | (1.608) |
| Height Deviation | -0.975*** | -0.809*** |
| | (0.262) | (0.141) |
| Northern Africa | -4.047 | -0.604 |
| | (4.021) | (2.060) |
| Western Africa | -9.534** | -19.697*** |
| | (3.843) | (1.503) |
| Eastern Africa | -3.053 | -13.004*** |
| | (3.874) | (1.320) |
| Central Africa | -4.746 | -16.060*** |
| | (4.241) | (1.845) |
| Southern Africa | 2.203 | -8.732*** |
| | (3.775) | (1.756) |
| Eastern Asia | 4.291 | 2.763 |
| | (3.824) | (2.260) |
| Southeastern Asia | 5.670 | 1.463 |
| | (3.957) | (1.768) |
| Southern Asia | -6.299* | -1.612 |
| | (3.801) | (2.056) |
| Western Asia | 5.946 | 1.606 |
| | (4.623) | (1.437) |
| Number of obs. | 135 | 242 |
| $R^2 - adj.$ | 0.336 | 0.606 |

Note: Robust standard errors in parentheses. Clustered at the country-decade level. Each unit represents a country-decade-combination. *Height Deviation* is the deviation from 180cm (Dutch male height equivalent in 1990). This has the advantage that the constant can be sensibly interpreted, i.e. life expectancy at a height level of 180 cm. Central Asia is the omitted region. The relationship is assessed separately for two different time periods to account for the fact that it is time-variant. *1820-1959* only includes observations from the 1820s until the 1950s. *1960-2000* includes observations from the 1960s until the 2000s. Asterisks indicate statistical significance: *** indicates significance on the 1 percent level, ** on the 5 percent level and * on the 10 percent level.

Table 4: Description and overview of the explanatory variables

| Explanatory variable | Description | Sources |
|---|---|---|
| Malaria | Indicator variable for the top ten countries that had the highest number of Malaria deaths in the population (in 1990). | Global Burden of Disease Collaborative Network. Global Burden of Disease Study 2019 (GBD 2019) Results. Seattle, United States: Institute for Health Metrics and Evaluation (IHME), 2021; adopted from ourworldindata.org/malaria |
| War | The variable describes the share of years in a decade characterised by war. | Clio Infra data base (https://clio-infra.eu) |
| Pandemic decade | Indicator variable for the pandemic (Spanish Flu) of 1918, based on the decade in which this pandemic took place. The dummy variable equals 1 if the birth decade lies in the 1910s. | Indicator variable based on the decade. |
| Health insurance | The indicator variable indexes the year in which health insurance was introduced. All subsequent decades were then coded as having health insurance as well, unless there was evidence that insurance had been eliminated again. | Cutler, David M. and Richard Johnson (2002) -- Cutler, D. M., & Johnson, R. (2002). The birth and growth of the social insurance state. https://scholar.harvard.edu/cutler/publications/birth-and-growth-social-insurance-state<br>Goudina, Tatiana & Rybalko, Larissa (1996) -- Goudima, T., & Rybalko, L. (1996). Social Insurance in Russia: History and Contemporaneity. Nordisk försäkringstidskrift, 1996, 342-50.<br>Kangas, Olli E. (2012) - Kangas, O.E. (2012), Testing old theories in new surroundings: The timing of first social security laws in Africa. International Social Security Review, 65: 73-97. https://doi.org/10.1111/j.1468-246X.2011.01420.x https://onlinelibrary.wiley.com/doi/full/10.1111/j.1468-246X.2011.01420.x<br>Social Security Programs Throughout the World: Asia and the Pacific, 2018 https://www.ssa.gov/policy/docs/progdesc/ssptw/2018-2019/asia/index.html<br>Social Security Programs Throughout the World: The Americas, 2019 https://www.ssa.gov/policy/docs/progdesc/ssptw/2018-2019/americas/index.html#fileList<br>Social Security Programs Throughout the World: Europe, 2018 https://www.ssa.gov/policy/docs/progdesc/ssptw/2018-2019/europe/index.html<br>See Appendix B |
| Life expectancy | Life expectancy at birth averaged by decade | Clio Infra data base (https://clio-infra.eu) |
| Income Gini | A combination of various estimates of inequality of income, based mostly on household surveys, tax evidence and other sources. | Clio Infra data base (https://clio-infra.eu) |
| Height | Average male height in cm. | Clio Infra data base (https://clio-infra.eu) |
| Height Gini | The calculation of the height Gini is described in the text. It | Clio Infra data base (https://clio-infra.eu) |

| | | |
|---|---|---|
| | is based on the coefficient of variation of height. | |
| GDP per capita | Gross Domestic Product (GDP) per capita. | Clio Infra data base (https://clio-infra.eu) |
| Numeracy (ABCC) | The ABCC index provides estimates of basic numeracy, using misreporting behaviour when individuals are rounding their age. | Clio Infra data base (https://clio-infra.eu) |

Table 5: OLS regressions of life expectancy on inequality

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Inequality | -0.231*** | -0.064* | -0.144*** | -0.144*** |
| | (0.039) | (0.035) | (0.041) | (0.041) |
| Malaria | | | -7.404*** | -7.335*** |
| | | | (0.928) | (0.937) |
| Health insurance | | | 4.802*** | 4.834*** |
| | | | (1.092) | (1.094) |
| War | | | 1.288 | 1.140 |
| | | | (1.146) | (1.158) |
| Pandemic | | | -0.0656 | |
| | | | (1.124) | |
| Time FE | Yes | Yes | Yes | Yes |
| Region FE | No | Yes | No | No |
| Constant | 45.01*** | 40.66*** | 41.65*** | 47.35*** |
| | (5.725) | (3.565) | (1.933) | (1.514) |
| Observations | 618 | 618 | 532 | 532 |
| R-squared | 0.685 | 0.760 | 0.740 | 0.741 |

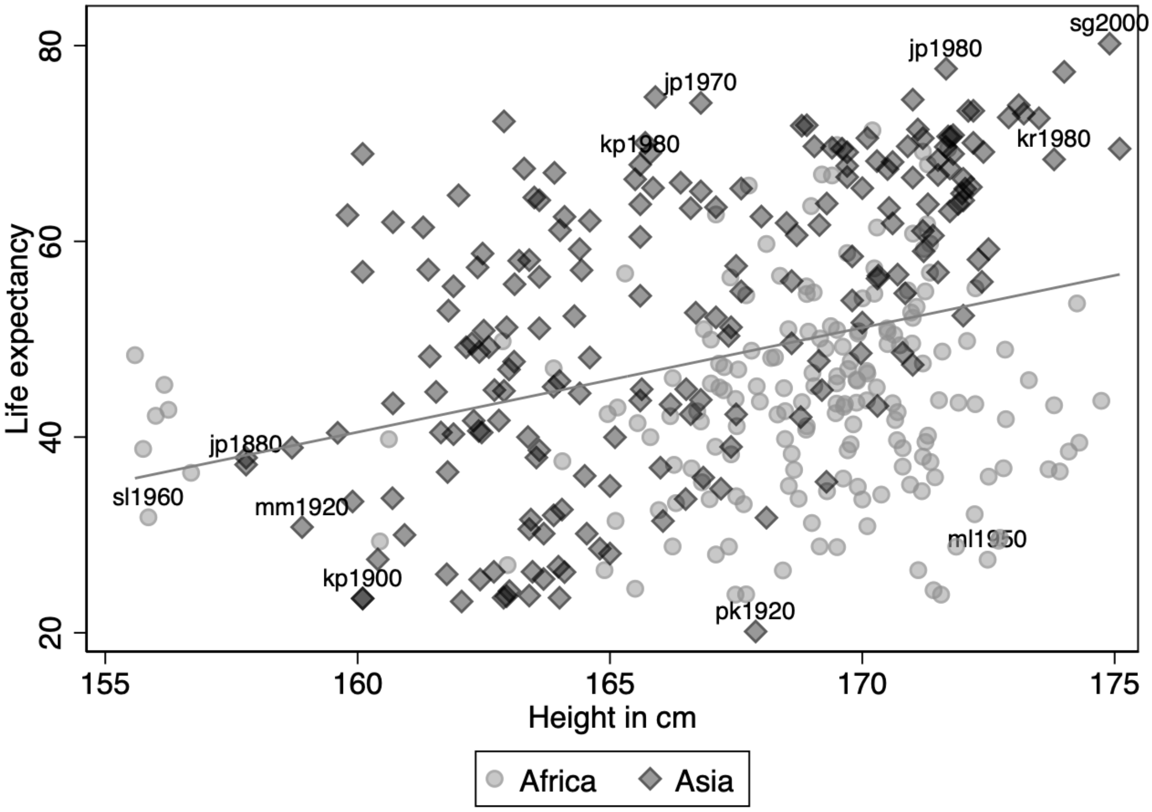
Note: Robust standard errors in parentheses. Clustered at the country-decade level. Each unit represents a country-decade-combination. Life expectancy and income Gini values partly interpolated or approximated using height. Asterisks indicate statistical significance: *** indicates significance on the 1 percent level, ** on the 5 percent level and * on the 10 percent level. The region fixed effects refer to the ten standard United Nations subregions into which Africa and Asia can be subdivided (United Nations, 1999: https://unstats.un.org/unsd/methodology/m49/). In model (1), 39% of the life expectancy values are based on height-based life expectancy estimations and 25.4% of the income inequality observations are based on height inequality estimations.

Table 6: IV regressions of life expectancy on inequality

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Incl. Region | All | Asia/ME | All | All | All |
| Incl. Life expect. Estimates | All | All | Non-height | Non-interpol. | All |
| *First stage* | | | | | |
| Wheat/sugar | -11.6*** | -13.9*** | -14.8*** | -11.6*** | -13.5*** |
| | (-3.47) | (-3.44) | (-3.54) | (-3.31) | (-3.62) |
| F-Stat | 11.2 | 11.9 | 12.8 | 11.0 | 13.9 |
| | | | | | |
| *Second stage* | | | | | |
| Inequality | -1.485*** | -0.642* | -1.459*** | -1.546*** | -0.962*** |
| | (0.500) | (0.328) | (0.476) | (0.515) | (0.367) |
| Health insurance | | | | | 11.40*** |
| | | | | | (1.677) |
| War | | | | | -1.940 |
| | | | | | (2.552) |
| Pandemic | | | | | -9.509*** |
| | | | | | (2.488) |
| Malaria | | | | | -7.683*** |
| | | | | | (1.459) |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| | | | | | |
| Constant | 133.8*** | 100.6*** | 132.6*** | 136.6*** | 85.34*** |
| | (22.86) | (14.81) | (21.75) | (23.53) | (16.72) |
| | | | | | |
| Observations | 463 | 212 | 284 | 458 | 438 |
| R-squared | 0.188 | 0.735 | 0.269 | 0.141 | 0.411 |

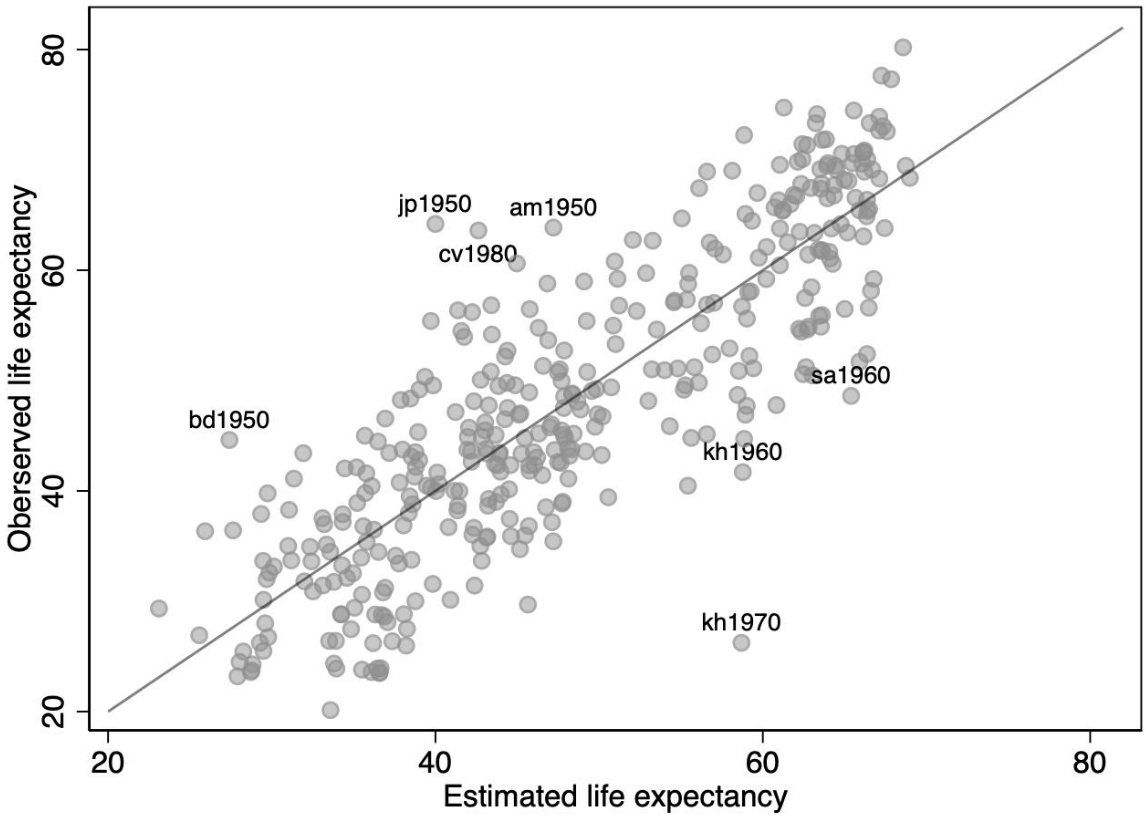
Note: Robust standard errors in parentheses. Clustered at the country-decade level. Each unit represents a country-decade-combination. Life expectancy and income Gini values partly interpolated or approximated using height (observations have been weighted by data quality in (1) through (4), see subsection data quality for details). Asterisks indicate statistical significance: *** indicates significance on the 1 percent level, ** on the 5 percent level and * on the 10 percent level.

Figure 1: Life expectancy and height in Africa and Asia




Note: The scatterplot shows the relationship between life expectancy and height. A given value of height is generally associated with higher life expectancy in Asia and with lower life expectancy in Africa. The number of observations is 178 for Africa and 199 for Asia. Each dot represents a country-decade unit. Abbreviations follow ISO-2-standard.

Figure 2: Observed and estimated life expectancy

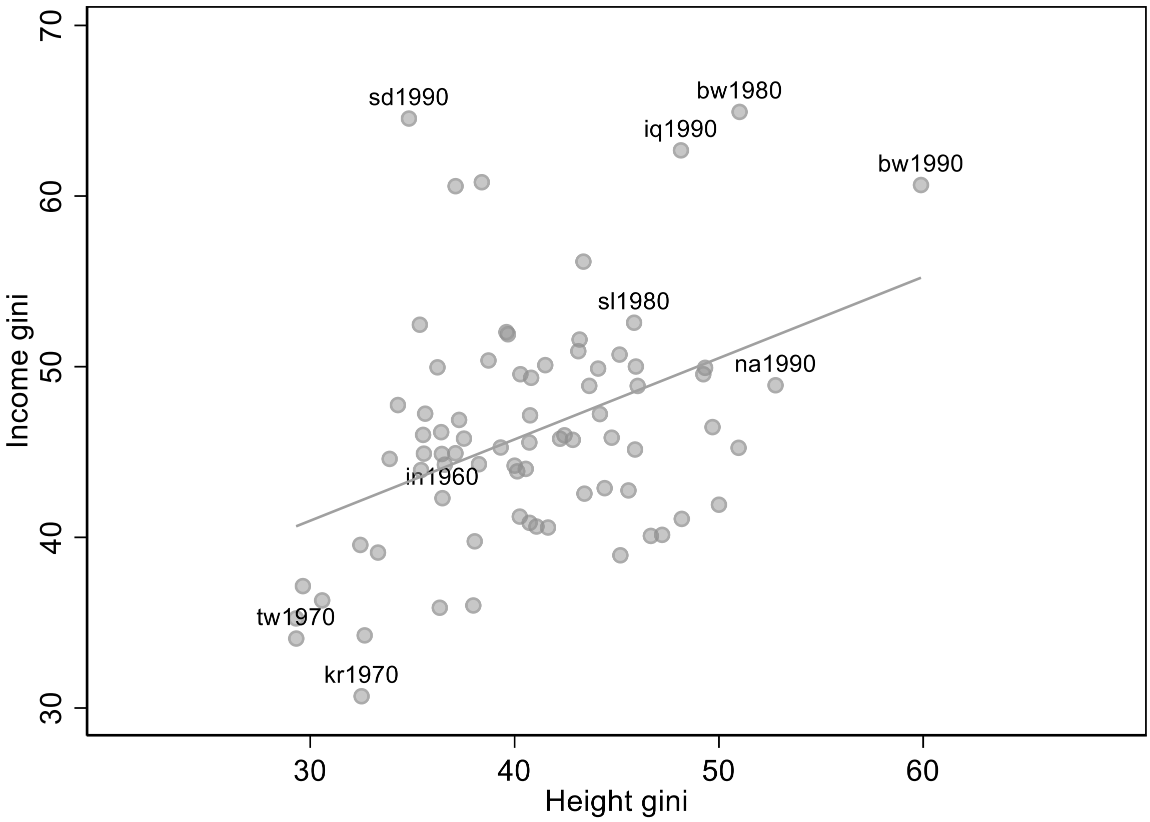



Note: The plot shows the relationship between observed and estimated life expectancy. The red line is at 45 degrees, indicating perfect correlation (not actual fitted values). For details on the estimation of life expectancy see Table 3. The correlation coefficient between observed life expectancy and estimated life expectancy is 0.85 (N=377).

The reasons for this separation are firstly, after ca. 1960, a strong increase in life expectancy took place that was exogenous to the relationship with inequality. Secondly, the statistical documentation changed substantially after 1960 with much more details reported in national statistics. This refers to medical advancements and e.g. the health programs launched by the WHO in the 1950s and 1960s.

Each dot represents a country-decade unit. Abbreviations follow ISO-2-standard.

Figure 3: Income Gini and height Gini

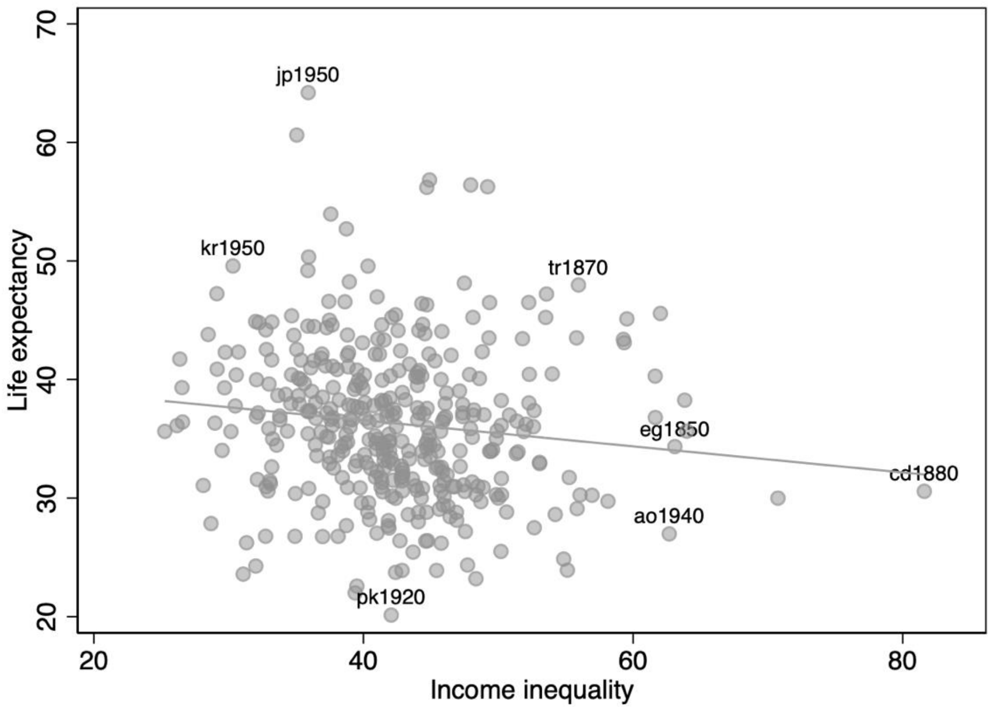



Note: The plot shows the relationship between income inequality and height inequality.

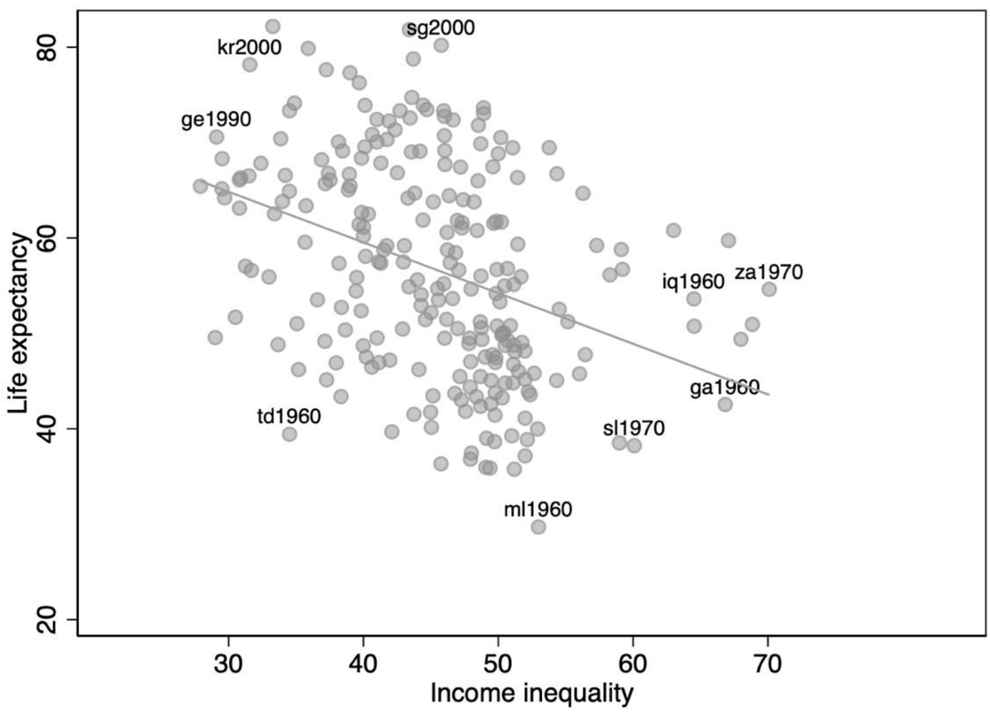
Each dot represents a country-decade unit. Abbreviations follow ISO-2-standard.

Figure 4: Life expectancy and inequality

Panel A: Observations decade 1820s to 1950s




Panel B: Observations of decades 1960s to 2000s



Note: The scatterplots show the correlation of life expectancy and inequality for two different time periods. Each dot represents a country-decade unit. Abbreviations follow ISO-2-standard.

## Appendix A: Education and GDP per capita as "bad controls"

How should *education* be dealt with in this context? One option would be to assess the relationship between life expectancy and inequality without including any indicator on education. Pickett and Wilkinson (2015, p.320) promote this approach, arguing that the inclusion of "mediating controls" like education, which are "on the causal pathway" from inequality to health, lead to an underestimation of the effect of inequality. We cannot include these two variables in the main regressions (tables 3 and 4), because income and education are clearly "bad controls" in the definition of Angrist and Pischke (2009). On the other hand, excluding education or GDP from the model may also raise the question whether it was "just education" or "just poverty" that caused the relationship between inequality and life expectancy.[13] Therefore, we include them here in the appendix to inform the reader that including these variables does not invalidate the inequality - life expectancy relationship.

Hence, we also conducted regressions in which we included GDP per capita and numeracy – the latter being one important component of education that can be measured for many countries already during the 19$^{th}$ century (see Table A1 to Table A3, Table A3 for the descriptives).

Increases in GDP per capita may lead to higher public expenditures on health care, which may improve population health (Preston, 1975, Szreter and Woolcock, 1995). Higher per capita GDP may also enable individuals to afford better nutrition, which can in turn increase life expectancy (Millward and Baten, 2007). Besides the other potential direction of causation, higher life expectancy may lead to higher GDP growth by increasing productivity

[13] The correlation coefficient between inequality and numeracy is -0.17 (p-value = 0.025) in this data set. Thus, higher numeracy is associated with lower inequality, or vice versa.

(Fogel, 2004, Case et al., 2005) or by improving the incentives to invest in human capital, which in turn will increase wages (Sachs and Malaney, 2002) and the country's productive capacity (Zijdeman and de Silva, 2014).

We also consider numeracy as possible background variable here, although it is also a "bad control". While it seems logical that basic education improves average health (Elo and Preston, 1996), through knowledge of hygiene for example, it can also be argued that higher life expectancy increases the incentives to invest in the acquisition of human capital (Sachs and Malaney, 2002), and thus may affect education.

While it has been stated that GDP per capita may be endogenous, several researchers control for this variable (see for example Babones (2008)) to disprove the claim that it is entirely the prevalence of absolute poverty, and not inequality, that determines health. We observe that controlling for GDP per capita leaves the estimated coefficient of inequality largely unchanged.

In Table A.1 and A.2, we control for both GDP and education by including the ABCC index, which is a measure of numeracy (A'Hearn et al. 2009). Including the control for education does not cause the coefficient of inequality to lose statistical significance.

Table A1: OLS regressions of life expectancy on GDP per capita and numeracy

| *Life expectancy* | (1) | (2) |
|---|---|---|
| Inequality | -0.248*** | -0.189** |
| | (0.0490) | (0.0779) |
| GDP/c. (ln) | 8.210*** | 7.482*** |
| | (0.395) | (0.730) |
| Numeracy | | 0.134*** |

| | | |
|---|---|---|
| | | (0.0278) |
| Time FE | Yes | Yes |
| Region FE | No | No |
| Constant | -14.85*** | -14.28** |
| | (3.605) | (6.385) |
| Number of obs. | 331 | 139 |
| R-squared | 0.803 | 0.785 |

Note: Robust standard errors in parentheses. Clustered at the country-decade level. Life expectancy and income Gini values partly interpolated or approximated using height. Asterisks indicate statistical significance: *** indicates significance on the 1 percent level, ** on the 5 percent level and * on the 10 percent level.

Table A2: IV regression of life expectancy on GDP per capita and numeracy

| | (1) |
|---|---|
| Incl. Region: | All |
| Incl. Life expectancy estimates: | |
| *First stage* | |
| Wheat/sugar | -20.4*** |
| | (-3.32) |
| F-Stat | 11.7 |
| *Second stage* | |
| Inequality | -0.633** |
| | (0.280) |
| GDP/c (ln) | 7.708*** |
| | (0.997) |
| Numeracy | 1.516 |

| | |
|---|---|
| | (3.119) |
| Time FE | Yes |
| Constant | 18.17* |
| | (10.26) |
| Observations | 122 |
| R-squared | 0.626 |

Note: Robust standard errors in parentheses. Clustered at the country-decade level. Life expectancy and income Gini values partly interpolated or approximated using height (observations have been weighted by data quality in (1) through (4), see subsection data quality for details). Asterisks indicate statistical significance: *** indicates significance on the 1 percent level, ** on the 5 percent level and * on the 10 percent level.

Table A3: Descriptive statistics of key variables and controls

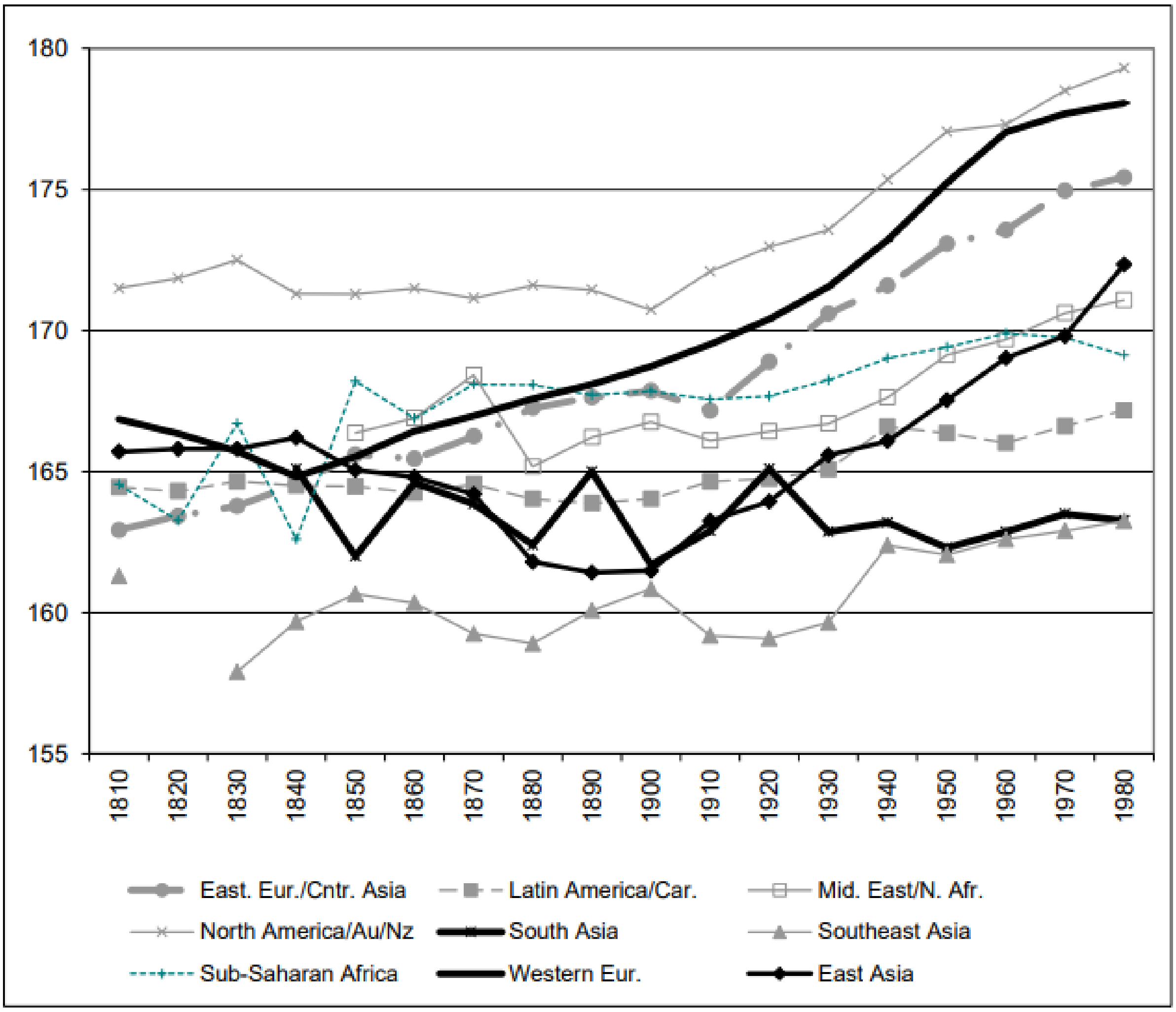
| Variable | N | Unit of analysis | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Numeracy | 550 | ABCC index | 76.13 | 23.15 | 5.41 | 100 |
| GDP per capita | 679 | 1990 GK dollars | 2679 | 4352 | 225 | 34,440 |

Statistics for numeracy and GDP per capita, based on Clio Infra data

**Appendix B List of data sources**

**Life expectancy:** Clio Infra data base (https://clio-infra.eu)
**Income Gini:** Clio Infra data base (https://clio-infra.eu)
**Height:** Clio Infra data base (https://clio-infra.eu)
**Height Gini:** Clio Infra data base (https://clio-infra.eu)
**GDP per capita:** Clio Infra data base (https://clio-infra.eu)
**Cattle per capita:** Clio Infra data base (https://clio-infra.eu)
**Numeracy (ABCC):** Clio Infra data base (https://clio-infra.eu)
**War**: Clio Infra data base (https://clio-infra.eu)
**Health insurance**: Cutler, David M. and Richard Johnson (2002) -- Cutler, D. M., & Johnson, R. (2002). The birth and growth of the social insurance state. https://scholar.harvard.edu/cutler/publications/birth-and-growth-social-insurance-state
Goudina, Tatiana & Rybalko, Larissa (1996) -- Goudima, T., & Rybalko, L. (1996). Social Insurance in Russia: History and Contemporaneity. *Nordisk försäkringstidskrift*, *1996*, 342-50.
Kangas, Olli E. (2012) - Kangas, O.E. (2012), Testing old theories in new surroundings: The timing of first social security laws in Africa. International Social Security Review, 65: 73-97. https://doi.org/10.1111/j.1468-246X.2011.01420.x
https://onlinelibrary.wiley.com/doi/full/10.1111/j.1468-246X.2011.01420.x
Social Security Programs Throughout the World: Asia and the Pacific, 2018
https://www.ssa.gov/policy/docs/progdesc/ssptw/2018-2019/asia/index.html
Social Security Programs Throughout the World: The Americas, 2019
https://www.ssa.gov/policy/docs/progdesc/ssptw/2018-2019/americas/index.html#fileList
Social Security Programs Throughout the World: Europe, 2018
https://www.ssa.gov/policy/docs/progdesc/ssptw/2018-2019/europe/index.html
**Malaria:** Global Burden of Disease Collaborative Network. Global Burden of Disease Study 2019 (GBD 2019) Results. Seattle, United States: Institute for Health Metrics and Evaluation (IHME), 2021; adopted from ourworldindata.org/malaria

**Appendix C: Global Height Trends**




Notes: The figure shows height trends by world region (using interpolations, weighted by population size).

Migrant heights are included (but account only for 0.7% of the sample). The standard world region classification has been used. The only exception is a group of 4 former British settler colonies (US, Canada, Australia & New Zealand) as they experienced a great share of Western European settlers and are characterized by land abundance which allowed superior nutrition and eventually qualified them to become food exporters in the first wave of globalization (Baten and Blum 2012).

Source: Baten and Blum (2014). See Baten and Blum (2012), Tables 1 and 9, for data coverage by country.

## Appendix D: Measuring the Influenza Epidemic 1918

Ideally, we would have included here a measure for the intensity of the Influenza pandemic of 1918. However unfortunately for Africa and Asia very few countries can be documented within explicit measure of excess mortality caused by the Influenza pandemic. Hence, we are using an indicator for the 1910s because during this decade the Influenza pandemic was by far the largest exceptional health influence in the countries under study. And given that such a pandemic is by definition a global event, many countries were severely affected. Any observable differences between countries might be partly due to measurement errors, particularly for the Indian and Indonesian case. Critical evaluations of the existing estimates have argued that most of the missing population increase between a pre-war census and a post war census has been attributed to the Influenza pandemic although other causes could have also caused a slower population growth compared to the pre-World War One growth trajectory.

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