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Income Inequality, Health Outcomes and Financial Crisis: Novel Evidence

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This study revisits the existing relationship between income inequality and population health by subjecting it to a battery of empirical testing using different measures of inequality and health outcomes for 33 high-income OECD countries. Apart from the impact of macroeconomic covariates we also explore the effect of the global financial crisis (2007/8) on health outcomes. For the empirical investigation we have adopted panel cointegration analysis to obtain long-run estimates that are free of endogeneity bias. For robustness we also adopt a panel quantile regression (QR) in an attempt to provide a more detailed picture of the underlying relationships at several points of the conditional distribution. We find that in the long run, income inequality affects adversely population health which is also confirmed by the quantile estimates. The causal dimension however is more ambiguous whilst the global financial crisis is found to have an insignificant impact on health outcomes.

Keywords: *population health, income inequality, infant mortality, life expectancy, financial crisis*

Introduction

The debate over the role of income inequality as a one of the determinants of population health has been intense. Despite the various channels identified in the literature through which income inequality affects an individual's health the precise mechanism through which disparities in society's income distribution adversely affects health outcomes remains ambiguous. In this domain, various hypotheses have been developed that focus on the implications of increases in individual income on the marginal health benefits as well as the societal impact on income inequality (Lynch et al. 2004).

On the empirical front, the evidence suggests that there might be a negative relationship between income inequality and population health whilst the *relative income hypothesis*, i.e., the proposition that income distribution is an important determinant of population's health, is more complex that initially envisaged (Mellor and Milyo 2002, Osler et al. 2002, Shibuya et al. 2002, Deaton and Lubotsky 2003, Lynch et al. 2004). Despite the lack of empirical conviction, it is widely acknowledged that since the 1970s the growing income inequality observed in many countries has been detrimental to the welfare of the society (Atkinson et al. 1995, Lindert 2000).

The relationship between income inequality and health has significant implications for policy making as redistributive economic policies that target

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greater social justice and better population health should be considered in countries to promote a heathier population (Kawachi and Kennedy 1999, Pickett and Wilkinson 2015, Neumayer and Plumper 2016). The reverse causal dimension between income inequality and heath has also been proposed in the extant theoretical literature. The mechanisms through which health affects inequality are also explored through labor market effects, educational effects, and marriage market effects (see, Leigh et al. 2012).

On the effects of economic crises on health outcomes, prior research suggests that economic crises do positively affect mortality rates (and presumably other measures of health). The conventional wisdom holds that health deteriorates as the economy weakens and vice versa. An extensive empirical work by Brenner (1987) provided evidence in support of the belief that during recessions or other sources of economic instability, overall mortality as well as alcoholism and admissions to mental institutions increased markedly. At the time this piece of research was questioned on technical grounds (e.g., Wagstaff 1985) and later studies that addressed these concerns (e.g., Forbes and McGregor 1984), generated evidence that appeared to be sensitive to the choice of countries, time spans as well as proxies for health. Subsequent empirical studies using state of the art econometric and modelling techniques designed to overcome any previous limitations (e.g., Laporte 2004, Gerdtham and Johannesson 2005, Tapia Granados and Diez Roux 2009) failed to provide robust results, as the nature of the data sets used in all likelihood yielded biased estimates due in the main to important factors omitted from the estimations and spurious correlations that characterize economic conditions and health.

Undoubtedly, the recent global financial crisis (GFC) in 2007/8 has had a crippling effect on the global economy, and the reverberations of this shock can still be felt many years later (Alexiou and Nellis 2016). The resulting economic recession caused unemployment to increase in some countries uncontrollably wiping off a huge percentage of their GDP.

The concerted response of many governments to the devastating economic impact of the GFC was the implementation of austerity measures that mainly focused on cutting public spending, the privatization of public services and market deregulation (Escolar-Pujolar et al. 2014). The impact of these very policies resulted in further exacerbating the extant socioeconomic problems (Stuckler et al. 2009, Karanikolos et al. 2013).

On the empirical front, Atkinson and Morelli (2011) provided evidence of financial crises causing increases in inequalities; however they failed to establish a clear pattern as each crisis evolved in a different manner. Notwithstanding, it should be stressed that evidence of an increase in health inequalities during periods of economic crisis are paramount and effectively observed in the way the pattern of different health variables such as mortality, mental health, self-perceived health, alcohol abuse, crime rate has unravelled (Rajmil et al. 2013).

Prior to assessing the effects of income inequality on health we need to also clarify that inequality is distinctly different from poverty, in that income inequality might or might not be significantly associated with health, whereas poverty is almost invariably negatively correlated to health. According to Eibner and Evans

(2005) there is a strong and negative relationship between absolute poverty found in poor countries - where incomes are relatively unequal - and health.

In this study, we subject the relationship between income inequality and population health outcomes to a battery of empirical testing using different measures of inequality and health to check the robustness of our results. In this direction we adopt three alternative methodological frameworks that provide a) efficient long-run estimates b) insights of the underlying relationships at several points of the conditional distribution of the dependent variable(s) and c) evidence on the causal dimension of the variables under scrutiny. Finally, the impact of the global financial crisis (2007/8) is also considered.

The rest of the paper is organized as follows. Next section touches on the methodological frameworks utilized for the empirical investigation whilst the section afterwards presents and discusses the results. Finally, some concluding remarks are provided.

Methodology

Our intention to collect data for both high-income OECD countries as well as for developing economies was hampered by data availability. As a result, due to too many missing observations in the sample with the developing economies, we decided to drop the initial idea of conducting a comparative analysis, and instead resorted to a dataset of 33 high-income OECD economies that spans the period 1990 to 2017. The dataset consists of the following high income OECD countries: Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States.

The baseline regression model of the health outcomes regression is a variant of the standard specifications encountered in the literature (see, Beckfield 2004).

$$\text{health}_{it} = a_0 + a_1\text{inequality}_{it} + a_2X_{it} + \varphi_1\text{crisis}_{it} + \varepsilon_{it}$$

where health denotes health outcomes as these are captured by infant mortality (infmort), and life expectancy (lifexpe); Inequality is captured by two measures based on the gini coefficient (i.e. ginidisp and ginimkt); X_{it} is a vector of control variables consisting of a GDP per capita (gdppc), education (edu), employment (EMP), health expenditure (healthgdp) and a dummy variable (crisis) that captures the 2007/8 global financial crisis.

We utilize the Gini index of inequality in equivalized household disposable income (post-tax, post-transfer) and a Gini index of inequality in equivalized household market income (pre-tax, pre-transfer) as advanced by Solt (2020). In so far as benefits assume a key redistributive role in alleviating inequality, we are of the view that benefits (as a share of income) tend to be more concentrated at the bottom of the income distribution than direct taxes and therefore have a greater

bearing than direct taxes in the redistribution process (Bourquin and Waters 2019). In view of this we opted for incorporating both measures of income inequality for robustness and comparison purposes. The Standardized World Income Inequality Database (SWIID 8.3) and the World Development Indicators (World Bank) were the main providers for the data used in this study. (See Tables A1 and A4 in the appendix for sources, definition of variables and descriptive statistics).

Cointegration Analysis

For the empirical investigation we have adopted panel cointegration analysis in an attempt to explore the relationship between health outcomes and inequality by obtaining long-run estimates that are free of endogeneity bias (see, e.g., Engle and Granger 1987).

Prior to engaging with cointegration analysis it is imperative that we check our series for unit roots. In lieu of the traditional tests for unit roots such as DF (Dickey-Fuller) or ADF (Augmented Dickey-Fuller) tests we utilize more robust testing techniques that have been shown in the respective literature to perform more efficiently than the traditional unit root tests applied to individual series (see Levin et al. 2002, Im et al. 2003). Evidence of a stationary linear relationship suggests that the non-stationary time series are cointegrated in which case a long-run equilibrium relationship amongst the variables of interest can be established.

In this direction we adopt a panel cointegration test that was advanced by Pedroni (2004). These tests are formulated as follows:

$$y_{it} = \alpha_i + \beta_1 X_{1,i,t} + \beta_2 X_{2,i,t} + \ldots\ldots + \beta_n X_{n,i,t} + v_{it} \quad (1)$$

where $X_{i,t}$ are the regressors and n the cross-sections. The residual regression equation assumes the following form:

$$v_{i,t} = \zeta_i v_{i,t-1} + z_{i,t.} \quad (2)$$

During this process the seven different statistics (i.e., Panel-v, panel-rho, panel non-parametric-t and panel parametric-t, group-rho, group non-parametric-t and group parametric-t) are estimated. Pesaran et al. (1999), argues that a dynamic heterogeneous regression can be embedded into the error correction specification by means of the ARDL approach to cointegration.

We employ an autoregressive distributed lag model (ARDL, p,q) in an attempt to obtain efficient long-run estimates. The general empirical specification of the ARDL expression can be modelled as follows:

$$Y_{it} = \sum_{j=1}^{p} \xi_{ij} y_{i,t-j} + \sum_{j=0}^{q} \zeta_{ij} X_{i,t-j} + v_t + \varepsilon_{it} \quad (3)$$

where X_{it} is a vector of explanatory variables and v_t captures the group-specific effect; i denotes cross-sections and t denotes time. In the context of cointegration the error term is an I(0) process and through re-parametrizing (3) the error correction specification can expressed in the following terms:

$$\Delta Y_{it} = \lambda_i y_{i,t-j} - \mu_i X_{i,t-j} \sum_{j=1}^{p-1} \xi_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \zeta_{ij} \Delta X_{i,t-j} + v_t + \varepsilon_{it} \quad (4)$$

where λ_i is the error correction coefficient which captures the speed of adjustment.

The ARDL specification and in particular the Pooled Mean Group estimator, provides consistent coefficients - as it includes lags of both dependent and independent variables - regardless of whether the regressors are exogenous or endogenous and irrespective of whether the variables are I(0) or I(1). The presence however of I(2) variables invalidates the methodology (Pesaran et al., 1999).

Further Empirical Probing: A Panel Quantile Approach

Broadly speaking, the traditional linear regression model looks at the relationship between a number of independent variables X, and a dependent variable y, based on the conditional mean function E(y|X). This rather narrow approach can be further enhanced by assessing the relationship between y and X at different points in their conditional distribution.

In an attempt to check the robustness of our results, we adopt a panel quantile regression (QR) in an attempt to provide a more detailed picture of the underlying relationships at several points of the conditional distribution of y simultaneously. QR which traces its origins to the seminal paper by Koenker and Bassett (1978) is more robust to non-normal errors and outliers; according to Alexiou and Vogiazas (2020) "it permits a richer characterization of the data by allowing us to consider the impact of a covariate on the entire distribution of y, not merely its conditional mean" (p. 301).

Most panel quantile estimators in the respective literature include additive fixed effects in the quantile function and provide estimates about the distribution of $(Y_{it} - f_i|G_{it})$, where Y_{it} is the outcome, G_{it} are exogenous variables, and f_i stands for fixed effects. According to Powell (2016), observations at the top of $(Y_{it} - f_i)$, may actually be at the bottom of the Y_{it} distribution and, consequently, additive fixed effect models can provide information about the outcome-relative-to-fixed-effect distribution rather than the effects of the treatment variables on the outcome distribution.

In this context, Powell (2016) proposes a panel data quantile method that provides estimates for the distribution of $(Y_{it}|D_{it})$, while allowing for individual level heterogeneity and maintaining the non-separable disturbance term typically used in quantile estimation. Most importantly the panel quantile estimator produces point estimates that can be interpreted in a similar way as cross-sectional regression results and are consistent for small *T*.

The regression model for quantile level τ of the response is given by:

$$Q_\tau(y_i) = \beta_0(\tau) + \beta_1(\tau)x_{i1} + \ldots + \beta_p(\tau)x_{ip}\,,\ i = 1, \ldots, n \quad (1)$$

and the β_j's are estimated by solving the least squares minimization problem:

$$\min_{\beta_{0(\tau)},\ldots,\beta_{p(\tau)}} \sum_{i=1}^{p} \rho_\tau(y_i - \beta_0(\tau) - \sum_{j=1}^{p} x_{ij}\beta_j(\tau)) \quad (2)$$

where $\rho_\tau(r) = \tau \max(r, 0) + (1 - \tau)|\max(-r, 0)$. Then, for each quantile level τ, the solution to the minimization problem yields a distinct set of regression coefficients.

Finally, in modelling the relationship between health and income one issue that should also be considered related to the reverse causality and the possibility of income being affected by health, in which case the impact of income on health may be overestimated. To address this issue, the causal dimension of the series is also examined by means of Granger Causality test to establish the direction of causality of the key variables (see Table A3 in Appendix).

Findings and Discussion

We commence our analysis by establishing the order of integration of the variables included in the models. An inspection of Table A2 in the Appendix suggests that our series exhibit a mixed order of integration, i.e., I(0) and I(1) as well as evidence of cointegration.

Table 1. *Long Run Estimates*

Variables	**Model 1 infmort**	**Model 2 infmort**	**Model 3 lifeexpe**	**Model 4 lifeexp**
ginidisp	0.211***		-1.874***	
	(0.01)		(0.146)	
ginimrkt		0.192***		-2.236***
		(0.009)		(0151)
emp	-0.219***	0.007	0.283***	-0.091
	(0.016)	(0.007)	(0.08)	(0.089)
Lgdppc	-2.412***	-2.651***	1.783***	1.612***
	(0.031)	(0.067)	(0.034)	(0.051)
gdppc^2	1.023***	1.046***	-1.912***	-1.389***
	(0.067)	(0.082)	(0.091)	(0.0089)
healthgdp	-0.297***	-0.388***	0.873***	2.088***
	(0.025)	(0.026)	(0.210)	(0.219)
inf	0.142***	0.08***	0.317*	0.224***
	(0.020)	(0.020)	(0.210)	(0.831)
edu	-0.234***	-0.371***	0.932***	0.835***
	(0.015)	(0.027)	(0.201)	(0.220)
crisis	0.638	0.872	-1.251	-1.981
	(0.892)	(0.845)	(1.037)	(1.971)

Notes: Robust standard errors in parentheses: ***, ** and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

Table 1 presents the long-run estimates of the four different specification. More specifically, according to models 1 and 2 – which use infant mortality (infmort) as the dependent variable – both measures of income inequality (ginidisp and ginimkt) are found to be highly significant indicating that high income

inequality is positively associated with higher infant mortality which is line with our prior expectations (see also Beckfield 2004).

The effects of level of education (edu) and employment (emp) on infant mortality are found to be negative and significant which is in line with our expectations. Similar results are also established by Ko et al. (2014). Health expenditure (healthgdp) is highly significant bearing a negative sign. It should be stressed however that health expenditure might be indeed assumed to improve health outcomes but the underlying relationship in the literature appears to follow a social gradient, where the infant mortality dwindles the most in the poorest quintiles (see, Baker et al. 2018).

In so far as, potential nonlinearities may exist between health outcomes and income (Gravelle et al. 2002) we have incorporated in our model a squared term (Lgdppc^2). GDP per capita is found to be negatively related to infant mortality whilst the squared term exhibits a positive association.

The measure of inflation (inf) is also significant exerting a positive impact on infant mortality whereas the dummy variable that captures the 2007/8 global financial crisis is found to be insignificant. The latter might provide sustenance to the concerns of those who question the impact of economic crises on health outcomes on mainly technical grounds (Gravelle et al. 1981) as the evidence are case sensitive i.e. depend on to the choice of countries, time spans as well as proxies for health.

When life expectancy (lifeexpe) is employed as a dependent variable, (models 3 and 4) the signs of the explanatory variables are in line with our expectations. More specifically, the significant and negatively signed measures suggest that as income inequality increases life expectancy dwindles (see Beckfield 2004, Mayrhofer and Schmitz 2014). Neumayer and Plumper (2016) in similar study, examining the effects of market income inequality and income redistribution via taxes and transfers on inequality in longevity using a cross-sectional time-series sample of up to 28 predominantly Western developed countries found that "income inequality before taxes and transfers was positively associated with inequality in the number of years lived; income redistribution (the difference between market income inequality and income inequality after taxes and transfers were accounted for) was negatively associated with longevity inequality" (p. 160).

Moreover employment (emp), GDP per capita (gdppc), health expenditure (healthgdp), education (edu) and inflation are found to be positively affecting life expectancy whilst the non-linear term (gdppc^2) is found to be negative and significant which is in line with the results produced by Gravelle et al. (2002). The crisis dummy however as previously fails to register a significant result.

Table 2. *Short Run Estimates*

Variables	**Model 5 D(infmort)**	**Model 6 D(infmort)**	**Model 7 D(lifeexpe)**	**Model 8 D(lifeexp)**
Error Correction	-0.082***	-0.077***	-0.069***	-0.013***
	(0.0062)	(0.0060)	(0.0057)	(0.150)
D(ginidisp)	0.103*		0.091	
	(0.061)		(0.062)	
D(ginimrkt)		0.155**		-0.114**
		(0.07)		(0.055)
D(emp)	0.016*	0.021**	-0.061***	-0.045*
	(0.010)	(0.011)	(0.022)	(0.024)
D(gdppc)	-2.563***	-2.451***	1.071	1.132
	(0.023)	(0.036)	(1.051)	(1.893)
D(gdppc^2)	1.711	1.982	0.981	0.769
	(1.008)	(1.567)	(0.969)	(0.852)
D(healthgdp)	-0.077***	-0.094***	0.135	0.051
	(0.025)	(0.032)	(0.085)	(0.076)
D(inf)	0.002	-0.001***	0.0005	-0.001
	(0.004)	(0.0043)	(0.009)	(0.008)
D(edu)	-0.025**	-0.023**	0.031	0.049
	(0.014)	(0.012)	(0.245)	(0.156)
crisis	0.012	0.035	-1.871	-1.461
	(0.028)	(0.236)	(2.4620	(1.522)
Constant	4.016***	9.15***	4.348***	12.20***
	(0.412)	(0.843)	(0.589)	(1.033)
No. of Obs.	609	609	609	609
Log LL	-769.6	-735.4	-217.3	-225.1

Notes: Robust standard errors in parentheses: ***, ** and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

As far as the short run estimates are concerned (see Table 2) the results are more ambiguous. To start with, the error correction term in all estimated models is found to be statistically significant and negative indicating the direction and speed of adjustment to its long-run equilibrium levels. The estimation results pertaining to models 5 and 6 are more or less akin to the respective ones established previously when the long run specifications were considered. In models 7 and 8 only one measure of inequality (ginimkt) is found to be significant bearing a negative sign whilst out of the rest of the control variables only employment is found to negatively affect life expectancy. The rest of the variables are found to be insignificant in both specifications including those that measured nonlinearities.

Table 3. *Table Quantile Regressions – Dependent Variable: Infant Mortality (infmort)*

Model 9								
Quantile	ginidisp	emp	Lgdppc	Lgdppc^2	healthgdp	inf	edu	crisis
0.10	0.111*** (0.020)	-0.022** (0.011)	-2.3671*** (0.02)	0.932*** (0.0763)	-0.111* (0.064)	0.187*** (0.046)	-0.026* (0.014)	-0.132 (0.154)
0.20	0.113*** (0.023)	-0.024* (0.014)	-2.672*** (0.078)	0.783*** (0.093)	-0.125** (0.050)	0.260*** (0.030)	-0.026** (0.014)	-0.298 (0.366)
0.30	0.139*** (0.015)	-0.032*** (0.012)	-1.631*** (0.063)	0.782** (0.0248)	-0.076* (0.040)	0.231*** (0.031)	-0.029*** (0.010)	-0.273 (0.260)
0.40	0.135*** (0.013)	0.041*** (0.009)	-1.983*** (0.073)	0.873*** (0.021)	-0.078*** (0.029)	0.232*** (0.038)	-0.029*** (0.006)	-0.285 (0.353)
0.50	0.138*** (0.016)	-0.046*** (0.009)	-1.975*** (0.063)	0.945*** (0.039)	-0.040 (0.032)	0.226*** (0.064)	-0.026*** (0.007)	-0.352 (0.360)
0.60	0.134*** (0.016)	0.039*** (0.009)	-1.782*** (0.046)	0.372*** (0.092)	-0.023 (0.028)	0.260*** (0.054)	-0.016*** (0.007)	-0.404 (0.555)
0.70	0.118*** (0.013)	-0.042*** (0.010)	-2.632*** (0.0728)	0.356*** (0.094)	-0.017 (0.026)	0.321*** (0.054)	-0.008 (0.006)	-0.459 (0.657)
0.80	0.120*** (0.011)	0.035*** (0.014)	-1.892*** (0.0467)	0.542*** (0.036)	-0.010 (0.024)	0.307*** (0.046)	0.001* (0.009)	-0.567 (0.566)
0.90	0.110*** (0.018)	0.0118 (0.020)	-2.679*** (0.0683)	0.467*** (0.067)	-0.002 (0.031)	0.248*** (0.032)	0.026*** (0.013)	-0.376 (0.279)
Model 10								
Quantile	ginimkt	emp	Lgdppc	Lgdppc^2	healthgdp	inf	edu	crisis
0.10	0.083*** (0.021)	-0.005 (0.012)	-2.901*** (0.028)	0.189*** (0.058)	0.003 (0.055)	0.207*** (0.059)	-0.014 (0.013)	-0.238 (0.182)
0.20	0.073*** (0.020)	-0.016 (0.012)	-2.893*** (0.278)	0.134*** (0.066)	0.008 (0.052)	0.248*** (0.037)	-0.012 (0.012)	-0.270 (0.151)
0.30	0.062*** (0.023)	0.013 (0.012)	-2.395*** (0.493)	0.150*** (0.058)	0.013 (0.049)	0.217*** (0.045)	-0.002 (0.013)	-0.208 (0.247)
0.40	0.065** (0.031)	-0.025*** (0.012)	-3.892*** (0.789)	0.144*** (0.062)	-0.009 (0.050)	0.254*** (0.047)	-0.003 (0.017)	-0.449 (0.168)
0.50	-0.030 (0.038)	-0.047*** (0.010)	-3.533*** (0.383)	0.112*** (0.044)	-0.050 (0.053)	0.249*** (0.067)	0.011 (0.022)	-0.388 (0.366)
0.60	0.005 (0.035)	0.052*** (0.010)	-2.803*** (0.478)	0.180*** (0.046)	-0.083 (0.061)	0.258*** (0.062)	0.027 (0.021)	-0.398 (0.371)
0.70	0.014 (0.030)	-0.060*** (0.009)	-2.784*** (0.493)	0.201*** (0.037)	-0.105 (0.056)	0.265*** (0.046)	0.025 (0.018)	-0.447 (0.559)
0.80	-0.013 (0.021)	0.054*** (0.014)	-3.034*** (0.789)	0.214*** (0.031)	-0.066 (0.075)	0.269*** (0.043)	0.042 (0.014)	-0.549 (0.697)
0.90	0.005 (0.018)	-0.016 (0.018)	-2.454*** (0.209)	0.238*** (0.030)	0.053 (0.027)	0.200*** (0.042)	0.072 (0.015)	-0.347 (0.268)

Notes: Standard error in parenthesis for each quantile (t). ***, ** and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

Table 4. *Quantile Regressions – Dependent Variable: Life Expectancy (Lifeexpe)*

Model 11								
Quantile	ginidisp	emp	Lgdppc	Lgdppc^2	healthgdp	inf	edu	crisis
0.10	-0.316*** (0.089)	0.184*** (0.078)	2.789*** (0.933)	0.153 (0.187)	0.102 (0.131)	-0.321 (0.114)	0.493*** (0.060)	1.186 (0.583)
0.20	-0.141*** (0.047)	0.043 (0.052)	3.821*** (0.781)	0.136 (0.096)	0.532*** (0.209)	-0.137*** (0.094)	0.616*** (0.032)	0.344 (0.589)
0.30	-0.110*** (0.046)	0.054 (0.041)	3.012*** (0.678)	0.139 (0.073)	0.586*** (0.173)	-0.148*** (0.092)	0.629*** (0.030)	0.141 (0.432)
0.40	-0.131*** (0.049)	0.066 (0.037)	2.876*** (0.692)	0.190* (0.069)	0.717*** (0.155)	-0.182*** (0.102)	0.615*** (0.030)	0.220 (0.427)
0.50	0.153*** (0.045)	0.040* (0.031)	2.916*** (0.872)	0.178*** (0.046)	0.675*** (0.136)	-0.258*** (0.106)	0.635*** (0.027)	-0.059 (0.411)
0.60	0.140*** (0.044)	0.048 (0.026)	3.043*** (0.891)	0.250*** (0.047)	0.646*** (0.126)	-0.248*** (0.114)	0.646*** (0.023)	-0.020 (0.436)
0.70	-0.145*** (0.048)	0.065** (0.022)	2.738*** (0.561)	0.229*** (0.047)	0.498*** (0.119)	-0.322*** (0.109)	0.658*** (0.021)	0.236 (0.482)
0.80	-0.109*** (0.045)	0.069*** (0.020)	2.984*** (0.783)	0.244*** (0.039)	0.433*** (0.129)	-0.436*** (0.090)	0.683*** (0.019)	0.204 (0.451)
0.90	0.196*** (0.060)	0.019*** (0.023)	2.984*** (0.714)	0.274*** (0.030)	0.436** (0.195)	-0.414*** (0.088)	0.696*** (0.025)	0.630 (0.547)
Model 12								
Quantile	ginimkt	emp	Lgdppc	Lgdppc^2	healthgdp	inf	edu	crisis
0.10	-0.596*** (0.116)	0.156*** (0.048)	2.311*** (0.136)	0.298 (0.308)	0.137*** (0.075)	-0.108 (0.079)	0.317*** (0.067)	0.524 (0.512)
0.20	-0.428*** (0.064)	0.103*** (0.039)	2.069*** (0.781)	0.278 (0.328)	0.482*** (0.144)	-0.174*** (0.090)	0.422*** (0.039)	0.183 (0.419)
0.30	0.320*** (0.050)	0.107*** (0.035)	3.072*** (0.042)	0.286 (0.291)	0.507*** (0.125)	-0.209*** (0.075)	0.489*** (0.032)	-0.157 (0.458)
0.40	-0.293*** (0.049)	0.103*** (0.037)	3.221*** (0.834)	0.176 (0.318)	0.498*** (0.122)	-0.249*** (0.082)	0.514*** (0.034)	-0.311 (0.486)
0.50	0.297*** (0.057)	0.072*** (0.034)	3.489*** (0.158)	0.065 (0.163)	0.610*** (0.116)	-0.235*** (0.098)	0.527*** (0.039)	-0.159 (0.447)
0.60	-0.303*** (0.066)	0.082*** (0.027)	2.583*** (0.373)	0.005 (0.155)	0.484*** (0.121)	-0.301*** (0.126)	0.544*** (0.041)	-0.047 (0.461)
0.70	0.294*** (0.055)	0.069*** (0.022)	3.448*** (0.933)	0.313 (0.192)	0.451*** (0.119)	-0.260*** (0.096)	0.566*** (0.034)	-0.212 (0.434)
0.80	-0.305*** (0.047)	0.073*** (0.019)	2.433*** (0.671)	0.582*** (0.128)	0.407*** (0.130)	-0.300*** (0.088)	0.572*** (0.028)	-0.044 (0.490)
0.90	-0.332*** (0.043)	0.062*** (0.020)	2.043*** (0.185)	0.681*** (0.069)	0.415*** (0.180)	-0.417*** (0.084)	0.577*** (0.026)	1.090* (0.579)

Notes: Standard error in parenthesis for each quantile (t). ***, ** and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

Tables 3 and 4 report the quantile regression estimates. As it can be discerned the previous long run estimated are confirmed at different points in the conditional distribution. In particular panel quantile regression analysis appears to be supporting the significant and adverse effect inequality can have on health outcomes. GDP per capita is also found to play a key role in determining health outcomes. When nonlinearities were explored it appears that in the specification where infant

mortality is the dependent variable, the squared term (gdppc^2) is highly significant bearing a positive sign and suggesting that too much income over time might cause infant mortality to increase. In the specification where life expectancy is the dependent variable the results are more ambiguous as the nonlinear term is found to be insignificant at the lower points of the conditional distribution but positive and highly significant at higher points suggesting that wealthier people are expected to live longer as their income increases.

As for the rest of the variables, health expenditure, in the infant mortality specification turns out to be negative and significant only at the lower points of the conditional distribution of model 9. In the specification where life expectancy is the dependent variable (models 11 and 12) however health expenditure appears to be having a positive and highly significant impact. Likewise, education is found to be significantly associated with infant mortality only in model 9 whereas in models 11 and 12 it is found to be significant bearing a positive sign. Price stability is found to be significant across all models whilst the dummy variable that accounts for the 2007/8 global economic crisis was found to be insignificant across all estimated models.

Finally, the Granger causality tests did not reveal any consistent and significant patterns (Table A3 in Appendix). More specifically, no causality was established between life expectancy and ginidisp, whilst a bidirectional feedback was established between life expectancy and ginimkt. The same pattern was also observed when the causal dimension between infant mortality and the two measures of inequality were considered. This stands in stark contrast to the study by Pickett and Wilkinson (2015) who, by reviewing the relevant literature, concluded that "the evidence that large income differences have damaging health and social consequences is strong and in most countries inequality is increasing. Narrowing the gap will improve the health and wellbeing of populations" (p. 316).

Conclusions

Previous socioeconomic studies suggest that income inequality should be perceived as a consequence of political and cultural factors as well as other holistic aspects that relate to health determinants at both micro and macrolevel. The existence of any a direct effect of income inequality on health outcomes is reduced to a hypothesized relationship that works through one or more health determinants.

The estimates generated in this study suggest that income inequality adversely affects health outcomes which is consistent with previous studies conducted in the area (see, Torre and Myrskylä 2014). Quantile regressions confirm in the most categorical manner that inequality negatively affects health outcomes at different points in the conditional distribution. The Granger causality tests however failed to reveal any consistent patterns, suggesting that the causal dimension is more convoluted than it is normally perceived.

As income per capita may reflect the economic conditions in a country, it has become customary in the large empirical literature on the determinants of health outcomes that GDP per capita is included as one of the key explanatory variables

that potentially have a significant effect on health outcomes. As Pritchett and Summers (1996) argue wealthier nations are bound to be healthier nations and any gains from rapid economic growth will be translated into health gains. Health outcome may also depend on country-specific factors such as education, nutrition or the speed and effective delivery of health-related services but also on exogenous factors such as for instance, advances in medical technology and the diffusion of health technology (Preston 2007).

Despite the highly significant effect that GDP per capita exerts on health outcomes the causal dimension however still remains ambiguous. More specifically the granger causality test points to a) a one-way direction that runs from life expectancy to income and b) a one way direction from income to infant mortality. Finally, the recent global economic crisis 2007/2008 was found to be insignificant across all estimated models.

Determining the key variables that can potentially affect health outcomes is indeed a complex modelling exercise as there are a host of factors that should be considered. Despite the robust results this study has generated it should be noted that the expected estimation outcomes might not be so straight forward to interpret as a number of inherent elements such as reciprocal association or relationships with time lags should also be taken into account.

Undoubtedly, health outcomes improve when income differentials shrink, and societies become more socially cohesive. A healthy population contributes to productivity gains and economic growth as well as to the sustainability of an ageing population. The lessons that policy makers should learn from, yet another study, is that decisions which increase inequality in our society, apart from creating a great sense of unfairness and injustice, are also bound to affect our wellbeing. Redistributive policies that target income inequality are therefore needed to improve both societal coherence and population health.

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Appendix

Table A1. *Description of Variables*

Variable	Definition	Source
ginidisp	Gini index of inequality based on household disposable (post-tax, post-transfer) income.	Standardized World Income Inequality Database, version 8.0, Solt (2019) (https://fsolt.org/swiid/)
ginimkt	Gini index of inequality based on household market (pre-tax, pre-transfer) income.	Standardized World Income Inequality Database, version 8.0, Solt (2019)
emp	Employment to population ratio (total %).	World Development Indicators, World Bank
healthexp	General government health expenditure (% of GDP).	World Development Indicators, World Bank
Lgdppc	Natural log of Gross Domestic Product per capita (US dollars).	Economic Outlook, OECD
inf	Inflation, consumer prices (annual %).	World Development Indicators, World Bank
edu	School enrolment (% gross).	World Development Indicators, World Bank
crisis	Crisis dummy (1 for the period 2007 onwards, and 0 otherwise.	
infmort	Mortality rate, infant (per1,000 live births)	World Development Indicators, World Bank
lifeexp	Life expectancy at birth, total (years)	World Development Indicators, World Bank

Table A2. *Panel Unit Root Tests (PANEL A) and Panel Cointegration (PANEL B)*

PANEL A	Levin, Lin Chu		Im, Pesaran and Shin		Fisher ADF		Fisher PP	
	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value
infmor	-14.7	0.00***	-13.3	0.00***	319.8	0.00***	592.4.2	0.00***
lifeexpe	-2.2	0.01***	-11.7	0.00***	23.6	0.09*	43.1	0.11
D(healthgdp)	-13.2	0.00***	-9.4	0.00***	210.4	0.00***	304.2	0.00***
D(inf)	-37.5	0.00***	-28.7	0.00***	362.07	0.00***	385.57	0.00***
edu	-6.2	0.00***	-7.1	0.00***	109.3	0.00***	160.3	0.00***
emp	-2.4	0.01***	-2.4	0.01***	89.5	0.03**	290.1	0.03**
D(Lgdppc)	-2.6	0.00***	-7.8	0.00***	140.4	0.00***	121.0	0.00***
ginidisp	-5.2	0.00***	-2.4	0.00***	105.21	0.00***	116.7	0.00***
ginimrt	-6.4	0.00***	-2.7	0.00***	114.7	0.00***	187.14	0.00***

Notes: "D" denotes first difference i.e. the number of times the variable had to be differenced to become stationary. In this case these variables integrated of order 1 i.e. I(1) whereas the rest are I(0). ***, ** and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively;

PANEL B			Weighted	
	Statistic	Probability	Statistic	Probability
Panel v	-0.083*	0.466	-3.89*	0.082
Panel rho	-3.671	0.872	-4.17	0.79
Panel PP	-2.103***	0.01	-8.69**	0.00
Panel ADF	-1.469**	-0.07	-1.80**	-0.03
Group rho	-4.56*	-0.08		
Group PP	-9.03***	0.00		
Group ADF	-2.92***	0.00		

Notes: Pedroni (2004) residual cointegration tests. The null hypothesis is no cointegration. The models have been specified with deterministic intercept and trend. ***, ** and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively; Lag selection chosen according to Swartz Information Criterion.

Table A3. *Pairwise Causality Tests*

Null Hypothesis:	F-Statistic	Null Hypothesis:	F-Statistic
lifeexpe does not Granger Cause gdppc	11.1173***	lifeexpe does not Granger Cause healthgdp	0.05518
gdppc does not Granger Cause lifeexpe	2.48974	healthgdp does not Granger Cause lifeexpe	0.92036
infmort does not Granger Cause gdppc	1.61128	infmort does not Granger Cause healthgdp	1.82113
gdppc does not Granger Cause infmort	11.4111***	healthgdp does not Granger Cause infmort	158.135***
lifeexpe does not Granger Cause ginidisp	0.9169	lifeexpe does not Granger Cause inf	27.9028***
ginidisp does not Granger Cause lifeexp	0.00146	inf does not Granger Cause lifeexpe	94.0016***
lifeexpe does not Granger Cause ginimkt	48.4059***	infmort does not Granger Cause inf	36.4453***
ginimkt does not Granger Cause lifeexpe	6.02649***	inf does not Granger Cause infmort	71.6669***
infmort does not Granger Cause ginimkt	80.1270***	lifeexpe does not Granger Cause edu	0.96197
ginimkt does not Granger Cause infmort	26.01733***	edu does not Granger Cause lifeexpe	4.55283**
infmort does not Granger Cause ginidisp	0.8934	infmort does not Granger Cause edu	0.39888
ginidisp does not Granger Cause infmort	0.0788	edu does not Granger Cause infmort	22.2458***

Notes: ***, ** and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively; Lag = 1.

Table A4. *Descriptive Statistics*

	ginidisp	ginimkt	healthgdp	infmort	lifeexpe	Lgdppc	edu	inf
Mean	30.00237	47.54772	5.995916	4.241530	78.95976	10.38283	102.1775	2.324639
Median	29.50000	47.90000	6.052636	3.900000	79.71951	10.56582	101.4939	2.081269
Maximum	48.50000	53.90000	9.278431	11.50000	83.60244	11.62597	126.5754	15.40232
Minimum	22.40000	37.20000	2.495476	1.500000	70.25854	8.843101	94.52988	-4.478103
Std. Dev.	4.646663	3.513979	1.560873	1.582508	2.990550	0.623446	4.160868	2.101558