The Measurement of Health Inequalities: Does Status Matter?

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Abstract

The measurement of health inequalities usually involves either estimating the concentration of health outcomes using an income-based measure of status or applying conventional inequality-measurement tools to a health variable that is non-continuous or, in many cases, categorical. However, these approaches are problematic as they ignore less restrictive approaches to status. The approach in this paper is based on measuring inequality conditional on an individual's position in the distribution of health outcomes: this enables us to deal consistently with categorical data. We examine several status concepts to examine self-assessed health inequality using the sample of world countries contained in the World Health Survey. We also perform correlation and regression analysis on the determinants of inequality estimates assuming an arbitrary cardinalisation. Our findings indicate major heterogeneity in health inequality estimates depending on the status approach, distributional-sensitivity parameter and measure adopted. We find evidence that pure health inequalities vary with median health status alongside measures of government quality.

Keywords: health inequality, categorical data, entropy measures, health surveys, upward status, downward status

JEL Codes: D63, H23, I18

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1. Introduction

Measuring health inequality presents a challenge quite different from the standard problem of measuring income or wealth inequality. The challenge principally lies in the measurement of health itself: health cannot be assumed to be directly and unambiguously observable and it may not make sense to treat it as a continuous variable. As a consequence one has to use indirect methods that may involve elicitation of a person's self-assessed health status or explicit modelling using observables that are thought to be related to health. Such indirect methods can be problematic. So the purpose of this paper is to examine the main practical approaches to inequality measurement in the health context and the extent to which different assumptions about health status affect inequality comparisons.

Why are indirect approaches to health measurement typically problematic? The first reason is because of the assumptions that have to be adopted in modelling health: if health status is taken as a latent variable, with what observables is it correlated?[1] There is evidently room for several alternative answers: some research suggests that SAH correlates with mortality, some with hospital records (Heien 2015, Idler and Benyamini 1997). The second – and perhaps more fundamental – reason that such approaches are problematic is that health cannot be taken as a monetary-equivalent measure and that, in many health models, it should be treated as an ordinal or categorical variable rather than a continuous variable. That being so, standard methods of inequality analysis and standard properties of inequality indexes do not apply (Van Doorslaer and Jones 2003). So, how is one to measure inequality?

This paper addresses the main theoretical and practical difficulties presented by the measurability problem of health-status inequality and, in doing so, examines the problems of working with self-assessed health (SAH) indicators, the use of alternative approaches to the measurement health inequality and the information content of different concepts of status. We compare our approach to the case of inequality analysis based on a standard but arbitrary cardinalisation of health using standard inequality indices.

The results from this paper go towards the identification of a more appropriately based definition of health status and of health-inequality measures. We provide researchers with a simple means of testing alternative ways of measuring inequalities of non-cardinal outcomes that may have significant policy implications. This is particularly important when one takes account of the fact that measures of health inequality are used to rank health systems, and increasingly measures of well-being are used by the World Health Organisation and other government bodies to evaluate institutions and public policies. Specifically, we undertake the following:

[1] On the correlation between SAH and objective measures of health status see Bound (1991).

1. We provide an alternative estimation of (pure) health inequalities using a measure of status that is not imposed through an arbitrary cardinalisation strategy, but based on two perspectives of the distribution of health status. We focus on concepts of status derived from the distribution of health outcomes to compute inequality measurements. This is an application of the cardinalisation method employed in the Cowell-Flachaire (2014) status-inequality approach. We compare these estimates to those that would emerge from simple direct cardinalisations of health status.

2. We provide the first multi-country estimate of health inequalities using the status-inequality approach.

3. We then examine the determinants of the two different perspectives of status-inequality (mentioned in 1 above) across countries taking into account determinants such as per capita income, average education demographics as well as a collection of indicators for political development. This allows one to examine a number of important questions: do poor countries exhibit higher health-inequality irrespective of status? Are specific demographics more likely to engender health inequalities? What is the role of institutional variables, and specifically measures of democratic development (which can explain policy sensitivity to health needs)? We control for cross-country fixed effects and regional consistency in inequality patterns.

The paper is organised as follows. Section 2 contains some necessary theoretical background, section 3 introduces the data set and explains our empirical strategy, section 4 contains our results and section 5 concludes.

2. Health-inequality measurement – principles and practice

For a coherent approach to the measurement of health inequality we need two basic concepts and a methodology for measuring or estimating values of these concepts and then aggregating the values.

2.1 Basic concepts: health and status

If we were able to treat “health” like “wealth” then a person's health could be taken as a continuous variable that is, in itself, an objectively measurable and observable measure of a person's status. For a broadly-defined interpretation of health this is unrealistic. One could try to use proxies – since the contribution of Idler and Benyamini (1997), categorical self-assessed measures of health are taken as acceptable proxies for individuals – but perception and observation might not necessarily match (Sen 2002). One could also focus on the inequality of individual components or aspects of health that can be objectively measured (just as particular components of wealth or income are interesting subjects of inequality analysis), but this is necessarily of limited interest and applicability.

Since there is no standard off-the-shelf measure of health status that is going to be generally suitable for inequality analysis, we need to be clear about two steps: (1) how to model health h_i for each individual $i = 1, ...n$ and, (2) given $\{h_1, ..., h_n\}$, how to model the status variable s_i that is to be used in inequality computation.

2.1.1 Individual health, h_i

Given the difficulties in observing a broadly defined indicator of individual $h_i$there are two main ways forward. First one might try to estimate a health production function assuming the following kind of relationship:

$$h_i = \Phi\left(\mathbf{X}_i\right) \; + \; \varepsilon_i, \tag{1}$$

where Φ is the production function, $\mathbf{X}_i$ represents a vector of determinants of health (such as income, demographics, institutions) and ε_i a random component. Depending on the nature of the assumed specification of Φ, $\boldsymbol{h_i}$ could be a continuous or discrete variable. Specifying and estimating such a function is challenging because health status is a latent variable that cannot be observed.

The second approach is to model $\boldsymbol{h_i}$ thus:

$$h_i \in \{c', c'', c''', ...\} \ , \tag{2}$$

where c', c'', c''' represent different health categories. Many national and international surveys contain information on measures of SAH in categorical form; the categories may or may not have a natural ordering.

So, in principle, an individual's health h_i can take the form of a censored variable, an interval variable, or an ordered categorical variable, depending on the underlying assumptions about how to conceptualise it and model it.

2.1.2 Individual status, s_i

How one models an individual's status depends in part on the way h_i is modelled. If one follows the production-function approach, it might be possible to use the h_i value as an indicator of health status, just as it pops out of equation (1), or a transformation of it. If one is using a specification such as that of equation (2) then a number of problems immediately present themselves: how to order the members of the set $\{c', c'', c''', \ldots\}$ how to calibrate the "distance" between members of the set of categories and so on. One might, alternatively, incorporate in the concept of status information about health and some other personal characteristic, such as income.

Whether one starts with equation (1) or (2), or perhaps something else, the analysis involves three main components: (1) extraction of suitable categorical variables on which to construct health and status indices; (2) computation of cardinal imputations, status measures and associated inequality indices and rankings; (3) an analysis of cross-country inequality comparisons. These three things are addressed in the following subsections.

2.2 Concentration curves and indices

The concentration curve and concentration indices (Costa-Font and Hernández-Quevedo 2012, Koolman and van Doorslaer 2004) form arguably the most popular approach in the health-inequality literature. At the core of this approach is the idea that a person's status should be based not only on health but also on other personal or social information, as discussed in section 2.1: this supplementary information is personal income or other similar indicators that are believed to co-vary with health. Individual status is usually taken to mean a person's position in the income hierarchy,[2] but the use of income-rank as a status variable is a matter of choice (why not consumption or wealth?) and its use can be problematic insofar as income is measured with limited precision. However, pursuing this approach makes it difficult to identify whether policies really affect health inequality, or simply affect determinants of health such as the distribution of material conditions (which in turn give rise to a fairer distribution of health status). Furthermore the approach can appear ad hoc rather than rigorously founded on economic theory.[3]

Studies that use income as a measure of social hierarchy on self-assessed measures of health are problematic, in several ways. First, they tend to underestimate income-related inequalities in health (Dowd and Todd 2011). Second, the distribution should perhaps be adjusted to eliminate factors such as age or gender which could be considered to distort the picture of inequality. Third, even if such adjustments are successfully made, the approach typically ignores the contribution of essentially "avoidable" determinants of health, or even potentially "ethically legitimate" differences in health resulting from preventive effort and choice (Le Grand 1987).

[2] See, for example, Marmot (2005), Wagstaff and van Doorslaer (2000). This was the position adopted in the early literature, with few exceptions (such as Le Grand 1987); recent research has argued that socioeconomic background is only one dimension of health inequality.

[3] An attempt has been made to justify the approach on the basis of the principle of income-related health transfers (Bleichrodt and van Doorslaer 2006, Fleurbaey 2006, Fleurbaey and Schokkaert 2012, page 1012), the plausibility of which is questionable.

2.3 Inequality of cardinal indicators

An alternative approach is to apply conventional inequality tools to specific cardinal indicators of health such as life expectancy, or measures of hypertension. Some of the socio-economic differences in health might not be pure socio-economic inequalities, but may be determined by lifestyles (Fleurbaey and Schokkaert 2009, 2012). Other inequalities, such as those resulting from poor health production in younger ages, or biologically driven gender differences in health, are, arguably, not avoidable (Wagstaff et al. 1991). Should one attempt to remove all avoidable components from the analysis and focus solely on the remaining health inequalities? To do so makes an implicit claim of what is an illegitimate inequality, an approach that might seem to be tendentious. Instead one might adopt a value-free choice.

The further difficulty with the cardinal-indicators approach is that some of the most important indicators of health status are categorical variables that do not have a natural cardinalisation. Clearly one could try to circumvent this by imputing some artificial index of individual health status as a function of the categories (Fonseca and Jones 2003). For example, in some cases the imputation is achieved through subjective evaluation by individuals (for example on a Likert scale) and in some cases by making use of quality of life indices (for example, EuroQuol-EQ5).[4] There are various types of cardinalisation methods that have been proposed in the literature such as imputation of quality of life scales (for example, values from Visual Analogue Scales), interval regression and so on, but there is insufficient discussion of the economic rationale for these methods or the practical implications of using one method rather than another and it has been shown that cardinalisation can be an important source of bias.[5] As a consequence, one should treat some of the existing literature with some caution.[6] A more promising approach involves a proposed cardinalisation of SAH status using an imputation of the values of Health-Related Quality of Life (HRQoL): one obtains the value of the cut-off point of each response to the ordinal question in order to estimate the determinants of SAH using an interval-regression approach (assuming income-related health inequality – Fonseca and Jones 2003, Van

[4] The same procedure can be applied to entities that do not have a natural ordering, such as vectors of attributes or endowments; one uses a utility function to force an ordering of the data. This is similar to one of the standard theoretical approaches to the measurement of multidimensional inequality; one computes the “utility” of factors and then computes inequality of utility, where the utility function is an appropriate aggregator (Maasoumi 1986, Tsui 1995). However the approach faces serious objections such as the arbitrariness of the cardinalisation and of aggregation. Even if the resulting well-being index appears reasonable over a wide subset of categories one might still be concerned about the way extreme values are represented in the index and their consequences for inequality comparisons.

[5] In a paper running a meta-regression of health inequality studies in the economics literature Costa-Font and Hernández-Quevedo (2013) find that the main reason for estimate heterogeneity is the way studies cardinalise health status.

[6] Some of the empirical attempts to examine such problems are in Costa-Font and Cowell (2013) where they use World Health Survey data to examine alternative pragmatic methods for measuring health-inequality and examining regional and country patterns of inequality orderings.

Doorslaer and Jones 2003). Let us consider further the underlying distribution-based concept as a basis for the evaluation of status.

2.4 Alternative approaches using categorical data

Here we consider approaches that use categorical data directly, without trying to impose *a priori* a particular cardinalisation. The theoretical literature on the problem of making inequality comparisons when the underlying equalisand is ordinal has mainly resulted in a number of rather limited propositions that are difficult to interpret or apply.[7] However, recent work on the analysis of distributions of categorical variables has shown how natural interpretations of individual *status* can be used to provide a robust approach to the inequality-measurement problem in this context without resort to arbitrary cardinalisation of ordinal concepts (Cowell and Flachaire 2014). The status concept is similar to concepts used in poverty and relative deprivation and in recent approaches to the inequality of opportunity (de Barros et al. 2008).

Status interpreted as an individual's position in the health distribution is important in understanding several relationships in the economics of health. For example Costa-Font and Costa-Font (2009) and Hausman et al. (2002) show that effect of income on SAH depends in part on the individual's position in the health distribution: this finding is potentially important in understanding the persistence of health inequalities over time, and more specifically suggest that their effect depends on individual position within a given health distribution. In the present context the status approach gives rise to an alternative way of making inequality comparisons; it also gives rise to a set of inequality indices that incorporate conventional distributional views such as degree of inequality aversion and that can be applied to commonly-used measures of individual well-being.

The Cowell and Flachaire (2014) approach tackles the problem by separating out carefully the two tricky components of inequality measurement mentioned in the introduction, the equalisand and the aggregation method. Each of these is underpinned by an axiomatic argument that goes based on first principles. The resulting Cowell and Flachaire method amounts to an aggregation of the discrepancies between each person's actual status and some status reference point. In such an approach clearly a lot rests on the precise definition of status. In the case of applications where the equalisand has a natural cardinalisation (income or wealth for example) then it makes sense to define status as just income or wealth. However, where only ordinal information is available – as with categorical data on health

[7] It involves a reworking of traditional inequality-ranking approaches focusing on first-order dominance criteria (Abul Naga and Yalcin 2008, Allison and Foster 2004, Zheng 2011). It is commonly suggested that the median could be used as an equality concept corresponding to the use of the mean in conventional inequality analysis, although it has been noted that comparing distributions with different medians raises special issues (Abul Naga and Yalcin 2010). But the approach runs into difficulty if quantiles are not well-defined, as may happen in the case of categorical variables – see Cowell and Flachaire (2014).

status – then we have to do more. Suppose that information is purely categorical, in that we only know how many people are in each category $k = 1, 2, \dots K$, but that the categories can be arranged in increasing order of their desirability. Then a simple argument shows that, if there are n_k persons in category $k = 1, 2, 3, \dots K$, the status of person i who is currently in category $k(i)$ must be a function of either $\sum_{\ell=1}^{k(i)} n_\ell$ or $\sum_{\ell=k(i)}^{K} n_\ell$. The first of these is a "downward looking" concept and the second is its "upward looking" counterpart. It may be appropriate to normalise by the size of the total population $n := \sum_1^K n_k$ so that person i's status is given by either the downward-looking version

$$s_i = \frac{1}{n} \sum_{\ell=1}^{k(i)} n_\ell, \tag{3}$$

or by the "upward-looking" counterpart of (3):

$$s_i' = \frac{1}{n} \sum_{\ell=k(i)}^{K} n_\ell; \tag{4}$$

On either definition status must lie between zero and one. If there were perfect equality (everyone in the same category) then it is clear that both (3) and (4) take the value 1. It turns out that this, the maximum-status value, is the only thing that makes sense as the reference point.

The inequality-measurement problem then amounts to aggregating the information in the vector $s := (s_1, s_2, \dots, s_n)$ in relation to the equality vector (1, 1, …, 1). On the basis of a small number of elementary axioms Cowell and Flachaire show that inequality must take the form of an index in the following family, indexed by α:

$$I_\alpha(\mathbf{s}) = \begin{cases} \frac{1}{\alpha(\alpha-1)} \left[\frac{1}{n} \sum_{i=1}^{n} s_i^\alpha - 1\right], & \text{if } \alpha \neq 0, \\ -\frac{1}{n} \sum_{i=1}^{n} \log s_i, & \text{if } \alpha = 0. \end{cases} \tag{5}$$

where $\alpha < 1$ is a parameter indicating the desired sensitivity of the index to a particular part of the income distribution: for low values of α the index $I_\alpha(\mathrm{s})$ is particularly sensitive to values of s_i close to zero. If s is given by (3) ($i = 1, \dots, n$) then we have an index of ordinal inequality based on downward-looking status; if we replace s with s' given by (4) then we have ordinal inequality defined on the corresponding upward-looking status concept.

So we have a *family* of indices that are suitable for making comparisons of inequality in terms of health status. In addition, members of the family can be adjusted by different health-inequality aversion parameters in a flexible way as other inequality indices. In what follows we shall suggest a way of using this to make health-inequality comparisons internationally.

Clearly, equation (5) has a form similar to the well-known Generalised Entropy class of inequality indices (Cowell 1980, Shorrocks 1980).

$$G_\alpha(\mathbf{s}) = \begin{cases} \frac{1}{\alpha(\alpha-1)}\left[\frac{1}{n}\sum_{i=1}^{n}\left[\frac{s_i}{\mu(\mathbf{s})}\right]^\alpha - 1\right], & \text{if } \alpha \neq 0, 1 \\ -\frac{1}{n}\sum_{i=1}^{n}\log\frac{s_i}{\mu(\mathbf{s})}, & \text{if } \alpha = 0, \\ \frac{1}{n}\sum_{i=1}^{n}\frac{s_i}{\mu(\mathbf{s})}\log\frac{s_i}{\mu(\mathbf{s})}, & 1, \end{cases} \tag{6}$$

where $\mu(s)$ is the mean of the vector s. Whereas $I_\alpha(s)$ has the reference point 1 the GE index $G_\alpha(s)$ has the reference point $\mu(s)$ and, obviously, this only makes sense where status is cardinal, in other words, if status defined in such a way that it is meaningful to add the status values together. With ordinal data one could impose an arbitrary cardinalisation and, in section 4 we will try out the performance of $G_\alpha(s)$ for two such arbitrary cardinalisations and compare them with the theoretically appropriate $I_\alpha(s)$.

3. Data and Methods

3.1 Data

In view of these points it is clear that the underlying data and the health status indicator derived from it could be of the following forms:

Continuous, censored. In some circumstances, health status can be measured using a censored continuous variable (for example when visual analogue scales are employed). However, there are still problems related to focal responses so that certain points in a scale are more common than others (De Boer et al. 2004).

Ordinal. Given the categorical nature of SAH, it may be reasonable to take the ordering of question responses as naturally given and to employ techniques designed for ordered variables. For example, an ordered probit model, could be used capture the degree of intensity of health or ill health, without explicitly cardinalising the health concept.

Our approach requires quantitative analysis of internationally comparable data that contain measures of health status. Accordingly the main data source to be used is the World Health Survey which contains data from seventy countries; it collects comparable multidimensional micro-data on income, employment education and health. There are two reasons for the choice of this data base: first, its great advantage for comparative work; second, its standardised world-wide structure can assist in examining cross country patterns across heterogeneous world regions that exhibits different levels of economic and social development.

The World Health Survey (WHS) is a general population survey, developed by WHO to address the need for reliable information and to cater to the increased attention to the role of health in economic and human development. Other alternative options (ISSP, Gallup etc) were not as rich in terms of controls and measurement. Indeed, the survey contains data from randomly selected adults (i.e. older than 18 years of age) who reside in seventy-one countries who implemented household face-to-face surveys, computer assisted telephone interview, or computer-assisted personal interview in 2002. Sample sizes range from 1,000 to 10,000.

Our measure of health status is the standard easier pf SAH status widely used in the literature; this is a categorical measure of health is based on the responses to the question "how would you rate your health today?" and yields a personal evaluation of overall health with potential responses in five categories ranging from "very good" to "very bad".[8] As a measure, it suffers from cultural adaptation problems that make cross-country comparison challenging, but it appears to be an adequate measure for computing within-country inequalities.

3.2 Cardinalisation

For categorical data a simple way to process the data is to rank the values underlying the latent variable health. But the "distance" between categories is unknown and an arbitrary scale may not be informative; there is no theoretically sound consensus strategy to measure such a latent variable from categorical responses.

3.2.1 "Natural" cardinalisation?

In some cases it is possible to employ existing quality-of-life measures of health status that are available in health surveys to impute a cardinal value to the categorical responses to the SAH questions, for example the imputation of values from the Health-Related Quality of Life scales as in Van Doorslaer and Jones (2003), Fonseca and Jones (2003).

[8] The detailed values are given in Table 5 in the Appendix

Another way forward is to obtain a linear index based on scaling the ordered variable to obtain a normalised health index (Cutler and Richardson 1997). However, this still requires arbitrary assumptions on the value and distribution of a person's health status. Makdissi and Yazbeck (2014) address the question of the categorical measurement of health variables by using a ratio-scale transformation that modifies the information provided and focuses on the ‘breadth’ rather than the ‘depth’ of the health-indicator information. However, they lose some important information on the distribution of the health variable and they focus on income-related health inequalities which involves important and questionable assumptions.

So, instead, some papers interpret SAH status as an individual's categorisation into an interval, which can be ascertained by finding a link between self-assessed measures of health and some health utility indices. For example, Van Doorslaer and Jones (2003) use the equivalent cardinal value of the cut-off point of each response to the ordinal question was obtained so as to estimate the cardinal value of SAH using an interval-regression approach.

3.2.2 Regression approach

Both ordered and interval regressions models can be used to transform a categorical outcome into a continuous variable based on the parameters of the regression. So, if the health variable allows an unambiguous ordering, then a logit or probit regression model will take into account the structure of the data.[9] By assuming an order the probability of respondents' classifying themselves on a specific scale can modelled in the standard fashion. However, even where this is an improvement with respect to binary measures of health for the purposes of measuring health inequality, it is still difficult to interpret the meaning of a change in the order between scales of SAH status.

However, the transformation is dependent in the covariates of the regression and on the arbitrary nature of different variable categories. The strategy we pursue here addresses this latter point and provides an alternative cardinalisation method, that we argue is more suitable to measure inequalities in health.

3.2.3 Pure health inequality?

Instead of trying to use the structure of the data to produce a cardinalisation of health status, Allison and Foster (2004) develop a stochastic dominance approach to 'pure health inequalities', which is not limited by the extent of assumptions implicit in partial inequality measurements of income-related health inequality. However, the range of results that are available from this approach is rather narrow and so it is likely to be limited.

[9] See for example the logistic regression technique used by Kunst and Mackenbach (1994).

In this paper we use the Cowell and Flachaire (2014) methodology discussed in section 2.4 to undertake international comparisons of inequality of SAH status.

3.3 Inequality comparisons

Our approach in this paper is to measure the inequality of SAH status using the WHS international data set and the robust Cowell and Flachaire (2014) approach that takes account of the categorical nature of the data and the problems of making comparisons between countries. This involves the following steps:

1. We estimate self-assessed health inequality using the Cowell and Flachaire (2014) class of measures for several values of the sensitivity parameter α ranging from -2 (effectively negative infinity) to -0.99 (arbitrarily close to upper bound of α). We do this for both downward-looking status s and upward-looking status s'.

2. We compare these measures of health inequality with those that would emerge from conventional inequalities using an arbitrary cardinalisation. In fact we take two different such cardinalisations. The first simply numbers the five health categories from low to high as (1,...,5) so that, if there are $(n_1, \dots, n_5)$ observations in each of the categories, the status vector is given by:

$$\mathbf{s}^{\uparrow} := \left(\underbrace{1, \dots, 1}_{n_1}, \underbrace{2, \dots, 2}_{n_2}, \underbrace{3, \dots, 3}_{n_3}, \underbrace{4, \dots, 4}_{n_4}, \underbrace{5, \dots, 5}_{n_5} \right). \quad (7)$$

   To capture the idea of inequality of ill health we also look at the "inverse" case where the same five health categories are labelled (5,…,1).[10]

$$\mathbf{s}^{\downarrow} := \left(\underbrace{5, \dots, 5}_{n_1}, \underbrace{4, \dots, 4}_{n_2}, \underbrace{3, \dots, 3}_{n_3}, \underbrace{2, \dots, 2}_{n_4}, \underbrace{1, \dots, 1}_{n_5} \right) \quad (8)$$

   We then compute $G_\alpha(s^{\uparrow})$ and $G_\alpha(s^{\downarrow})$, using the same values of α as for the ordinal inequality statistics computed in step 1.

3. We use rank-correlation analysis to examine the association of country inequality orderings under the alternative definitions of status (3), (4), (7) and (8) for different

[10] The different status measures here address the so-called: 'mirror problem' discussed by Clarke et al. (2002) who find that concentration indexes for SAH show inconsistent results when 'health' or 'ill-health' is as a dependent variable.

values of the inequality sensitivity parameter. In other words we look at the correlations between pairs from $\{I_\alpha(s), I_\alpha\}(s'), G_\alpha\left(s^\uparrow\right), G_\alpha\left(s^\downarrow\right)\}$ for a number of values of α.

4. We regress $I_\alpha(s)$ (downward) and $I_\alpha(s')$ (upward) on a number of explanatory variables in order to get some insight on the factors associated with high health inequality. Focusing on inequality avoids problems that may arise from systematic response bias between countries.[11] We carry out a similar analysis using the simple cardinalisation $G_\alpha(s^\uparrow)$ and the inverse cardinalisation $G_\alpha(s^\downarrow)$.

5. Furthermore we examine possible patterns of health inequality by looking at the way in which (i) $I_\alpha(s)$ for each country varies and (ii) the way country orderings change as the parameter α varies.

3.4 Inequality regression Analysis

What factors underlie the SAH-inequality rankings for different specifications of status variable? We can use standard regression analysis to address this question, assuming a linear relationship for the variables that may potentially influence health inequalities by country. Given the small number of observations we limit the number of variables to avoid running into limited degrees of freedom. Our dependent variable is a country-specific inequality index I_α, G_α for each country i and our independent variables are the country-specific income (Y_i), median SAH (H_i),[12] indicators of institutional performance (such as rule of law, corruption, government effectiveness, democracy), Z_i and a number of controls for country-specific characteristics (such as the proportion of old age population, female population ratio), X_i. The estimated equation is as follows:

$$\{I_\alpha G_\alpha\} = \gamma_0 + \gamma_1 Y_i + \gamma_2 H_i + \gamma_3 X_i + \gamma_4 Z_i + e_i$$

where e_i is a random error. We hypothesize whether the four measures of inequality are driven by the same country-specific determinants. Namely, would an improvement in government effectiveness or income reduce health inequalities? Would it do so in the same way irrespective of the measure of inequality or the value of α? Is there a non-linear effect of income (Kuznets curve) on income or health? Are changes in the composition of the

[11] Comparing median categories across countries is regarded as uninformative given that some countries habitually over-report. The term “moderate health” means different things across countries because people's expectations are different. Some progress has been made in using anchoring vignettes that is increasingly used to correct for this type of bias see Kapteyn et al. (2007) and Rice et al. (2012).

[12] The variables $(Y_i)$and (H_i)allow for the possibility of there being a Kuznets curve in income or in health.

countries' population driving the changes in health inequality? The following section reports the specific variables in the regression analysis.

4. Results

Table 1 provides the summary statistics for 70 country-level observations, organised as follows:

Dependent variables: Ordinal inequality indices. The first eight rows give the sample statistics of $I_\alpha(\cdot)$, the Cowell-Flachaire (2014) for inequality of SAH, for both downward-looking status s and upward-looking status s'. This is for $\alpha \in \{-2, -1, 0, 0.99\}$.

Dependent variables: Cardinal inequality indices. The next eight rows give the sample statistics of $G_\alpha(\cdot)$, the Generalised Entropy inequality index using the simple cardinalisation of SAH $s^\uparrow$, and the inverse cardinalisation $s^\downarrow$. Again, this is for $\alpha \in \{-2, -1, 0, 0.99\}$.

Independent variables. From the literature we might expect the following to have an effect on health inequality:

- Income levels defined as GDP per capita at the country level;
- the median category of health status: may help to disentangle a potential Kuznets curve effect;
- the proportion of females (fempop_2005) and the proportion of the elderly (pop65_2005) in each country: one might expect that health inequality is higher where there are more elderly;
- six measures of institutional characteristics produced by the World Bank (corrupt_2005, rule_2005, reg_2005, goveff__2005, voiceacc_2005, ope_2005): one might expect lower quality to increase inequality, the intuition being that the less efficient the state is for general purposes, the worse it will be at channelling funds to reduce inequalities;
- regional dummies.

Visual and Graphical Analysis

To illustrate whether the different status concepts produce different results in terms of inequality rankings Figure 1 shows the geographical distribution of inequality for the four concepts of status (downward-looking ordinal s upward-looking ordinal s', simple cardinal $s^\uparrow$, inverse cardinal $s^\uparrow$). It employs a central value of the sensitivity parameter, $\alpha = 0$. It is immediately clear that the different status concepts reveal quite different inequality patterns: see, for example, the switch between the relative position of India and Russia in inequality rankings as one switches from downward-looking status s to upward-looking status s'. Figure 2 shows how the distribution of inequality changes with the sensitivity parameter. It is evident that changing the value of α changes the inequality ranking of the countries, but with no clear patterns: although Russia's inequality ranking continually increases with α, India achieves the highest inequality ranking at $\alpha = 0$, and Brazil at $\alpha = -1$.

Correlation Analysis

An obvious way to check for the overall effect of different status concepts on comparisons of SAH inequality is to examine the extent to which different status concepts produce similar inequality orderings across the 70 countries in the sample. This can be done by computing correlation coefficients for inequality estimates for each possible pair of status concepts; the estimates are, of course, contingent on a particular value of the sensitivity parameter α. Table 2 provides the Spearman correlation coefficients for inequality rankings using pairwise comparisons of the four different status concepts; this is done separately for each of the following cases $\alpha = -2, 0, 0.99$. We find that for low levels of the sensitivity index $(\alpha = -2)$ the upward-looking status inequality rankings $I_\alpha(s')$ correlates negatively with $G_\alpha(\mathrm{s}^\uparrow)$ but positively with $G_\alpha(\mathrm{s}^\downarrow)$ (the Generalised Entropy inequality index using, respectively, the simple cardinalisation and the inverse cardinalisation of SAH); but there is no significant correlation of $I_\alpha(s')$with $I_\alpha(\mathrm{s})$. Consistently, the ranking using the downward-looking status concept $I_\alpha(\mathrm{s})$ is negatively correlated with $G_\alpha(\mathrm{s}^\downarrow)$. The negative correlations of $\left(I_\alpha(\mathrm{s}'), G_\alpha(s^\uparrow)\right)$ and of $\left(I_\alpha(\mathrm{s}), G_\alpha(s^\uparrow)\right)$ become larger when $\alpha = -1$. By contrast, when inequality is evaluated at $\alpha = 0.99$, there is a positive correlation between each pairwise combination of inequality orderings: only in this extreme case do we find evidence of a similar pattern of inequality across countries, whatever the status concept.

Results from Regression Analysis

Now let us examine the apparent role of income, overall health level, social institutions performance and country characteristics in explaining the pattern of health inequalities for the different health- status concepts. In Table 3 we find some evidence that GDP, government effectiveness and the share of female in the population increase health inequalities when a downward-looking ordinal health-status concept is used and the distributional sensitivity parameter is "bottom-sensitive" ($\alpha = -2$ and $\alpha = -1$). However, such coefficients reverse sign when α takes values of 0 and 0.99. We find for $\alpha = -1$ some evidence of reduction of inequalities after a certain level of health.

Table 1: Summary Statistics

Variable	Definition	Mean	Std. Err.
Ordinal inequality indices			
down_i2	$I_{-2}(s)$	34.475	7.292884
down_i1	$I_{-1}(s)$	1.184714	`0.017345
down_i0	$I_{-0}(s)$	0.601429	0.004337
down_i099	$I_{-0.99}(s)$	34.00371	0.237403
up_i2	$I_{-2}(s')$	1.123429	0.10497
up_i1	$I_{-1}(s')$	0.533857	0.016055
up_i0	$I_0(s')$	0.530571	0.005766
up_i099	$I_{0.99}(s')$	33.984	0.237727
Cardinal inequality indices			
g2	$G_{-2}(s^{\uparrow})$	0.059505	0.0031
g1	$G_{-1}(s^{\uparrow})$	0.044311	0.002068
g0	$G_0(s^{\uparrow})$	0.036522	0.00158
g099	$G_{0.99}(s^{\uparrow})$	0.032383	0.001356
gl2	$G_{-2}(s^{\downarrow})$	0.127	0.0031
gl1	$G_{-1}(s^{\downarrow})$	0.1018	0.0026
gl0	$G_0(s^{\downarrow})$	0.0881	0.0024
gl099	$G_{0.99}(s^{\downarrow})$	0.0821	0.0024
Independent variables			
gdp_pc2005	Gross Domestic Product	1 4037.18	379.64
median_cat~y	Median Health Status	2.1286	0.009348
fempop_2005	% Female population	50.506	0.06265
pop65_2005	% population over 65	9.076714	0.143807
corrupt_2005	Control of Corruption	0.1261	0.02663
rule_2005	Rule of Law	0.102714	0.025796
reg_2005	Regulatory Quality	0.169857	0.024874
goveff_2005	Government effectiveness	0.196143	0.026391
voiceacc_2005	Voice and Accountability	0.129143	0.02603
ope_2005	Openness	77.2271	0.51429
east_asia_~c	East Asia Region	0.1	0.007479
europe_cen~a	Europe and Central Asia	0.414286	0.012281
latin_amer~n	Latin-American region	0.1	0.007479
middle_eas~a	Middle Eastern Region	0.057143	0.005787
south_asia	South Asian Region	0.071429	0.006421
subsaharan~a	Sub Saharan Africa	0.2571429	0.0108959

Figure 1: Country distribution of inequality: four different status concepts ($\alpha = 0$)

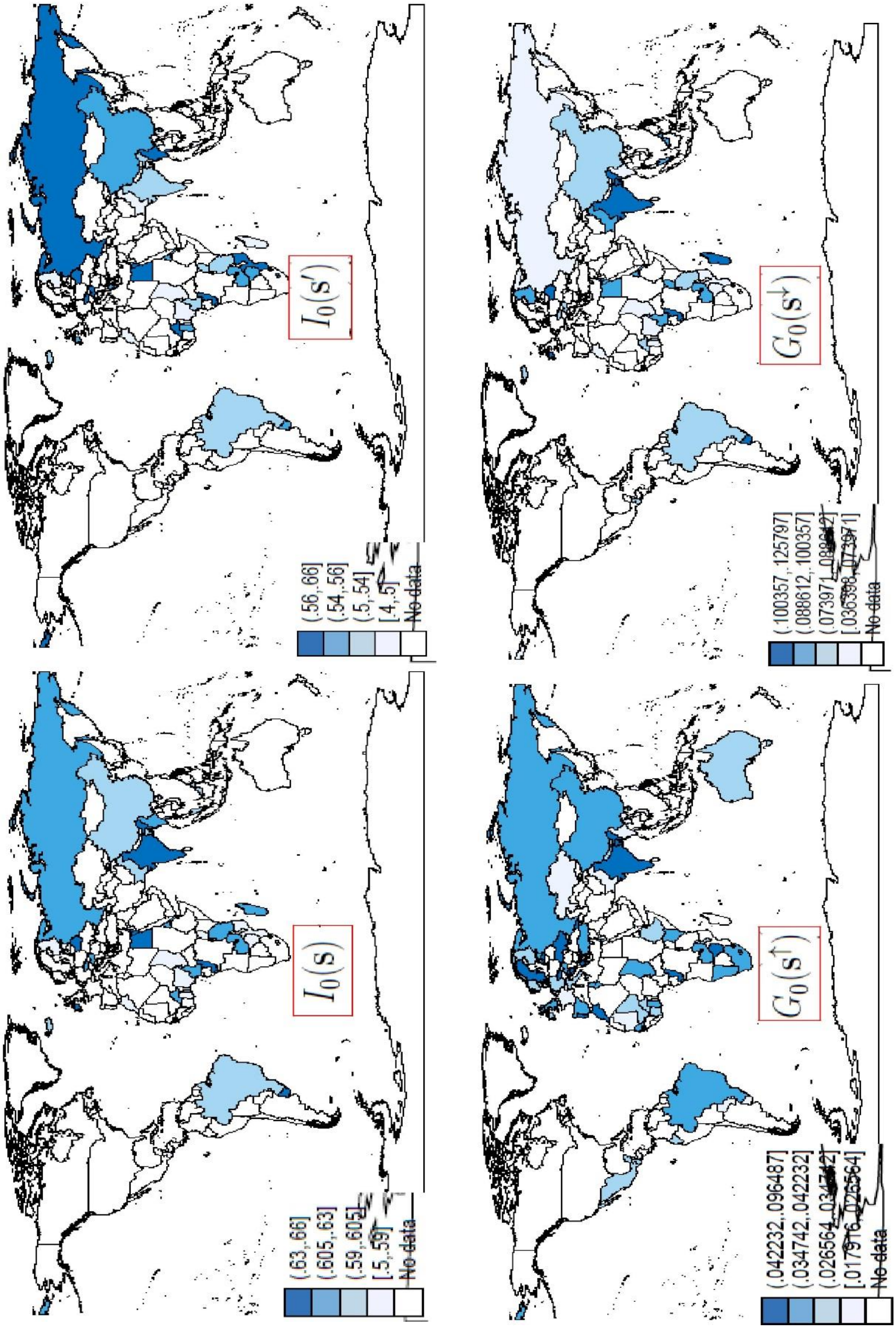

Figure 2: Sensitivity of country distribution of inequality to α: downward looking status

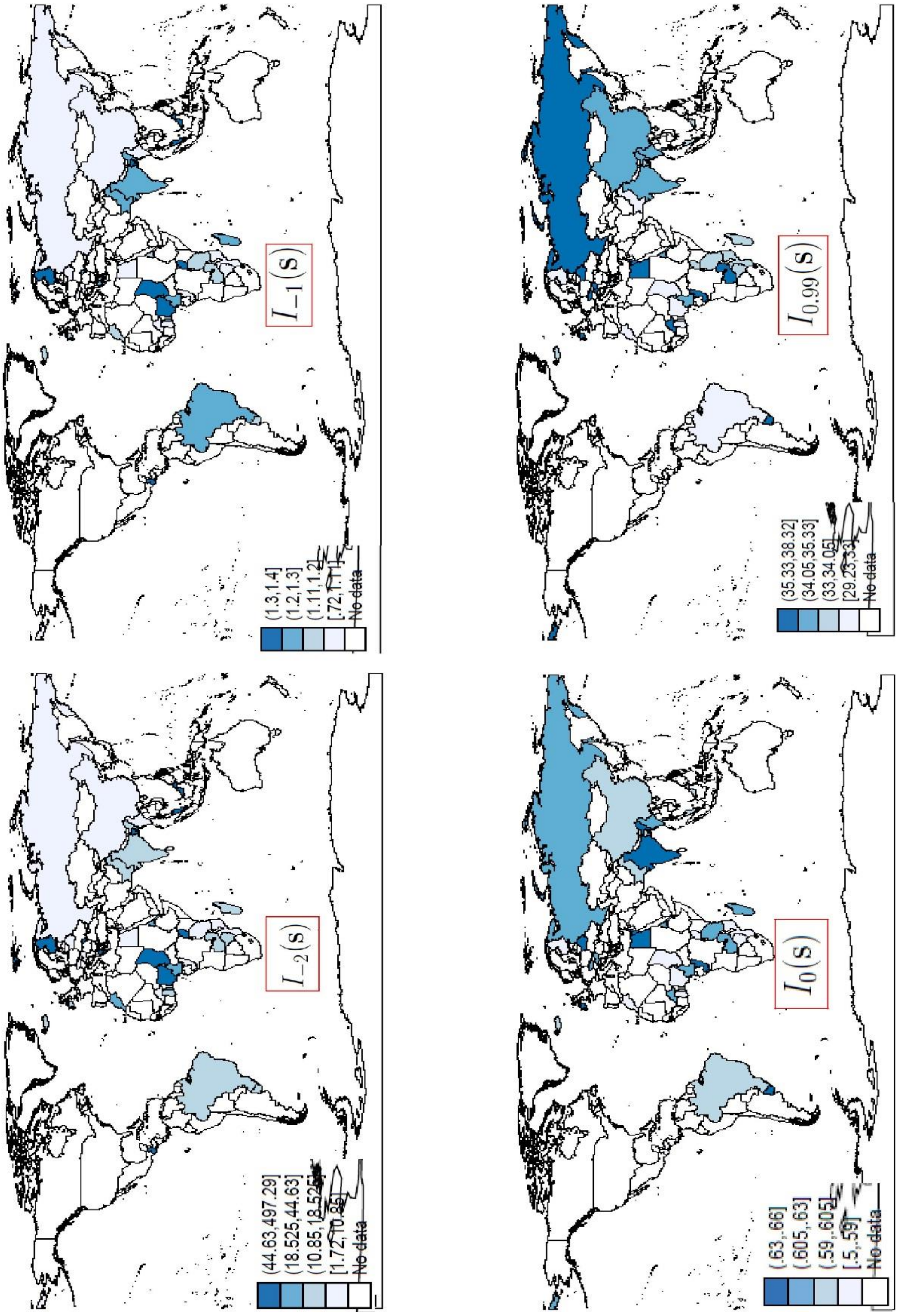

Table 2: Pairwise correlation for inequality using different status concepts

	$\alpha = -2$			$\alpha = -1$	
	$I_{-2}(s)$	$I_{-2}(s')$		$I_{-1}(s)$	$I_{-1}(s')$
$I_{-2}(s)$	1	-0.1274	$I_{-1}(s)$	1	-0.8385*
$G_{-2}(s^{\uparrow})$	0.2841	-0.4419*	$G_{-1}(s^{\uparrow})$	0.4785*	-0.8582*
$G_{-2}(s^{\downarrow})$	-0.5893*	0.3056*	$G_{-1}(s^{\downarrow})$	-0.6283*	0.1543
	$\alpha = 0$			$\alpha = 0.99$	
	$I_{0}(s)$	$I_{0}(s')$		$I_{0.99}(s)$	$I_{0.99}(s')$
$I_{0}(s)$	1	0.363*	$I_{0.99}(s)$	1	0.7395*
$G_{0}(s^{\uparrow})$	0.7695	0.6389*	$G_{0.99}(s^{\uparrow})$	0.7972*	0.798*
$G_{0}(s^{\downarrow})$	-0.2605*	0.7389*	$G_{0.99}(s^{\downarrow})$	0.3202*	0.3286*

Note: * significant at the 5% level.

In contrast to the previous tables we find now more extended evidence in Table 4 that except for values of α close to 0.99, median health correlated with health inequalities. Now we find that regulation positively correlates with higher inequality at low levels of α $(-2,-1)$ but it is not significant otherwise. Consistently with previous result, government effectiveness is associated with less inequalities at values of α close to 0.99. As before, for values of α of 0.99 we find that female share and GDP reduced health inequalities.

When we use the GE measure using the simple cardinalisation in Table 5 we find that, irrespective of α, median income increases inequality which is a finding we only found for up-status inequality when α was -1. Now, government effectiveness, reduced inequalities in all values of α. Overall R^2 values are large given the small number of observations. Interestingly, when we examine the determinants of GE on the "inverse" cardinalisation (Table 6) we find that median health reduces health inequality on a similar magnitude irrespective of α with values ranging from 0.01 to 0.023 suggesting that doubling health status would reduce inequality by between 1 and 2.3%.

Table 3: Determinants of Inequality Down (OLS)

VARIABLES	(1) down_i2	(2) down_i1	(3) down_i0	(4) down_i099
median_category	-26.45	-0.251***	-0.0029	0.916
	(19.47)	(0.0359)	(0.0127)	(0.658)
gdp_pc2005_01	0.00185*	3.37e-06*	-1.06e-06	-7.19e-05**
	(0.00103)	(1.89e-06)	(6.72e-07)	(3.47e-05)
fempop_2005	8.458***	0.0178**	-0.00539*	-0.296**
	(4.193)	(0.00772)	(0.00274)	(0.142)
pop65_2005	1.493	-0.0064	0.0003	0.0217
	(2.552)	(0.00470)	(0.00167)	(0.0862)
ope_2005	-0.433	-0.0007	0.00035	0.0321**
	(0.411)	(0.000756)	(0.000268)	(0.0139)
voiceacc_2005	-12.87	-0.0042	0.0119	0.334
	(17.91)	(0.0330)	(0.0117)	(0.605)
polstab_2005	11.32	-0.0102	-0.0055	-0.0742
	(11.56)	(0.0213)	(0.00756)	(0.391)
goveff_2005	91.47**	0.165**	-0.0470**	-2.647**
	(35.30)	(0.0650)	(0.0231)	(1.193)
reg_2005	-125.1***	-0.133**	0.0127	1.285
	(32.18)	(0.0593)	(0.0210)	(1.088)
rule_2005	-16.77	-0.0237	0.0276	0.499
	(31.30)	(0.0576)	(0.0205)	(1.058)
corrupt_2005	11.74	-0.0077	0.00363	0.832
	(26.68)	(0.0491)	(0.0174)	(0.902)
healthexp_2005	-8.392	-0.0067	0.00635	0.328
	(5.933)	(0.0109)	(0.00388)	(0.200)
Constant	-278.4	0.924**	0.824***	43.20***
	(219.8)	(0.405)	(0.144)	(7.427)
Observations	69	69	69	69
R-squared	0.391	0.634	0.262	0.336

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

Table 4: Determinants of Inequality Up (OLS)

VARIABLES	(1) up_i2	(2) up_i1	(3) up_i0	(4) up_i099
median_category	1.605***	0.231***	0.0570***	0.934
	(0.180)	(0.0313)	(0.0140)	(0.658)
gdp_pc2005_01	-4.73e-06	-2.00e-06	-1.50e-06**	-7.22e-05**
	(9.49e-06)	(1.66e-06)	(7.41e-07)	(3.47e-05)
fempop_2005	-0.0722*	-0.0107	-0.00609**	-0.296**
	(0.0387)	(0.00675)	(0.00302)	(0.142)
pop65_2005	0.0402*	0.00636	0.00209	0.0225
	(0.0236)	(0.00411)	(0.00184)	(0.0862)
ope_2005	-0.00131	0.000593	0.000652**	0.0323**
	(0.00379)	(0.000661)	(0.000296)	(0.0139)
voiceacc_2005	-0.108	-0.0151	0.00132	0.331
	(0.165)	(0.0289)	(0.0129)	(0.605)
polstab_2005	0.178	0.0225	0.00393	-0.0694
	(0.107)	(0.0186)	(0.00833)	(0.391)
goveff_2005	-0.613*	-0.0801	-0.0440*	-2.639**
	(0.326)	(0.0569)	(0.0254)	(1.193)
reg_2005	0.887***	0.119***	0.0365	1.292
	(0.297)	(0.0518)	(0.0232)	(1.088)
rule_2005	0.0200	-0.0338	-0.0146	0.476
	(0.289)	(0.0504)	(0.0226)	(1.058)
corrupt_2005	-0.224	0.00430	0.0218	0.842
	(0.246)	(0.0430)	(0.0192)	(0.902)
healthexp_2005	-0.0810	-0.00655	0.00281	0.327
	(0.0548)	(0.00955)	(0.00428)	(0.200)
Constant	1.697	0.552	0.650***	43.16***
	(2.029)	(0.354)	(0.158)	(7.428)
Observations	69	69	69	69
R-squared	0.750	0.674	0.487	0.338

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

Table 5: Determinants of Inequality GE (OLS)

VARIABLES	(1) g_i2	(2) g_i1	(3) g_i0	(4) g_i099
median_category	0.0356***	0.244***	0.0188***	0.0162***
	(0.00841)	(0.00544)	(0.00406)	(0.00342)
gdp_pc2005_01	-6.28e-07	-4.20e-07	-3.17e-07	-2.65e-07
	(4.44e-07)	(2.87e-07)	(2.14e-07)	(1.81e-07)
fempop_2005	-0.00268	-0.00177	-0.00132	-0.00108
	(0.00181)	(0.00117)	(0.000874)	(0.000736)
pop65_2005	0.000490	0.000324	0.000247	0.000212
	(0.00110)	(0.000713)	(0.000532)	(0.000448)
ope_2005	4.71e-05	4.49e-05	4.19e-05	3.90e-05
	(0.000177)	(0.000115)	(8.56e-05)	(7.21e-05)
voiceacc_2005	0.00258	0.000505	-0.000426	-0.000986
	(0.00774)	(0.00501)	(0.00374)	(0.00315)
polstab_2005	-0.000428	9.88e-05	0.000320	0.000449
	(0.00499)	(0.00323)	(0.00241)	(0.00203)
goveff_2005	-0.0305*	-0.0225**	-0.0183**	-0.0163**
	(0.0152)	(0.00987)	(0.00736)	(0.00620)
reg_2005	0.00912	0.00760	0.00689	0.00669
	(0.0139)	(0.00900)	(0.00671)	(0.00565)
rule_2005	0.0202	0.0127	0.00877	0.00671
	(0.0135)	(0.00875)	(0.00653)	(0.00550)
corrupt_2005	-2.29e-05	0.00199	0.00286	0.00336
	(0.0115)	(0.00746)	(0.00556)	(0.00469)
healthexp_2005	0.00336	0.00218	0.00158	0.00128
	(0.00256)	(0.00166)	(0.00124)	(0.00104)
Constant	0.0990	0.0681	0.0526	0.0437
	(0.0949)	(0.0614)	(0.0458)	(0.0386)
Observations	69	69	69	69
R-squared	0.371	0.408	0.435	0.456

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

Table 6: Determinants of Inequality Inverse GE (OLS)

VARIABLES	(1) g_i2	(2) g_i1	(3) g_i0	(4) g_i099
median_category	-0.0191**	-0.0215***	-0.0222***	-0.0233***
	(0.00910)	(0.00718)	(0.00645)	(0.00646)
gdp_pc2005_01	-5.13e-07	-2.82e-07	-1.51e-07	-6.48e-08
	(4.80e-07)	(3.79e-07)	(3.41e-07)	(3.41e-07)
fempop_2005	-0.00152	-0.000887	-0.000532	-0.000311
	(0.00196)	(0.00155)	(0.00139)	(0.00139)
pop65_2005	-0.000268	-0.000462	-0.000582	-0.000696
	(0.00119)	(0.000941)	(0.000846)	(0.000847)
ope_2005	0.000180	8.82e-05	2.99e-05	-1.28e-05
	(0.000192)	(0.000151)	(0.000136)	(0.000136)
voiceacc_2005	0.00338	0.00335	0.00320	0.00321
	(0.00837)	(0.00661)	(0.00594)	(0.00594)
polstab_2005	-0.00178	-0.00235	-0.00276	-0.00323
	(0.00540)	(0.00426)	(0.00383)	(0.00384)
goveff_2005	-0.0215	-0.0147	-0.0119	-0.0112
	(0.0165)	(0.0130)	(0.0117)	(0.0117)
reg_2005	-0.00317	-0.00512	-0.00584	-0.00634
	(0.0150)	(0.0119)	(0.0107)	(0.0107)
rule_2005	0.00777	0.0101	0.0124	0.0152
	(0.0146)	(0.0115)	(0.0104)	(0.0104)
corrupt_2005	0.0136	0.00715	0.00330	0.000630
	(0.0125)	(0.00984)	(0.00884)	(0.00885)
healthexp_2005	0.00342	0.00285	0.00260	0.00258
	(0.00277)	(0.00219)	(0.00197)	(0.00197)
Constant	0.219**	0.176**	0.151**	0.140*
	(0.103)	(0.0811)	(0.0728)	(0.0729)
Observations	69	69	69	69
R-squared	0.278	0.341	0.382	0.405

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

5. Conclusion

In the case of wealth inequality, getting better estimates is, to some extent, largely a function of getting better data; but in the case of health inequality, more is involved. Even if one has very good, carefully collected data on self-assessed health, almost always one has to deal with the fact that the data will be categorical in nature and require special treatment in order to make reliable inequality comparisons. Here we have followed the Cowell and Flachaire (2014) status-inequality approach that defines a family of inequality indices indexed by a sensitivity parameter α. The status concept could be downward or upward-looking, and we employ an arbitrary cardinalisation to measure results from generalised entropy indices.

In this paper we find that, for low values of the sensitivity parameter α (where the index is most sensitive to the bottom of the distribution) status does matter to a point that we find no, or even negative, correlation between up and down versions of status. In contrast, for zero or positive values of α the association becomes positive and large. Similarly, when we compare different measures of status with the corresponding cardinal inequality index (the generalised entropy measure, G_a), using the arbitrary 1-to-5 cardinalisation, we find that for negative values of α there is a negative correlation between up-status (ordinal) I_α and G_α; this flips and becomes positive for $\alpha \geq 0$. We find a similar story if we use the inverse – 5-to-1 – cardinalisation for health status; the negative correlation between I_α and (cardinal) G_α that is observed for $\alpha < 0$ becomes positive for high values of the sensitivity parameter α.

Regression analysis indicates a number of different determinants of inequality measures. Specifically, we find that median health status only increases as α becomes close to unity. In that case, government effectiveness reduces health inequality. Government effectiveness reduces inequality if a down-status measure is employed, for positive value of α and the opposite applies for negative values of α.

Our findings in the Appendix indicate no evidence of a Kuznets curve on health and on GDP, and no association with health expenditure.

The paper has important policy implications. First, our findings suggest that government attempts to reduce health inequalities need to pay specific attention to the nature of the data, and they need to specify the sensitivity to inequality in different parts of the distribution (the parameter α) in accordance with the values of a specific society. Second, we find evidence of heterogeneous determinants of different inequality measures. Our results suggest robust evidence that health inequalities are sensitive to some measures of institutional performance (e.g., government effectiveness). However, these results need to be taken with caution given the small number of observations.

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Appendix

The data are taken from the World Health Organization's World Health Survey, which is described here: http://www.who.int/healthinfo/survey/instruments/en/index.html. In particular, for our categorical variable, we use the responses to one specific question in this survey's collection of individual questions about overall health.

"Q2000: In general, how would you rate your health today? The respondent should answer according to how he/she considers his/her health to be and give his/her best estimate. Both physical and mental health must be taken into consideration."

Table 5 reports the answers to this question across 70 countries. The titles of Columns (1) to (5) give the categories used in the survey: we follow the natural order taking (1) as the best category and (5) as the worst. The total number of respondents is in column (6): if in any row this total exceeds the sum of columns (1) to (5), the difference is attributable to non-response.

Table 7: Responses in WHS to self-rated health question

		(1)	(2)	(3)	(4)	(5)	(6)
	Country	*Very good*	*Good*	*Moderate*	*Bad*	*Very Bad*	*Total*
1	Australia	487	775	446	74	11	1793
1	Austria	423	390	200	36	4	1053
3	Bangladesh	494	1949	2132	741	228	5544
4	Belgium	252	487	197	48	11	995
5	Bosnia	271	328	279	127	23	1028
6	Brazil	715	1934	1881	348	119	4997
7	Burkina Faso	1254	2104	1137	288	36	4819
8	Chad	889	1767	1371	549	37	4613
9	China	982	1485	1215	277	34	3993
10	Comoros	312	631	523	261	30	1757
11	Congo	693	550	693	252	33	2221
12	Côte d'Ivoire	661	1215	955	266	21	3118
13	Croatia	200	302	312	132	43	989
14	Czech	160	350	311	90	19	930
15	Denmark	320	472	166	40	4	1002
16	Dominican	722	1806	1560	397	34	4519
17	Ecuador	650	1945	1569	378	53	4595
18	Estonia	70	293	499	134	16	1012
19	Ethiopia	2138	1549	972	220	47	4926
20	Finland	158	395	391	64	3	1011
21	France	255	525	192	34	2	1008
22	Georgia	265	778	1111	476	125	2755
23	Germany	229	582	343	85	13	1252
24	Ghana	1379	1433	830	234	46	3922
25	Greece	347	325	246	63	19	1000
26	Guatemala	730	1790	1747	472	24	4763
27	Hungary	139	579	503	155	34	1410
28	India	2159	3577	2616	1311	202	9865
29	Ireland	366	257	101	29	5	758
30	Israel	519	405	234	40	23	1221
31	Italy	182	449	305	46	15	997
32	Kazakhstan	265	1894	2088	231	18	4496

…continued

	Country	*Very good*	*Good*	*Moderate*	*Bad*	*Very Bad*	*Total*
33	Kenya	1115	1798	1144	309	40	4406
34	Lao	1787	2005	906	168	17	4883
35	Latvia	35	244	390	155	32	856
36	Luxembourg	164	246	155	33	2	700
37	Malawi	2855	1334	838	231	33	5291
38	Malaysia	1194	3495	1111	204	12	6016
39	Mali	1334	1526	895	266	11	4032
40	Mauritania	941	1672	1024	154	9	3800
41	Mauritius	850	1677	827	427	104	3885
42	Mexico	7193	18112	11221	2002	218	38746
43	Morocco	598	1454	1754	821	372	4999
44	Myanmar	1215	3412	1100	157	2	5886
45	Namibia	1622	1249	863	204	45	3983
46	Nepal	1455	3908	2505	767	53	8688
47	Netherlands	189	640	214	41	2	1086
48	Norway	314	456	140	46	13	969
49	Pakistan	1770	2996	1315	263	25	6369
50	Paraguay	1700	1920	1370	133	16	5139
51	Philippines	817	5127	3759	354	19	10076
52	Portugal	62	342	390	180	55	1029
53	Russia	261	1102	2192	770	91	4416
54	Senegal	646	1028	984	217	24	2899
55	Slovakia	400	798	506	94	17	1815
56	Slovenia	90	238	193	53	9	583
57	South Africa	837	865	467	129	42	2340
58	Spain	1051	2984	1689	502	117	6343
59	Sri Lanka	1844	3019	1535	298	22	6718
60	Swaziland	198	451	508	676	236	2069
61	Sweden	262	354	235	133	14	998
62	Tunisia	1236	1850	1476	411	58	5031
63	Turkey	1301	4909	4035	869	189	11203
64	UAE	536	472	146	18	6	1178
65	UK	318	498	278	82	17	1193

…continued

	Country	*Very good*	*Good*	*Moderate*	*Bad*	*Very Bad*	*Total*
66	Ukraine	129	659	1364	594	103	2849
67	Uruguay	725	1632	547	63	9	2976
68	Vietnam	398	1368	1489	225	10	3490
69	Zambia	1436	1292	816	228	39	3811
70	Zimbabwe	837	1263	1501	385	65	4051

Table 8: Inequality and health expenditure ($\alpha = -0$)

VARIABLES	(1) down_i0	(2) up_i0	(3) g0
healthexp_2005	0.00136	-0.00388	-0.000327
	(0.00184)	(0.00241)	(0.000671)
Constant	0.593***	0.556***	0.0387***
	(0.0128)	(0.0167)	(0.00466)
Observations	70	70	70
R-squared	0.008	0.037	0.003

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

Table 9: Kuznets curve on GDP

VARIABLES	(1) down_i0	(2) up_i0	(3) g0
gdp_pc2005	-3.96e-07	-1.03e-06	-1.90e-07
	(7.40e-07)	(0.77e-07)	(2.28e-07)
gdp2	0	0	0
	(0)	(0)	(0)
Constant	0.607***	0.541***	0.0387***
Observations	70	70	70
R-squared	0.025	0.038	0.023

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

Table 10: Kuznets curve on health

	(1)	(2)	(3)
VARIABLES	down_i0	up_i0	g0
median_category	-0.00365	-0.00365	-0.0216
	(0.0952)	(0.0952)	(0.0296)
media2	-0.00121	-0.00121	0.00826
	(0.0198)	(0.0198)	(0.00616)
Constant	0.615***	0.615***	0.0440***
	(0.111)	(0.111)	(0.0347)
Observations	70	70	70
R-squared	0.01-	0.010	0.278

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