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Aggregation bias-correcting approach to the health–income relationship: Life expectancy and GDP per capita in 148 countries, 1970–2010

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ABSTRACT

A large amount of data consisting of 148 countries for the years 1970 to 2010 is analysed in the context of the health–income relationship. The literature suggests that the biased income–health effect obtained with macro data can be a result of the aggregation of individual concave income functions on average health. This aggregation problem is analysed in detail, and a bias-correcting method is proposed to overcome it. The results with new model alternatives show that they correct the income effects on average health in the right direction; that is, they produce smaller parameter estimates than biased models. Augmenting the results with the quantile regression approach, which is sensitive to health differences between countries, indicates that the poorest countries' income gradient is still much larger than that of rich countries. However, the median life expectancy effect of the log of *GDP* per capita across the countries decreased during the sample decennials. The results for income inequality measured with the Gini coefficient indicate that the effects of inequality on health are still significant in the poorest countries but non-significant among rich countries after the year 2000. We argue that the proposed bias-correcting method retains the interest in macro health modelling and offers new model alternatives in other contexts.

1. Introduction

Aggregation from microunits to macroentities is a lasting problem in economics. The literature reports many different forms of biases that macro or aggregative relationships will generate when compared with the underlying micro-level presentations. Typically these aggregation problems are case dependent, and in some cases conditions can be derived to preserve the structural micro model at the macro level (see e.g. Denton and Mountain, 2011; Monteforte, 2007; Pesaran, 2003). However, for the vast majority of cases, the conditions are very demanding or unknown, and quite often even a simple micro relation estimated with macro data has different parameter values from the micro data results. This is especially true for non-linear micro relations estimated with aggregate data, such as mean values. The major reason for these problems is that micro-model estimations with mean values are used instead of aggregating non-linear microrelationships. For example, if the micro theory states that relationship $y = \alpha + \beta \ln x$ is valid and we have data from two micro units $\{(y_1, x_1), (y_2, x_2)\}$, then $\bar{y} = \alpha + \beta \ln \bar{x}$ is not the same as $\bar{y} = \alpha + \beta(\frac{1}{2} \ln x_1 + \frac{1}{2} \ln x_2)$, and the OLS estimate from $\bar{y} = \alpha + \beta \ln \bar{x}$ for β is biased.

Interestingly, the log function with health status as a function of income is found to be highly important in the health economics literature. Besides the involved aggregation problem when estimating the function with aggregative data, it surprisingly produces a spurious negative correlation between health status and spread of income distribution. Thus, when we regress different countries' index of health status on their GDP per capita level, for example, we obtain the result that larger income dispersion decreases health status. Evidently, this result is relevant to any other field in economics that uses a similar type of concave functions. Especially, any empirical research that connects aggregate measurements non-linearly based on micro-level arguments should be beware of the distributional effects that non-linearity exposes.

Partly in response to this aggregation problem in health–income relationship analysis, a vast literature exists that is shared by public health researchers, sociologists, and economists on health, incomes, and income inequality (Cutler et al., 2006; Deaton, 2006, 2003, 2002a, 2001; Judge et al., 1998; Kawachi and Kennedy, 1999; Leigh et al., 2009; Lynch et al., 2004; Marmot, 2002; Mullahy et al., 2004; Subramanian and Kawachi, 2004; Wagstaff and van Doorslaer, 2000). The main outcome of this perhaps disparate literature is that the income level matters for health, especially for poor people, and the focus of research must be on the individual-data level. New and more

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sophisticated approaches are still used to analyse the connections between health, incomes, and inequalities with the addition of different health outcomes and many covariates and auxiliary variables (e.g. Kim et al., 2008; Mackenbach, 2012; Zheng, 2012).

We do not dwell on this new literature. Instead, we try to understand what the earlier literature offers on the methodological level and to provide some pathways to follow, especially when still working with aggregate data (Section 2). In particular, we show that the aggregation bias in earlier aggregate models can be reduced when attention is paid to the evident errors-in-variables problem in these models. Section 3 proceeds with the data presentation and three model alternatives to test the average health status dependency on the log of GDP per capita and the GINI index across nearly 150 countries in the years 1970 to 2010. The main estimation results are given in Section 4. We show that there exists – contrary to biased results – a U-shaped evolution between the life expectancy and the log of *GDP* per capita during the years 1970–2010 obtained with our new bias-correcting methods. In addition the proposed method provides results that are comparable with micro-level results. The conclusions are presented in Section 5.

2. Aggregation bias of the *lnGDPc* variable in the health–income model

2.1. Health status as a function of income

Much of the so-called income gradient literature on health has focused on the individual-level relationship between income (Y_i) and health (HS_i), which has a concave form:

$$HS_i = f(Y_i) \text{ with } f' > 0 \text{ and } f'' < 0. \tag{1}$$

The functional form in (1) is the *absolute income hypothesis* (AIH), which implies that

a) The health and the (absolute) level of income are positively correlated, and
b) The positive slope of the relationship deceases with income.

The AIH implies that the proportional relationship between income and good health is the same at all income levels, which infers that the absolute increase in health for *each dollar of income* is much larger at the bottom of the income distribution than at the top (Deaton, 2002a, p. 4). The logarithm function is a concave function, and it has been shown to have some good statistical properties in this context (Jones and Wildman, 2008). This means that the regression model augmented with other health-affecting covariates and controls $\boldsymbol{X_i}$, like

$$HS_i = \alpha + \beta \ln Y_i + \boldsymbol{d}'\boldsymbol{X}_i + \varepsilon_i \tag{2}$$

is a promising starting point for health–income gradient analysis.

The problem here is that the AIH is not a robust hypothesis at the aggregate level. This is because the aggregation is distribution free only when the relationship between health and income is *linear*. Thus, regressing the average health on the average income non-linearly and on income distribution measures produces results that are artificial, since all the higher moments – not only mean income – exist for any non-linear function of a (random) variable.

2.2. Aggregate approach

Consequently, individual-level model results do not necessary hold for aggregate data-level models, which are widely used, for example, in the social policy literature. Now the regression models appear as follows:

$$HS_k = \alpha + \beta \ln \overline{Y}_k + \boldsymbol{d}'\boldsymbol{X}_k + \varepsilon_k, \tag{3}$$

where k can refer to different regions, income classes, or social groups. Similar AIH distributional effects are now valid as above if we refer to the average income differences between the k units in the sample. However, this agenda is not fully warranted, since the model in Eq. (3) is still prone to the aggregation problem.

If we take the starting point that health is an *individual-level* phenomenon, we should derive Eq. (3) in an appropriate way, starting from the individual level; that is, Eq. (3) is *not* aggregated correctly if Eq. (2) is *the true model* for individual behaviour in unit k. This can be shown in the following way. Assume that for all individuals in k, the following income gradient model is valid (excluding the additional terms in Eq. (3) for simplicity):

$$HS_{i,k} = \alpha + \beta \ln Y_{i,k} + \varepsilon_{i,k}, \quad i = 1, .2, \ldots, n_k. \tag{4}$$

The k-level aggregate equation is obtained by adding this equation over n_k income receivers in aggregation unit k:

$$HS_k \equiv \frac{1}{n_k}\sum_{i=1}^{n_k} HS_{i,k} = \alpha + \beta\left(\frac{1}{n_k}\sum_{i=1}^{n_k} \ln Y_{i,k}\right) + \varepsilon_k. \tag{5}$$

This aggregation *does not include* any biases, since the aggregation is made over the individual-level income gradient functions; that is, $\frac{1}{n_k}\sum_{i=1}^{n_k} f(Y_{i,k})$, where $f(Y_{i,k}) = \ln Y_{i,k}$.

The aggregation in Eq. (5) provides *the mean of log incomes*, or the *log of geometric mean income*, $\overline{Y}_G = \exp(\frac{1}{N}\sum_{i=1}^{N} \ln Y_i)$. Thus, the correct form of Eq. 3 under the assumption that model parameters α_k and β_k are equal across k different units is

$$HS_k = \alpha + \beta \ln \overline{Y}_{G,k} + \boldsymbol{d}'\boldsymbol{X}_k + \varepsilon_k, \ \ \textbf{\textit{not}}\ HS_k = \alpha + \beta \ln \overline{Y}_k + \boldsymbol{d}'\boldsymbol{X}_k + \varepsilon_k, \tag{6}$$

where $\overline{Y}_k = \frac{1}{n_k}\sum_{i=1}^{n_k} Y_i$. Consequently, using the wrong presentation for individual behaviour at the aggregate level in Eq. (3) biases the income gradient estimates.

The genesis of the aggregation problem in Eq. (3) can be seen when we take the second-order Taylor approximation around the mean income for the concave income gradient function (Eq. (1)):

$$HS_i = f(\overline{Y}) + f'(\overline{Y})(Y_i - \overline{Y}) + \tfrac{1}{2}f''(\overline{Y})(Y_i - \overline{Y})^2 + R_n. \tag{7}$$

If $E[Y_i] = \mu_Y = \overline{Y}$ and $VAR[Y_i] = \sigma_Y^2$, then the second-order approximation for the expected (population) health level is

$$\begin{aligned} E[HS_i] &\approx f(\overline{Y}) + f'(\overline{Y})E[(Y_i - \overline{Y})] + \tfrac{1}{2}f''(\overline{Y})E[(Y_i - \overline{Y})^2] \\ &\approx f(\overline{Y}) + \tfrac{1}{2}f''(\overline{Y})\sigma_Y^2. \end{aligned} \tag{8}$$

Thus, the sample estimate for the expected health level – the sample mean $\overline{HS}$ – is related negatively to income dispersion because of $f''(\overline{Y}) < 0$. Therefore, the larger is the spread of income in the economy, the lower is the average health level for the given mean income.

This transfer or "concavity-induced income inequality" effect (Deaton and Muellbauer, 1980; Stoker, 1993) is also called a statistical artefact of aggregation (Gravelle, 1998). The finding that there is a negative partial correlation between the average health and a measure of spread of income may therefore not be evidence that individual health is adversely affected by income inequality. It is simply the result of the curvilinear relationship between income and health level operating at the individual level (Gravelle et al., 2002, p. 579; Lynch et al., 2004, p. 61). Note that the result in Eq. (8) is still more complicated when we observe that income distributions are typically not symmetric but skewed; that is, $E[(Y_i - Y_{MED})] \neq 0$. To add a positive comment about the aggregate model, Eq. (3) entails that it reflects in an average sense the relationship between health and incomes at the aggregative level, but its individual-level implications are biased and even spurious.

The transfer result in Eq. (8) is most alarming for the *income inequality hypothesis* (IIH). It states that

a) Individual health is affected by income inequality, and
b) Greater income inequality produces worse health among the population.

Part a is the outcome of our individualistic approach to health, and part b asserts that the greater income inequality has an effect on the health status distribution; that is, the mean health level.

We see clearly that the AIH and IIH are closely related to each other at the aggregative level as long as health is a concave function of income at the individual level; consequently, the second moment of income (dispersion) reduces the expected health. The curvilinear relation between income and health at the individual level is a sufficient condition to produce health differences between populations with the same average income but different distributions of income (Deaton, 2002b).

To overcome the problem of aggregation, we must turn to the individual-data model, which also entails some variables like the *GINI* coefficient to measure the income inequality effects on health. However, when individual data on health and incomes are not available, we need an aggregate model alternative that has a consistent aggregation solution; that is, it preserves the micro-economic presentation. In the following we propose a method that has some merits when we are bound to aggregate data and provides results that are not sensitive to aggregation biases.

2.3. Correcting for aggregation bias

The evident non-linear aggregation problem over individuals (Stoker, 1993) can be avoided by using $\ln \overline{Y}_{G,k}$ as a mean income variable. Thus, Eq. (6) preserves the individual-level interpretation. However, we seldom know the geometric mean of incomes $\overline{Y}^G = \exp(\frac{1}{N}\sum_{i=1}^{N} \ln Y_i)$. To calculate it, we need individual-level observations, and if we have them we should conduct individual-level regressions, not problematic aggregate-level regressions. Thus, the problem is basically that we are provided with only aggregate-level information, like HS_k and $\overline{Y}_k$, and are not able to obtain the correct aggregation form for the income gradient hypothesis. To overcome this problem, the following approximation method can be used. Jensen's inequality implies for concave functions that

$$\sum_{i=1}^{N} f(X_i) = f\left(\sum_{i=1}^{N} X_i - \theta\right). \tag{9}$$

Applying this idea to the *logarithm function* in the context of the aggregate mean income gives

$$\frac{1}{N}\sum_{i=1}^{N} \ln(Y_i) = \ln(\overline{Y} - \theta) \quad \Rightarrow \quad \theta = \overline{Y} - \exp\left(\frac{1}{N}\sum_{i=1}^{N} \ln Y_i\right). \tag{10}$$

As we do not known the mean of log incomes – the log geometric mean $\ln \overline{Y}_G = \frac{1}{N}\sum_{i=1}^{N} \ln Y_i$ – and cannot solve for θ, we use the following practical second-best solution.[1]

The *second-order Taylor approximation* around $\overline{Y}$ for $\ln(\overline{Y} - \theta)$ has the following form[2]:

$$\ln(\overline{Y} - \theta) \approx \ln \overline{Y} - \frac{\theta}{\overline{Y}} - \frac{1}{2}\frac{\theta^2}{\overline{Y}^2}. \tag{11}$$

For large values of $\overline{Y}$, we can omit the second-order term. This gives the result

$$\ln(\overline{Y} - \theta) \approx \ln \overline{Y} - \frac{\theta}{\overline{Y}}. \tag{12}$$

Applying the first-order result to our basic region- or group-level health model like Eq. (6) gives

$$HS_k = \alpha + \beta\left(\ln \overline{Y}_k - \frac{\theta_k}{\overline{Y}_k}\right) + \mu_k = \alpha + \beta \ln \overline{Y}_k - \frac{\beta\theta_k}{\overline{Y}_k} + \mu_k. \tag{13}$$

The model presents two options. First, if we make a heroic parametric assumption that $\theta_k = \theta$ for all income units k, we have

$$HS_k = \alpha + \beta \ln \overline{Y}_k - \gamma\frac{1}{\overline{Y}_k} + \mu_k \text{ where } \gamma = \beta\theta. \tag{14}$$

This means that the parameter θ (if needed) is identifiable from the OLS estimate for γ.

Next we propose also a two-stage estimation procedure to estimate β consistently by using approximation result $\ln(\overline{Y} - \theta) \approx \ln \overline{Y} - \theta/\overline{Y}$. Now we first regress $\ln \overline{Y}_k$ on $\theta_k/\overline{Y}_k$ and use estimate $\hat{\theta}_k$ to correct for aggregation bias, i.e. we calculate $\ln \overline{Y}_k^* = \ln \overline{Y}_k - \hat{\theta}_k/\overline{Y}_k$ and estimate model

$$HS_k = \alpha + \beta \ln \overline{Y}_k^* + \mu_k. \tag{15}$$

This procedure corresponds to the errors-in-variable problem (see Appendix A1) that is an alternative formulation of aggregation bias found in model $HS_k = \alpha + \beta \ln \overline{Y}_k + \mu_k$.

Finally, if take the random-coefficient model (*RCM*) approach, which assumes $\theta_k = \theta + \nu_k$, where for example $\nu_k \sim N(0, \sigma_\theta^2)$, the model has the form

$$HS_k = \alpha + \beta \ln \overline{Y}_k - \gamma_k\frac{1}{\overline{Y}_k} + \mu_k \text{ where } \gamma_k = \beta\theta_k. \tag{16}$$

The classical *RCM* approach needs a panel data setting, but in the modern *RCM* context (mixed or hierarchical models), we can use also cross-sectional data, where θ_k is the classifying parameter for different regions or income groups.

The last question is whether we should also include in models 14–16 the *GINI* coefficient to measure income inequality and test for the income inequality hypothesis (IIH). Adding *GINI* coefficients to models can be defended with the arguments that $GINI_k$ is based on person-level information and models 14 and 15 are approximations of a model that preserves the individual-level approach; that is, the spurious “concavity-induced income inequality” effect is less evident in these aggregation bias-corrected models.

3. Data and test models

3.1. Data

Annual data from 148 countries (both developed and developing) covering 41 years (1970–2010) were collected from different sources. Data for life expectancy at birth as a measurement of the average population health were collected from the World Development Indicators (World Bank, 2014a).

Gross domestic product per capita data were PPP converted into GDP per capita (Laspeyres) at 2005 constant prices. They were collected from the Penn World Table 7.1 (Heston et al., 2012). The World Bank IBRD-IDA (2014b) database and the UN database (2014) were consulted for Georgia, Qatar and Latvia. Gapminder.org (2014) was accessed for data on Armenia, Azerbaijan, Belarus, Bosnia Herzegovina, Estonia, Lithuania, Kazakhstan, Slovenia, Turkmenistan and Ukraine.

Income inequality data were obtained from SWIID Version 4.0 from September 2013 (Solt, 2009). The “gini_market” data were taken, which were the estimate of the Gini index of inequality in equivalized (square root scale) household market (pre-tax, pre-transfer) income. Here the Luxembourg Income Study data were used as the standard. UNU WIDER (2014) data were also collected with reference to the unit of analysis. The data were more often weighted with household than personal weight. In connection to the area covered, data that covered both urban and rural areas were obtained as available in the database. When considering the quality rating, only high- (i.e. 1) and average-

[1] If the individual incomes are log-normally distributed, we have the following exact result:
$\ln \overline{Y}_G = \ln \overline{Y} - \frac{1}{2}\sigma^2$, where σ^2 is the variance of log incomes.

[2] $f(x) \approx f(x_0) + f'(x_0)(x - x_0) + \frac{1}{2}f''(x_0)(x - x_0)^2$, where $x = \overline{Y} - \theta$ and $x_0 = \overline{Y}$.

quality (i.e. 2) rated observations were considered. Household income data meant gross income. With reference to revision, the newest observations were considered as far as possible. Data from the Inequality Project hosted by the University of Texas (University of Texas Inequality Project, 2014) complemented the data already mentioned.

3.2. Models and estimation strategy

The following 3 models with 148 countries in the years 1970–2010 (k=1,...,148, t=1,...,41, 6068 observations) were estimated:

Model A: $LE_{kt}=\alpha_1+\beta_1 lnGDPc_{kt}+\gamma_1/GDPc_{kt}+\delta_1 GINI_{kt}+\varepsilon_{kt,1}$
Model B: $LE_{kt}=\alpha_2+\beta_2 lnGDPc_{kt}+\delta_2 GINI_{kt}+\varepsilon_{kt,2}$
Model C: $LE_{kt}=\alpha_3+\beta_3 lnGDPc_{kt}{}^*+\delta_3 GINI_{kt}+\varepsilon_{kt,3}$.

LE is the life expectancy at birth in years. *GDPc* is the GDP per capita at 2005 constant prices. These values were then multiplied by 0.01 and the natural log was taken (*lnGDPc*). Income inequality was measured by *GINI* coefficients. The ε_{kt}s are the error terms of the models.

The first equation (model A) is based on micro(economic) foundations wherein a person's incomes and prevailing income distribution in his/her social environment have effects on his/her health. The variable $1/GDPC_{kt}$ is the correction term stemming from the inadequate aggregation of the log of income effect on health at the micro level. Model B is the reference model that includes the aggregation bias, and the coefficient β_2 is expected to be biased upward. The model lacks the (micro)economic interpretation. Finally, model C corrects for the aggregation bias via the estimation of the errors-in-variables bias (for more details, see Appendix A1; Stock and Watson, 2011, pp. 361–364). $lnGDPc_{kt}{}^*$ in model C is equal to

$$\ln GDPc_{kt}^* = \ln GDPc_{kt} - \frac{\hat{\theta}_k}{GDPc_{kt}},$$

with $\hat{\theta}_k$ coming from *OLS* regressions $\ln GDPc_{kt}$ on $1/GDPc_{kt}$ for each of the sample countries separately with time series observations. Note that in this two-step estimation strategy for model C we need to correct the standard errors of coefficients in the second step estimation.

We consider first the following panel data models in estimating models A–C.

Group means model: $\bar{y}_k = a + \bar{\boldsymbol{x}}_k'\boldsymbol{\beta} + \bar{\varepsilon}_k, \quad k = 1, \ldots, N$
Fixed-effects model: $y_{kt} = a_k + \boldsymbol{x}_{kt}'\boldsymbol{\beta} + \varepsilon_{kt}, \quad k = 1, \ldots, N, \quad t = 1, \ldots, T$
Fixed-effects model with AR(1) errors: $y_{kt} = a_k + \boldsymbol{x}_{kt}'\boldsymbol{\beta} + \varepsilon_{kt}$, with $\varepsilon_{kt} = \rho\varepsilon_{k,t-1} + \mu_{kt}, k = 1, \ldots, N, t = 1, \ldots, T$
Random-coefficient model (RCM): $y_{kt} = a + \boldsymbol{x}_{1kt}'\boldsymbol{\beta} + z_{kt}\gamma_k + \varepsilon_{kt}$, with $\gamma_k = \gamma + \mu_k, \quad k = 1, \ldots, N, t = 1, \ldots, T$.

The group means model is used here as it averages out the random measurement errors and collects observed and latent group heterogeneity in the group means (see Greene (2013), Section 11.3.4). The fixed-effects model is an obvious choice in this context. We estimate the model in the robust form; that is, augmented with White and Newey–West standard error corrections for group heterogeneity and autocorrelation in models A and B. For model C we use the clustering approach. Standard errors are calculated with clustering the errors at the country level. The fixed-effects model with AR(1) errors allows explicitly for error autocorrelation to be present in the model. Finally, the random-coefficient model (RCM) is used only for model A, in which we specify the aggregation correction to take place at the group level, meaning that each country has a specific correction parameter $\gamma_k = \beta\theta_k$, where $\theta_k = \theta + v_k$ (see above, Eq. (16)).

To have as many results as possible for the suggested aggregation correction method, we also estimate models A–C for 41 yearly cross-sections. This also gives a more detailed and transparent picture of how the life expectancy–income relationship evolved during the sample years. However, the cross-sectional OLS estimation gives only the average effect results for each year. We also need some distribution effects, as the countries in the sample show large discrepancies in life expectancy. We could estimate models for example on a yearly basis for different income level or health status country groups with separate OLS regressions. However, this would give a vast amount of inefficient OLS regression results. We can obtain better results more efficiently with the *quantile regression approach*, which has been quite popular in recent years (see e.g. Huang et al., 2007). It estimates the conditional quantile functions instead of the mean conditional function as OLS regression does.

By focusing only on the conditional mean function $E[y|\boldsymbol{x}]$, the OLS regression gives an incomplete summary of the joint distribution of $\{y_i, \boldsymbol{x}_i\}_{i=1}^N$. When the sample size is small, the OLS model errors are heteroskedastic and non-normal-like in our yearly samples. *Median* and *quantile regression* methods have advantages beyond this, providing a richer characterization of the data. Median regression is more robust to outliers than OLS regression. Moreover, quantile estimators can be consistent under a weaker stochastic assumption than possible OLS estimation (Cameron and Trivedi, 2005, p. 85).

The linear quantile regression model can be defined as

$$Q(y|\boldsymbol{x}) = \boldsymbol{x}'\boldsymbol{\beta}_q \text{ such that } \mathrm{Prob}[\varepsilon_q \le y - \boldsymbol{x}'\boldsymbol{\beta}_q] = q, \quad 0 < q < 1.$$

q refers to different quantiles, like $q = 0.1, 0.2, \ldots, 0.5, 0.6, \ldots, 0.9$, where q=0.5 gives the median regression (i.e. *MAD* or *LAD* estimator). When $\varepsilon|\boldsymbol{x}$ is normally distributed, $MED[\varepsilon|\boldsymbol{x}]$ is zero and $E[y|\boldsymbol{x}] = MED[y|\boldsymbol{x}] = \boldsymbol{x}'\boldsymbol{\beta}$ (Greene, 2013, p. 243; for more details, see Koenker (2005), Koenker and Hallock (2001)).

4. Results

4.1. Panel model results

Before presenting the estimation results, we show in general terms that the *log of GDPc* is a suitable transformation in this context. Fig. 1 shows on the left side the cross-plot between life expectancy (*LE*) and *GDPc* and then on the right side that between *LE* and *lnGDPc* for all the data points in the sample (6068 observations). We add to the figures the marginal distributions, 95% correlation CIs, and non-parametric curve fitting results. The left graph shows a clearly concave relationship between life expectancy and *GDPc*.

After taking the *ln* – transformation of *GDPc*, the relationship turns linear. Some data points, at an especially low life expectancy, do not fit into this setting, but their role is non-significant. The left graph is very important per se as it shows how unequal the yearly *GDPc* distributions are. The same is true is for life expectancy. Note also the flat part of the curve above 30,000 US dollars per year.

The panel model estimation results are collected in Table 1. The estimated coefficient values for the variables *lnGDPc* and *lnGDPc** support our results concerning the aggregation bias in model B. For all the panel data model estimations, the coefficients for *lnGDPc* and *lnGDPc** are smaller in models A and C than in model B. In the group means and FE-AR(1) models, the coefficient differences are quite large, indicating that the results in model B are clearly biased. Note that the coefficient values are much smaller in the FE-AR(1) model estimations than in the other models, because they are based on quasi-differenced variable values depending on the size of the estimated AR(1) process. The estimated values for the AR(1) coefficients were in the range of 0.90 to 0.95. The model alternative with country-specific error autocorrelations gave similar results without altering the reported values in Table 1. Homogeneity of the country-specific fixed effects ($\alpha_k = \alpha \, \text{for all} \, k$) was rejected for all the FE models. Similarly, the χ^2 test rejected the non-randomness of the coefficients γ_k in the RC model. With respect to the GINI variable, the results in Table 1 are poor. Only

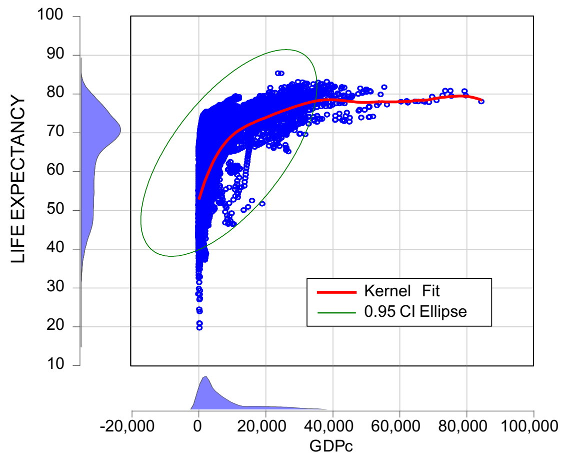

Fig. 1. Cross-plots of the *LE*, *GDPc*, and *lnGDPc* variables (years 1970–2010, 148 countries, 6068 observations).

Table 1
Panel data model estimates for models A–C. Number of observations: N=148, T=41 (1970–2010), $N\times T$=6068.

	Constant[a]	*lnGDPc*	1/*GDPc*	*lnGDPc*[*]	*GINI*	R^2
Model A						
Group Means	6.30[*]	**4.65**[*]	−42.60[*]		−0.33[*]	0.795
FE-Robust	–	**6.21**[*]	−1.60		−0.003	0.888
FE-AR(1)	–	**0.58**[*]	−1.18		0.001	0.480
RCM	44.34[*]	**5.84**[*]	−114.88[*]		0.006	0.356
Model B						
Group Means	53.85[*]	**6.33**[*]			−0.31[*]	0.233
FE-Robust	–	**6.27**[*]			−0.003	0.889
FE-AR(1)	–	**0.65**[*]			0.001	0.476
Model C						
Group Means	46.98[*]			**5.51**[*]	−0.31[*]	0.782
FE-Robust-C[b]	–			**4.53**[*]	0.06	0.712
FE-AR(1)	–			**0.29**[*]	0.001	0.535

[a] The *FE* models do not have common intercepts as the models are estimated with country-specific intercepts for all countries.
[b] Standard errors calculated with clustering errors at the country level.
[*] 5% significant level.

in the group means models is the coefficient value for GINI significant in statistical terms with a non-positive sign implied by the income inequality hypothesis (IIH).

4.2. Cross-sectional results

The insignificant income inequality results with the FE and RCM panel models indicate that our panel model approach has been too general by masking the country heterogeneity and time developments in the life expectancy levels and their relations to income inequality. Note that the health sectors in both developing and developed countries experienced vast changes during the sample period of 1970–2010. We argue that yearly cross-sectional estimations track these time-dependent changes in the model parameter estimates better than the FE or RCM estimations do. Thus, to gain a more transparent picture of aggregation bias with respect to model B, next we estimate the models for each sample year separately. This will produce 41 different coefficient estimates for each year in the sample, proving how *lnGDPc* and *GINI* affected *LE* during the sample period of 1970–2010. Thus, for models A–C, the total number of observations in each case is 148. Standard errors of the coefficient estimates were estimated with White's diagonal *HCSE* corrections.

The following graphs (Fig. 2, below) show the yearly based cross-sectional regression coefficients from the estimated models (more

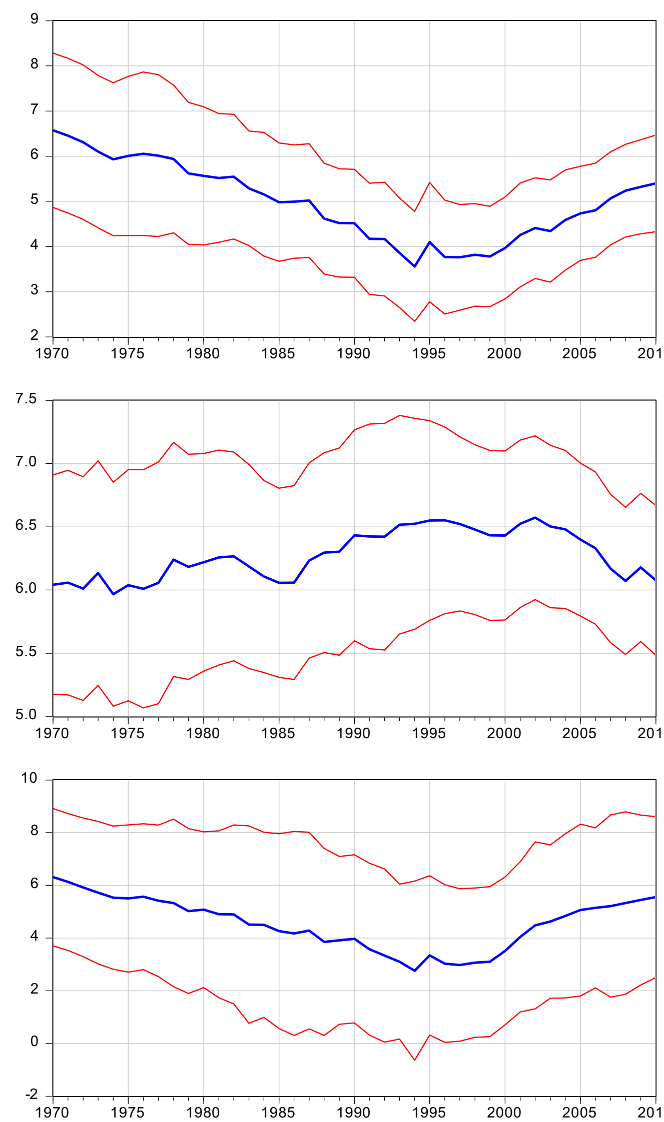

Fig. 2. Yearly coefficient values of the *lnGDPc* variable in models A–C (1970–2010) with 95% CIs.

detailed estimation results can be provided upon request). The most interesting result is the U-shaped evolution between the life expectancy and the log of *GDP* per capita during the years 1970–2010 obtained with our new bias-correcting methods.

Model B, the biased reference approach, does not show this type of behaviour. The result indicates that model B is misspecified and harmed by the errors-in-variables problem. The relationship between the log of *GDP* per capita and the average health status, like life expectancy, is more complex between countries than model B implies. The extent to which the results are only an outcome of our bias-correction procedures or something else is an open question. However, the evident large negative correlation between the variables *lnGDPc* and *1/GDPc* may induce some multi-collinearity into the analysis. The correlations are in the range of −0.818 to −0.886. These are not the levels causing refutation of the results with model A. Note that model C is not sensitive to multi-collinearity and it produces results that are closer to model A than model B.

The estimates' values for coefficients with *lnGDPc* and *lnGDPc** decrease from the beginning of the sample period until the mid-1990s. They have the minimum values in the years 1994–1996, and after this period they start to rise again. This cannot be due to any business cycle-dependent phenomenon, since the observed U-shape is too smooth in shorter time periods. Thus, we argue that, across the sample of 148 countries, the average income effects on average health almost halved in the years 1970–1995 but afterwards started to increase again.

The effects of income inequality on life expectancy are less conflicting between the models (see Fig. 3, below). The negative inequality effect on health became less prominent during the sample years. Irrespective of the model, in 1970 it was −0.4 and at the end of the sample period, 2010, it was −0.1 or 0 (with model C), meaning that the IIH effect measured with the *GINI* coefficient has lost its negative impact on life expectancy. This robust result is highly interesting, since it is similar to individual-data findings in developed countries. Income inequality, despite increasing globally after 1990, lost its impact on health after 2000. However, note that this is a mean regression result across the sample countries. It does not necessarily apply to all countries at different income levels. This means that we have to look at countries with different average health levels.

4.3. Quantile regression results

In general quantile regression methods provide a convenient approach to show how a regression model gives different response results of regressors when we concentrate on different parts of the model error term distribution. We estimated models A–C with quantile methods for data values of samples from different decades (i.e. for the 1970s, 1980s, 1990s, and 2000s). We report only the values for model A for the variables *lnGDPc* and *GINI*. Appendix A2 gives details of the decennial OLS and quantile regressions for model A. Note that the OLS residuals from the models are non-normal, in some cases having large negative tails (see Appendix A2). The results for models B and C are comparable and can be provided upon request (Fig. 4).

We observe that, for the countries with the lowest level of life expectancy (the poorest countries), specifically quantiles less than 0.3, the income gradient is still much higher than that for the countries with high life expectancy (quantiles more than 0.7), independently of the period used. However, the "income effect quantile curve" has shifted downwards, especially for the middle quantiles 0.3–0.7, from the level of the 1970s. We take this as evidence of

i) A decreasing median effect of the log of average income across the countries on life expectancy during the years 1970–2010, and
ii) In the poorest countries, the income health effects are still vastly more prominent than those in rich countries.

Fig. 5 presents the results for the income inequality variable with *GINI* coefficients. The inequality effects are still much larger in the poor countries than in the rich countries. The "inequality effect quantile curve" has shifted upwards, especially for the non-poor countries, and the upper 95% CI obtains the 0-line in the 2000s for the rich countries.

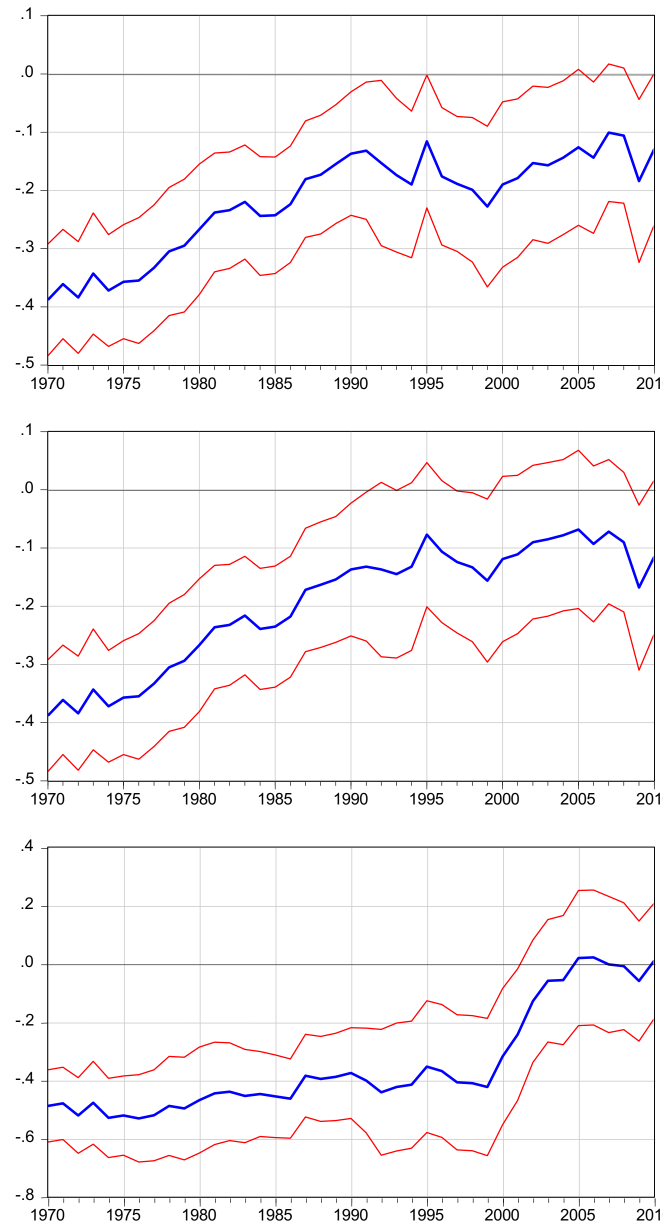

Fig. 3. Yearly coefficient values of the income inequality (*GINI*) variable in models A–C (1970–2010) with 95% CIs.

Thus, we argue that

i) Income inequality has a smaller median effect on life expectancy across the countries in present times than earlier, and
ii) In the poorest countries, the income inequality health effects are still significant both in statistical and in health terms.

4.4. Related results in literature

The obtained results raise an interesting question: How they relate to the results found in literature? Before any comparison can be made we have to exclude all model specification that do not use the correct absolute income hypothesis (AIH) specification, i.e. health is a concave function of income. In their literature review Wagstaff and von

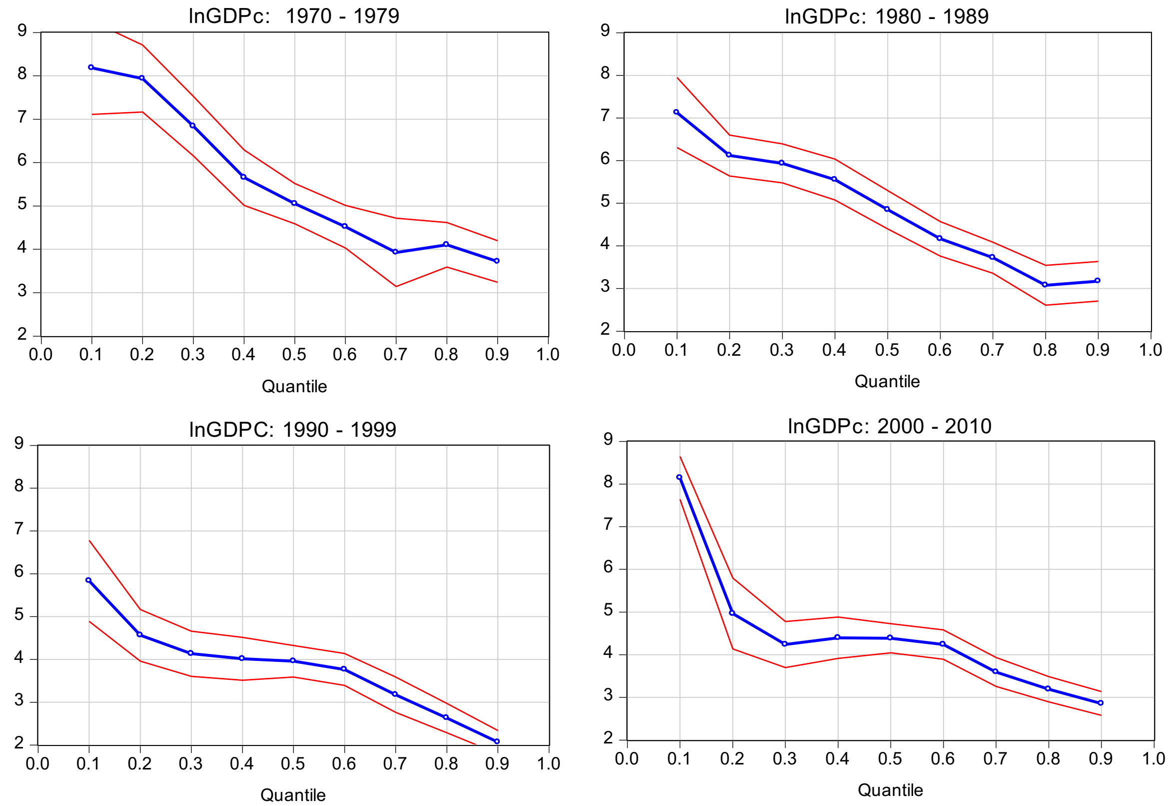

Fig. 4. Quantile regression results with 95% CIs for the variable *lnGDPc* (model A) in the sample decennials.

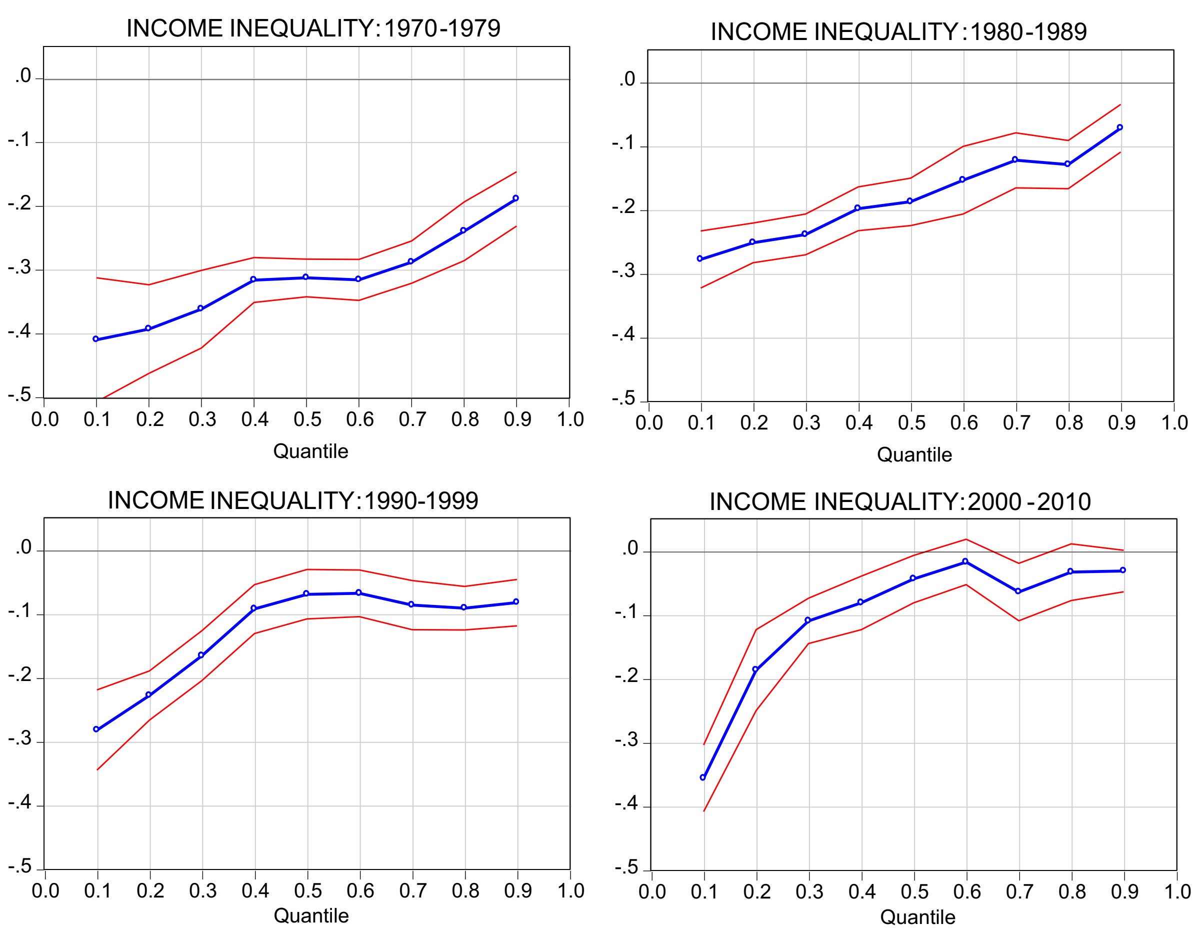

Fig. 5. Quantile regression results with 95% CIs for the variable *GINI* (model A) in the sample decennials.

Doorslaer (2000) notice that quite few studies - especially in public health literature - use the correct functional form (see also Wildman et al. (2003), Deaton (2003)). Note that our results being aggregation consistent, i.e. maintaining the micro relation, we could compare our results both to individual and aggregation level results. However individual level studies focus typically on observed dichotomous health level variable (i.e. 0/1=death/alive or sick/well) or on ordinal subjective health valuations, and the models are estimated with discrete choice methods. The coefficient values on log of income in these studies are not fully comparable with community or country based OLS models where continuous health measures like average life expectancy are regressed on log of mean income.

The study by Babones (2008) comes closest to our approach. He uses similar model and his data is from years 1970 and 1995 with 134 countries. He reports standardized coefficient estimates for log of GDP per capita on life expectancy at birth to be between 0.580 and 0.827 for both years and for different sample configurations. He uses crude aggregation bias correction method based on the lognormal distribution and concludes that "...the ecological correlation between income and health is an overestimate of the individual correlation between income and health." (p. 1622). The estimated income inequality effects on life expectancy measured with GINI-coefficient are between −0.412 and −0.163. Note Ellison (2002) gives similar results for 120 countries in year 1991 after experimenting with different income levels and functional forms. More recently Biggs et al. (2010) report the log of GDP per capita effects on life expectancy at birth to be 6.04. When they control for decreasing inequality and poverty the estimates are larger. They use fixed effects panel model for 22 Latin American countries in years 1960–2007.

Although the micro-based methods and results are not directly comparable with macro outcomes some results with valid correspondence can be found. Mackenbach et al. (2005) study with the LOESS-function the shape of the relationship between household equivalent income and self-assessed health in seven European countries during 1990s. They report that the relationship is generally curvilinear and characterized by less improvement in self-assessed health per unit of rising income. This result can be observed in all sample countries. A $10.000 additional household equivalent income is associated with an increase of 0.09–0.29 points of self-assessed health. Olsen and Dahl (2007) uses European Social Survey (ESS) data from year 2003 with 21 countries to model continuously survey health responses (self-assessed health with five categories) on many individual socio-economic variables and some macro variables. They use hierarchical linear model and report that log of GDP per capita is the indicator that is most strongly associated with better health after controlling for individual-level characteristics. The income effects for women and men were 0.618 and 0.478 in full sample and for labour force they were 0.067 and 0.493. They conclude that results are in line with previous findings (Castilla, 2004; Beckfield, 2004; Fritzell and Lundberg, 2005). Note that income inequality health effects – if present in these studies – were either non-significant or very small.

5. Discussion and conclusions

A large amount of data consisting of 148 countries in the years 1970–2010 was analysed in the context of the health–income relationship. The current literature emphasizes individual data, deriving results for health and incomes. However, the aggregative approach is still active, because country-level data on GDP per capita, income inequality, and average health status are still widening and gaining a longer time span. Both at the individual and at the aggregative data level, some results indicate that the absolute income effect (AIH) on health is still strong but the inequality effect (IIH) is disappearing from developed countries.

The literature also suggests that part of the inequality effect obtained with macro data is a result of a concave mean income function on average health. We showed that this estimation strategy is seriously biased because of incorrect aggregation, which we analysed in detail. A method based on the first-order Taylor approximation is suggested to overcome this aggregation-induced errors-in-variables bias. Two bias-correcting model alternatives are provided that correct for aggregation bias and still preserve the individual-level interpretation of estimated income effects on average health.

The results show that bias-correcting models produce quite different results for the log *GDP* per capita effects on life expectancy across the sample countries in the years 1970–2010 from the biased non-corrected reference model. Especially in the period from 1985 to 2005, the biased model with yearly cross-sections gives income effect estimates that are too large compared with the bias-corrected ones. However, the income inequality effects estimated with the *GINI* coefficients are not affected by the model alternatives. Across the models the inequality effects on life expectancy are still negative and are not significant in statistical terms after the late 1990s.

To achieve more transparent income and inequality effects on life expectancy distribution across the sample countries, the bias-correcting model was also estimated with the quantile regression approach, which is sensitive to the life expectancy data distribution. It produces income regression effects at different quantiles of the life expectancy model error distribution.

The coefficients for the log of *GDP* per capita were significant throughout the four decades in both OLS and quantile regressions. In the decade of 1970–1979, when *lnGDPc* increased by 1%, life expectancy increased on average by 0.061 years in the OLS regressions and 0.051 years in the median LAD regressions. We know that the income gradient is higher for poorer countries than for richer ones. However, the coefficient values of *lnGDPc* fall over the years for all the countries. In the last decade (2000–2010), the respective *lnGDPc* values were 0.047 and 0.044 in OLS and median LAD, respectively. The results with quantile regression other than the median for four different decennials in the sample show that the poorest countries' income gradient is still much higher than that of the rich countries.

When comparing the OLS and quantile regression results for the period 1970–1979 with the bias-correcting model, the significant coefficient estimates for the *GINI* variable are very similar (−0.351 for OLS and −0.312 for median LAD). In the 1980s the effects of income inequality on life expectancy decreased marginally in absolute values. All the coefficients were, however, significant for both the regression types. Between 1990 and 1999 the income inequality effects on life expectancy were −0.154 with OLS and −0.062 with median LAD. In the 1990s the *GINI* coefficient with median LAD was less than that with OLS. One reason for this was that the changes in income inequality amongst the poorest countries still affected life expectancy more than the same changes did in the richer countries. In the last decade (2000–2010), when examining the *GINI* for the 148 countries, one can identify a similar diminishing inequality effect, and the richer countries were comparatively less affected by the changes in the *GINI* than the poorer ones. Note that the full-sample panel data model estimates for income distribution effects were insignificant.

In general terms we argue that our bias-correcting approach to the health–income relationship with panel FE and RCM, cross-section OLS, and quantile regressions is a promising modelling alternative that has shown its merits in this context. It corrects the (absolute) income effects in the right direction, and the results for income inequality do not conflict with the results found in the current literature based on micro data. The method retains the interest in macro data modelling and offers new model alternatives in other contexts. Future work with the method will show its full potential.

Acknowledgements

We gratefully acknowledge helpful comments from the editor and two anonymous referees. Errors remain ours.

Appendix A1. Errors in the variable problem in model $HS_k = \alpha + \beta \ln \overline{Y}_k + \varepsilon_k$

The basic theory of measurement error and errors-in-variables bias in the OLS model has the following structure. The correct model with variable x measured without errors is

$$y = \alpha + \beta x + \varepsilon.$$

However, if the true x is unknown and we observe a poorly measured signal of it, say x^*, we have $x^* = x + \mu$, where μ is the random measurement error. It can be shown that the bias in the OLS estimation for β is (see Stock and Watson (2011), pp. 361–363)

$$\widehat{\beta}_{OLS} - \beta = -\beta \frac{COV[x + \mu, \mu]}{VAR[x^*]}, \tag{A1}$$

where β is the true value. Now we apply this approach to the generic model

$$HS_k = \alpha + \beta \ln \overline{Y}_k + \varepsilon_k,$$

where $x^* = \ln \overline{Y}_k$ and $x = \ln \overline{Y}_k - \frac{\theta}{\overline{Y}_k}$. This gives for $x^* = x + \mu$ that $\mu_k = \frac{\theta}{\overline{Y}_k}$.

Note that, as $\mu_k = \frac{\theta}{\overline{Y}_k}$ is not independent of $\ln \overline{Y}_k$, the bias is

$$\widehat{\beta}_{OLS} - \beta = -\beta \frac{COV\left[\ln \overline{Y}_k, \frac{\theta}{\overline{Y}_k}\right]}{VAR[\ln \overline{Y}_k]}. \tag{A2}$$

Because of the result

$$COV\left[\ln \overline{Y}_k, \frac{\theta}{\overline{Y}_k}\right] = \theta COV\left[\ln \overline{Y}_k, \frac{1}{\overline{Y}_k}\right],$$

and since we know that $COV\left[\ln \overline{Y}_k, \frac{1}{\overline{Y}_k}\right] < 0$, the bias now takes the form

$$\widehat{\beta}_{OLS} - \beta = -\beta \frac{\theta\left[COV\left[\ln \overline{Y}_k, \frac{1}{\overline{Y}_k}\right]\right]}{VAR[\ln \overline{Y}_k]} > 0. \tag{A3}$$

The results state that the OLS estimate for β_{OLS} in the model $HS_k = \alpha + \beta_{OLS} \ln \overline{Y}_k + \varepsilon_k$ *is biased upwards* and the *size of the bias* is $\beta\theta[COV[\ln \overline{Y}_k, \frac{1}{\overline{Y}_k}]/VAR[\ln \overline{Y}_k]$.

Now, if we use the augmented regression model A,

$$HS_k = \alpha + \beta_A lnGDPc_k + \frac{\gamma}{GDPc_k} + \varepsilon_k,$$

then the OLS estimate for β_A in this model is smaller than that in the measurement error model; that is, $\beta_A < \beta_{OLS}$, because in the model the term $\frac{\gamma}{GDPc_k} = \frac{-\beta_A\theta}{GDPc_k}$ corrects for the measurement error because $lnGDPc_k$ and $\frac{1}{GDPc_k}$ are correlated.

An alternative approach to correct for bias is to use directly the approximation

$$\frac{1}{N_k}\sum_{i=1}^{N_k} \ln Y_i \approx \ln \overline{Y}_k - \frac{\theta_k}{\overline{Y}_k}$$

by regressing $\ln \overline{Y}_k$ on $\frac{1}{\overline{Y}_k}$. Thus, we regress on the time series observation of each country k

$$\ln GDPc_{k,t} = d_k + \theta_k \frac{1}{GDPc_{k,t}} + \eta_{k,t} \tag{A4}$$

to obtain country-specific OLS estimates $\widehat{\theta}_k$ and use these to obtain the transformed values

$$\ln GDPc^*_{k,t} = \ln GDPc_{k,t} - \frac{\widehat{\theta}_k}{GDPc_{k,t}}. \tag{A5}$$

In practice all this means that we should estimate equations

$$HS_k = \alpha_1 + \beta_1 lnGDPc_k + \frac{\gamma_1}{GDPc_k} + \delta_1 GINI_k + \varepsilon_k, \tag{A}$$

$$HS_k = \alpha_2 + \beta_2 \ln GDPc_k + \delta_2 GINI_k + \varepsilon_k, \tag{B}$$

$$HS_k = \alpha_3 + \beta_3 \ln GDPc^*_k + \delta_3 GINI_k + \varepsilon_k \tag{C}$$

and compare OLS estimates $\widehat{\beta}_1$ and $\widehat{\beta}_3$ with $\widehat{\beta}_2$ to evaluate the estimate bias in model B.

Appendix A2. OLS and quantile (median) regression results for model A in the four sample decennials

OLS Variable	1970–1979 Coefficient (p-value)	1980–1989 Coefficient (p-value)	1990–1989 Coefficient (p-value)	2000–2010 Coefficient (p-value)
Constant	*53.121*	*54.922*	*60.334*	*57.475*
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
lnGDPc	*6.145*	*5.137*	*4.024*	*4.766*
	(0.835)	*(0.000)*	*(0.000)*	*(0.000)*
1/GDP	*1.126*	*−26.399*	*−63.760*	*−45.665*
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
GINI	*−0.351*	*−0.214*	*−0.154*	*−0.147*
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
R^2	**0.692**	**0.734**	**0.764**	**0.715**
Normality1)	**43.66***	**145.56***	**925.12***	**1027.84***
Number of obs.	**1480**	**1480**	**1480**	**1628**

1) Bera–Jarque test for residual normality: $\chi^2(2)$ test with the 5% critical value of 5.91.

MEDIAN Variable	1970–1979 Coefficient (p-value)	1980–1989 Coefficient (p-value)	1990–1989 Coefficient (p-value)	2000–2010 Coefficient (p-value)
Constant	*57.510*	*55.492*	*57.574*	55.629
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
lnGDPc	*5.0546*	*4.848*	3.956	*4.383*
	(0.000)	*(0.000)*	(0.000)	*(0.000)*
1/GDP	*−28.638*	*−38.359*	−67.800	*−57.102*
	(0.000)	*(0.000)*	(0.000)	*(0.000)*
GINI	*−0.312*	*−0.187*	−0.069	*−0.043*
	(0.000)	*(0.000)*	(0.001)	*(0.020)*
Pseudo R^2	**0.449**	**0.526**	**0.553**	**0.524**
Number of obs.	**1480**	**1480**	**1480**	**1628**

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