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DISCUSSION PAPER SERIES

IZA DP No. 13292

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ABSTRACT

Ex Ante Inequality of Opportunity in Health among the Elderly in China: A Distributional Decomposition Analysis of Biomarkers

We present a comprehensive analysis of *ex ante* inequality of opportunity (IOp) in health among Chinese adults aged 60+ and decompose the contributions of different sets of circumstances. Data are drawn from the 2011 and 2015 waves of the China Health and Retirement Longitudinal Study (CHARLS) linked with the 2014 CHARLS Life History Survey. We use a range of blood-based biomarkers, and apply a re-centered influence function (RIF) approach and a Shapley-Shorrocks decomposition to partition the contribution of circumstances across different quantiles of the biomarker distributions. We find that IOp accounts for between 3.75% and 29.57% of total health inequality in old age across the range of biomarkers. Shapley-Shorrocks decompositions show that spatial circumstances such as urban/rural residence and province of residence are the dominant determinants of IOp for most of the biomarkers. Distributional decompositions further reveal that the relative contributions to IOp in health of household socioeconomic status and health and nutrition conditions in childhood increase towards the right tails of the distribution for most of the biomarkers, where the clinical risk is focused.

JEL Classification: D63, I12, I14

Keywords: biomarkers, CHARLS, China, inequality of opportunity, Shapley-Shorrocks decomposition, unconditional quantile regressions

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1. Introduction

As one of the five of the Sustainable Development Goals (SDGs), reducing health inequalities has become an important issue worldwide (Niessen *et al.*, 2018) and thus has a place at the centre of the health policy agenda (Bleich *et al.*, 2012). A key concern is to identify the underlying sources of health inequalities over the lifecourse (Gong *et al.*, 2020). Not all of these sources of health inequality are equally objectionable. As suggested by earlier studies (e.g., Alesina & Angeletos, 2005; Rosa Dias, 2009; Trannoy *et al.*, 2010; Wendelspiess Chávez Juárez & Soloaga, 2014), health inequalities due to factors that reflect individual choices, such as lifestyles, might be ethically acceptable and, to some extent, regarded as fair. In contrast, sources of health inequality such as family socioeconomic characteristics which are beyond individuals' control are typically regarded as illegitimate and objectionable. This perspective on social attitudes toward health inequalities and inequity chimes with the literature on inequality of opportunity (IOp), which has emerged in social choice theory and economics (Roemer, 1998, 2002; Roemer & Trannoy, 2016).

Following Roemer's conceptual framework for IOp (Roemer, 1998, 2002; Roemer & Trannoy, 2016), the literature partitions the factors associated with an outcome of interest (e.g., health) into two components: "efforts", for which to some extent individuals are held responsible, and "circumstances", which are beyond individual control (Carrieri & Jones, 2018; Jusot *et al.*, 2013). As such, health inequalities attributable to the direct contribution of effort are legitimate but the inequalities attributable to the direct contribution of circumstances and their indirect influence on efforts (referred as IOp) are illegitimate (Davillas & Jones, 2020).

Emanating from both early-life circumstances and efforts over the lifecourse, health inequalities are prevalent in old age (see, e.g., Marmot *et al.*, 2008). In particular,

childhood circumstances or background are often considered the most objectionable determinants of adult outcomes (Kim, 2016) and as illegitimate sources of health inequalities (Carrieri & Jones, 2018; Davillas & Jones, 2020; Jusot *et al.*, 2013).

China offers an interesting and unique setting for studying IOp in health among the elderly for two key reasons. First, China has the world's largest ageing population and is also one of the fastest ageing societies worldwide (Tian, 2016). In 2019, 254 million people were aged 60 and over, accounting for 18.1% of the population, and this is projected to reach 491.5 million (36.5% of the population) by 2050 (United Nations, 2019). Although it took Western countries around half a century to double the number of people aged 65 years or over (from 7% to 14%), China is expected to do so in half that time (Kinsella & Wan, 2009). By 2050, the share of the elderly in China's population is projected to match that of many of today's developed countries, and exceed that of countries such as the US, Denmark, New Zealand and Australia (Zhao *et al.*, 2014b). Second, with unprecedented recent economic growth, the overall health status of the Chinese population has improved substantially, with life expectancy growing from 68 in 1981 to 77 in 2019 (World Population Review, 2019). However, the rapid economic growth has not been accompanied by equally substantial improvements in health inequalities and this has become a source of concern (Baeten *et al.*, 2013; Tang *et al.*, 2008). Rising health disparities are widespread in China and this is particularly evident among older people (World Health Organization, 2015).

To address these issues, this study uses data from the 2011 and 2015 waves of the China Health and Retirement Longitudinal Study (CHARLS) linked with the 2014 CHARLS Life History Survey to provide a comprehensive assessment of *ex ante* IOp in health and its underlying sources among Chinese adults aged 60+. A growing empirical literature has investigated IOp in health in developed societies, but less research on this topic exists for developing countries like China. In addition, many of

these studies rely on self-reported health (SRH) measures that are inherently ordinal (Davillas & Jones, 2020) and may suffer from reporting bias (Bago d'Uva *et al.*, 2011; Bago d'Uva *et al.*, 2008; Rossouw *et al.*, 2018). Further, following Roemer's (1998) framework, many existing studies use mean-based decompositions to identify the primary sources of IOp in health. This means that equality of opportunity corresponds to equality of mean outcomes across types, adopting the principle of utilitarian reward and implying inequality neutrality within types (e.g., Ferreira & Gignoux, 2011).

Thus, we extend the previous literature in four respects:

First, we provide an in-depth analysis of IOp in health in China, which has the world's largest ageing population. Quantifying the absolute level of IOp in health and identifying its key sources would be useful for reducing health inequality, and promoting healthy longevity for Chinese elderly population in future.

Second, unlike studies that use SRH, we use blood-based biomarkers that are each directly relevant to diagnosis, monitoring and the clinical management of specific chronic health conditions (Davillas & Jones, 2020). These objective biomarkers may suffer from measurement errors but are unlikely to show the kinds of reporting bias that exist for SRH, which has been shown to vary systematically with income and other socioeconomic status (SES) measures, calling the reliability of SRH into question (Bago d'Uva *et al.*, 2011; Bago d'Uva *et al.*, 2008; Rossouw *et al.*, 2018). Furthermore, based on the individual biomarkers, we construct an indicator of allostatic load (AL) (e.g., Carrieri *et al.*, 2020; Davillas & Jones, 2020), which has been used as a comprehensive, multi-system measure of cumulative biological dysregulation across major physiological systems because of the accumulation of stressful exposures (McEwen & Stellar, 1993).

Third, we introduce a comprehensive set of childhood circumstances spanning: early exposure to war; parental health and health behaviors; childhood health and nutrition;

household socioeconomic status; access to healthcare; and provincial and urban/rural residence. This addresses a concern that poor information on childhood circumstances may lead to an underestimate of IOp and therefore mislead policymakers into a false sense of complacency that health inequality is largely fair (Kanbur & Wagstaff, 2016).

Lastly, in addition to mean-based Shapley-Shorrocks decomposition (Shorrocks, 2013), we also apply unconditional quantile regression (UQR) based on re-centered influence function (RIF) (Firpo *et al.*, 2009) approach to explore how the impacts of circumstances on IOp in health vary across the whole distribution of biomarkers. This distributional analysis relaxes the assumption of inequality neutrality within types. We employ Shapley-Shorrocks decompositions at different quantiles of the biomarker distribution to identify the underlying sources of these inequalities, with a particular focus on the upper tails, where clinical risks are typically focused (Davillas & Jones, 2020).

The remainder of the paper is organized as follows. Section 2 reviews some relevant literature. Section 3 describes the empirical strategy and the datasets used, and then Section 4 presents the results. Section 5 discusses the major findings and concludes.

2. Previous literature

A range of previous studies have assessed IOp in health especially in Europe (Bricard *et al.*, 2013), including the UK (Carrieri & Jones, 2018; Davillas & Jones, 2020; Rosa Dias, 2009), France (Trannoy *et al.*, 2010) and Luxembourg (Deutsch *et al.*, 2018). Specifically, Rosa Dias (2009), drawing on data from the UK National Child Development Study, reveals considerable IOp in SRH. Using data from the Survey on Health, Ageing and Retirement in Europe (SHARE), Trannoy *et al.* (2010) confirm that observed circumstances, particularly parental socioeconomic status (SES) and

health status, play important roles in SRH inequality among adults aged 49 years and older in France. Similarly, using data from SHARE and the English Longitudinal Survey on Ageing (ELSA), Pasqualini *et al.* (2017) find that country-specific circumstances and early-life conditions account for 40% of the explained variation in SRH of adults aged 50+. This result is reinforced by Kim (2016) who underlines the role of unobserved circumstances in explaining the IOp in health (SRH and grip strength) among individuals aged 50+ based on SHARE data set. Drawing on data from the 2008/2009 Retrospective Survey of *SHARELIFE*, Bricard *et al.* (2013) also find that IOp in SRH accounts for almost 57.4% of total explained inequality in SRH that is attributed to circumstances and efforts among adults aged 50+.

More recently, using data from the 2003-2012 Health Survey for England, Carrieri and Jones (2018) use biomarkers as objective health measures to decompose *ex post* IOp in the UK and find that circumstances (including cohort of birth, gender, individual education, and area of residence) account for between 56% and 95% of the explained inequality[1] in cholesterol, glycated haemoglobin and an ill-health index.[2] Likewise, Carrieri *et al.* (2020), based on data from the General Population Sample (GPS) of UK Household Longitudinal Study (UKHLS), find that around two thirds of total inequality in AL is attributed to circumstances. Using the same data set, Davillas and Jones (2020) further reveal that observed circumstances (education and childhood SES) explain 4-22% of total health inequality and that the contribution of socioeconomic circumstances increases towards the right tail of the biomarker distribution, where health risks are more pronounced.

We know of only one study that analyses IOp in health in China: based on data from the 2013 and 2015 CHARLS linked with the 2014 CHARLS Life History Survey,

[1] The explained part of health inequality here is the total inequality excluding the contribution of unobserved factors and random noise.

[2] The ill-health scores are defined based on the first component of a principal component analysis on cholesterol, glycated haemoglobin, and fibrinogen.

Yan *et al.* (2020) use mean-based Shapley decomposition to assess the contribution of childhood circumstances to health inequalities ranging from cognitive health, mental health, physical health and SRH, to mortality of older adults, and show that childhood circumstances account for between 1% and 23% of total health inequality in old age depending on the outcome used. Within these observed circumstances, regional and urban/rural residence make the dominant contribution. Overall, several aspects of these previous studies are worth emphasizing: First, the empirical results suggest that circumstances play an important role in explaining total health inequality and observed circumstances such as household SES and parental education and health are important sources of IOp in health. Second, most past research employs SRH outcomes and only a few studies introduce biomarkers as objective measures of health (Carrieri *et al.*, 2020; Carrieri & Jones, 2018; Davillas & Jones, 2020). Third, due to data availability, limited information on childhood circumstances may underestimate IOp and therefore give policymakers a false sense of complacency that health inequality is largely fair (Kanbur & Wagstaff, 2016). Finally, a limitation in most studies (including the previous work for China), as Davillas and Jones (2020) highlight, is the focus on a mean-based approach rather than analyzing the tails of the distribution as well.

To remedy these shortcomings, we perform a comprehensive analysis of IOp in health to explore how the contributions of circumstances may vary over the whole distribution of biomarkers using the RIF approach. We also employ a Shapley-Shorrocks decomposition at different percentiles of the biomarker distribution to assess the underling sources of these inequalities, with a particular focus on the upper tails of the biomarkers. The 2011 and 2015 CHARLS collect blood-based biomarkers and the 2014 CHARLS Life History Survey also allows us to introduce a rich set of childhood circumstances that may contribute to IOp.

3. Methods and data

3.1 Empirical strategies

3.1.1 Measuring ex ante IOp in health – mean-based regressions

Following Roemer's (1998) framework, the determinants of any outcome (health in our case) can be separated into two components: circumstances (C_i), for which individuals are not held responsible, and efforts (E_i), which are under the partial control of individuals. Inequalities due to circumstances (i.e. IOp) should be compensated (*compensation principle*) whereas inequalities arising from different efforts are normatively acceptable (*reward principle*). Following the existing literature on IOp in health (see, for instance, Davillas & Jones, 2020; Ferreira & Gignoux, 2011; Rosa Dias, 2009), we assume that circumstances are unaffected by efforts, but efforts may be influenced by circumstances. A generalized health production function for health outcome y_i of individual *i* can be defined as:

$$y_i = h(C_i, E(C_i, v_i), u_i) \quad (1)$$

where v_i and u_i are unobserved error terms. Specifically, v_i represents random variation in effort that is independent of C_i, and u_i denotes random variation in the health outcome that is independent of C_i and E_i.

There are two methods to quantify IOp, namely, the *ex ante* and *ex post* approaches (Fleubaey & Peragine, 2013; Fleurbaey & Schokkaert, 2009; Li Donni *et al.*, 2014). The *ex post* approach seeks equality of health among individuals who have exerted the same degree of effort, regardless of their circumstances. However, the *ex ante* approach to IOp is based on the principle that there is equality of opportunity if all individuals face the same opportunity set, prior to the realization of efforts and outcomes (Fleurbaey & Schokkaert, 2009; Li Donni *et al.*, 2014). The *ex ante* approach implies that all individuals have equal opportunity in health when there are no differences in health due to different circumstances (Davillas & Jones, 2020;

Fajardo-Gonzalez, 2016; Fleubaey & Peragine, 2013; Ramos & Van de gaer, 2016). Since IOp is defined by comparing the outcome distribution between types of circumstances, the *ex ante* approach only requires observed circumstances. This method is also less data demanding because it only allows for a limited set of relevant factors, independent of individual responsibility (Jusot & Tubeuf, 2019). Thus, following previous research, we adopt an *ex ante* approach that emphasizes inequality in the distribution of health across social types.

We begin with a direct *ex ante* parametric approach using the mean-based regressions proposed by Ferreira and Gignoux (2011, 2014). The direct method measures inequality in a counterfactual where all inequalities are attributable to circumstances. The counterfactuals, which eliminate health inequalities due to efforts, are defined by replacing each individual health outcome y_i with the relevant type-specific mean μ^k and then we use an inequality index to quantify IOp (Ferreira & Gignoux, 2011). We adopt parametric estimation, which does not suffer from the curse of dimensionality especially for a rich set of circumstances, due to insufficient sample size for specific social types (groups of individuals who share identical circumstances). Given the presence of unobserved circumstances, our IOp measures can be interpreted as lower bound estimates of overall IOp (Davillas & Jones, 2020; Ferreira & Gignoux, 2011).

Assuming additive separability and linearity of $h(\cdot)$ and $E(\cdot)$ (Davillas & Jones, 2020), we generate a linear reduced form for health:

$$y_i = C_i\psi + \varepsilon_i \tag{2}$$

where ψ denotes the total effect of circumstances on IOp in health and include both the direct and indirect effects of circumstances. Then we use predictions $E(y_i|C_i)$ from the reduced form as the counterfactual outcome:

$$\tilde{y}_i = C_i\hat{\psi} \tag{3}$$

where $\hat{\psi}$ are the OLS estimates of the coefficients from equation (2). IOp in health can be estimated applying an inequality measure, $I(\cdot)$, to $\tilde{y}_i$. Following Ferreira and

Gignoux (2011), we use the mean logarithmic deviation (MLD) inequality index as the measure of $I(\cdot)$ due primarily to its suitability for the ratio-scale nature of health measures (Davillas & Jones, 2020; Ferreira & Gignoux, 2011). MLD belongs to the generalized entropy family of inequality measures (GE(ω), where ω is a scaling parameter representing the weight given to distances between individual health at different parts of the health distribution) and is the limiting case when ω=0 (GE(0)) (Cowell & Flachaire, 2015). The absolute IOp (θ_a) and relative IOp (θ_r) (expressed as a fraction of overall health inequality) are defined, respectively, as follows:

$$\theta_a = I(\tilde{y}_i) \tag{4}$$

$$\theta_r = \frac{I(\tilde{y}_i)}{I(y_i)} \tag{5}$$

3.1.2 Shapley-Shorrocks decomposition of IOp

We also decompose the direct *ex ante* IOp in health into its underlying sources. Specifically, the regression-based Shapley decomposition method can identify the contributions of each circumstance to the total IOp in health (Fajardo-Gonzalez, 2016; Shorrocks, 2013). The main advantage of this decomposition technique is that it is path independent, i.e., the order of changing circumstances for the decomposition does not affect the results. Additionally, it is also exactly additive, meaning that the different components sum up to the total IOp (Wendelspiess Chávez Juárez & Soloaga, 2014). To do so, we first estimate MLD inequality measures for all possible permutations of circumstance variables, and then average the marginal effects of each circumstance in every case on total IOp in health to obtain the contribution of each circumstance to IOp in health (Davillas & Jones, 2020; Wendelspiess Chávez Juárez & Soloaga, 2014; Yan *et al.*, 2020). As a robustness check, we also apply the Shapley-Shorrocks decomposition to the variance.

3.1.3 RIF regressions

Using linear parametric regressions to compute the counterfactuals implies inequality neutrality within each type, i.e., IOp in health emerges from inequality of mean outcomes across different types (Davillas & Jones, 2020). However, this assumption may be regarded as too restrictive and we may wish to give greater weight to the contribution of circumstances in the upper tail of the distribution of biomarkers, where individuals are at great risk of chronic health problems (Davillas & Jones, 2020). To relax the assumption of inequality neutrality within types, we use the RIF unconditional quantile regression approach (Firpo *et al.*, 2009) to estimate marginal effects of circumstances at different points of the distribution. Then we quantify the contribution of each circumstance to the IOp in health at different quantiles of the biomarker distribution. We regress the RIF vector on the circumstance variables:

$$RIF\big(y_i;\ \ q_Y(\tau)\big) = C_i\alpha^{\tau} + \varepsilon_i^{\tau} \tag{6}$$

where α^{τ} represents the coefficients at different quantiles and ε_i^{τ} is the error term. Then the estimated counterfactuals used in the direct approach for each individual at quantile, τ, are:

$$\tilde{y_i^{\tau}} = C_i\hat{\alpha^{\tau}} \tag{7}$$

Finally, applying an inequality index (e.g., MLD) to the predicted counterfactuals, we can calculate the corresponding IOp in different quantiles (Davillas & Jones, 2020). Since the RIF equations are additive and linear, we can also use a Shapley-Shorrocks decomposition to identify the relative contribution of circumstances to IOp in health at the different quantiles.

3.2 Data and study population

The data are draw from the CHARLS, administered by the National School of Development together with the Institute for Social Science Surveys at Peking University, a nationally representative longitudinal survey of the middle-aged and

elderly in China, including assessments of social, economic, and health circumstances of community-residents (Zhao *et al.*, 2014a). The CHARLS sample is obtained via multistage stratified probability proportional to size (PPS) sampling design (Zhao *et al.*, 2014a). The national baseline survey was conducted in 2011-2012 on 17,708 respondents residing in 10,257 households in 450 villages/urban communities. Two follow-up interviews were conducted in 2013 and 2015. In 2014, there was a retrospective Life History Survey, including demographics, household SES, health, work and wealth history of respondents. The CHARLS is part of a group of ageing surveys worldwide that are harmonized to the Health and Retirement Study (HRS) in the US, ELSA in England, and SHARE in Europe.

CHARLS successfully collected and assayed venous blood samples in both the baseline wave in 2011 (11,847 blood samples) and in the 2015 follow-up (13,013 blood samples) (Chen *et al.*, 2019). Analysis of these blood samples involved two stages: a complete blood count (CBC) analysis was performed at local county health centers, and then the samples were sent to the study headquarters to be assayed (Chen *et al.*, 2019).

As shown in the Appendix, Figure A.1, we match the 2013 and 2015 CHARLS to the 2014 Life History Survey to enable linkage of respondents' biomarkers with their childhood circumstances. Given that some individuals interviewed in 2011 or 2015 are not included in 2014, we use t-tests to check whether there are statistically significant differences in the means of the demographic variables between the matched sample and the original samples in 2011 or 2015. As shown in Table A.1 of the Appendix, we do not find any evidence of significant differences, other than for age in 2011, between the two samples in 2011 and 2015. We retained the individuals without missing values for any of the circumstances from the matched sample. Table A.2 in the Appendix reveals no evidence of statistical differences between the matched sample and the matched sample without the missing values of childhood

circumstances (with the exception of age in both waves 2011 and 2015). Since we attempt to retain the largest sample possible for analysis of each of the health measures, the number of observations for each differs slightly because of missing data for the individual health biomarkers. Our final analysis samples range from 2,643 to 3,302 in 2011 and 4,448 to 4,937 in 2015 (see Appendix Figure A.1, S1-S9). As Table A3 in the Appendix shows, there are no statistically significant differences between our analysis samples (S1-S9) and the full sample, indicating that there is not an issue with sample selection on observables in our study.

3.3 Health measures

We use several physical measurements and blood-based biomarkers as the health outcomes, that are associated with major chronic conditions such as obesity, high blood pressure, diabetes and cardiovascular diseases (Davillas & Jones, 2020). Specifically, our physical measurements are firstly the waist to height ratio (WHR), defined as waist circumference divided by height, a useful indicator to measure adiposity and to predict multiple metabolic risk factors (Gu *et al.*, 2018), and secondly systolic blood pressure (SBP), an indicator for hypertension.

Following Edes and Crews (2017), we use six blood-based biomarkers, namely, glycated hemoglobin (HbA1c), cholesterol ratio, triglycerides, C-reactive protein (CRP), white blood cell count (WBC) and creatinine. HbA1C (in %), is measured by high performance liquid chromatography (Chen *et al.*, 2019), and is found in high levels in individuals with elevated blood sugar (e.g., diabetes). The cholesterol ratio, calculated as the ratio of total cholesterol to high-density lipoprotein cholesterol, is associated with a higher risk of cardiovascular disease (CVD) and mortality risks (Prospective Studies Collaboration, 2007). Triglycerides, measured in mg/dL by the Oxidase method (Chen *et al.*, 2019), is an indicator of dyslipidaemia and is also associated with CVD (Yan *et al.*, 2012). We use two biomarkers for systemic

inflammation: CRP (in mg/L) is an acute-phase protein found in the blood that is synthesized in the liver in response to inflammation, and WBC (in thousands) is a measure of total white blood cells, generally indicative of infection and also associated with lung cancer risk (Brenner *et al.*, 2014). Finally, creatinine (in mg/dL) is used as a biomarker for renal functioning (Edes & Crews, 2017).

Similar to Davillas and Jones (2020) and Carrieri *et al.* (2020), we additionally construct a composite measure – allostatic load (AL) – which combines the two physical measures (WHR, SBP) and six biomarkers (HbA1c, cholesterol ratio, triglycerides, CRP, WBC and creatinine). AL is well suited for measuring IOp because it captures chronic physiological responses that are linked with social and environmental stress (Davillas & Jones, 2020; McEwen, 2015; Seeman *et al.*, 2004). Following Davillas and Jones (2020), we transform each of the nurse-collected and the blood-based markers into standard deviation units and sum them, with higher values indicating worse health. The descriptions of each physiological system contributing to the AL index are summarized in Table 1.

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Table 1 about here

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3.4 Circumstances

Following the existing literature (Davillas & Jones, 2020; Trannoy *et al.*, 2010; Yan *et al.*, 2020), we classify the circumstances into eight domains (see Table 2):

(1) Gender (1 = male, 0 = female);

(2) Age;

(3) Region/province: including urban or rural residence, (1 = rural, 0 = urban) and province of residence. In China, socioeconomic conditions in different regions vary substantially because of disparities in access to health care, pension policies, state provisions, and social experience between urban and rural (Wu *et al.*, 2015; Zimmer & Kwong, 2004);

(4) War. China experienced the War with Japan and the Civil War in the 1930s and 1940s. We use two dummies measuring whether an individual was born during the War with Japan or the Civil War, respectively;

(5) Parental health status and health behaviors in childhood: including parental health status (1 = long time in bed; 0 = none), mother's smoking (1 = yes; 0 = no), and father's smoking (1 = yes; 0 = no) and drinking (1 = yes; 0 = no);

(6) Health nutrition and conditions in childhood. It is widely acknowledged that poor social conditions early in life such as hunger and other adversities exert long-term impacts on individuals' health capital (e.g., Alvarado *et al.*, 2008; Barker, 1994; Cui *et al.*, 2020). As such, we include SRH before age 15 (1 = much less healthy, 2 = somewhat less healthy, 3 = about average, 4 = somewhat healthier, 5 = much healthier) and whether they experienced hunger before age 17 (1 = yes; 0 = no);

(7) Household status in childhood, including parental political status (1 = the Communist Party member; 0 = no), mother's education (1= illiterate; 0 = literate), father's education (1= illiterate; 0 = literate) and self-reported household SES compared with the average family in the same community/village at that time (1 = a lot worse off than them, 2 = somewhat worse off than them, 3 = same as them, 4 = somewhat better off than them, 5 = a lot better off than them);

(8) Access to healthcare in childhood. Evidence in the health literature suggests that early-life access to healthcare services make a substantial difference in healthy longevity (Gu *et al.*, 2009). We define this based on the question "did you go to see a

doctor in general/specialized hospital or township clinics the first time you got ill since you remember?" (1 = yes; 0 = no).

4. Results

4.1 Descriptive statistics

Table 2 presents descriptive statistics for our study sample. Regarding the nine physical measurements and blood-based biomarkers, the mean values of HbA1c, triglycerides, CRP and creatinine are 5.276, 135.2, 1.722, and 0.812, respectively. Interestingly, during 2011-2015, there is a significant upward trend in these four biomarkers, suggesting that some chronic diseases (e.g., CVD) in old age have increased dramatically in China (Yan *et al.*, 2012; Yang *et al.*, 2010). AL also rose slightly from 30.2 in 2011 to 30.8 in 2015. Such an increase in AL may promote additional somatic damage and chronic disease as the outcome of stressors and allostatic response (Edes & Crews, 2017). These results are in line with the fact that China has been undergoing an epidemiological transition, shifting from a nation with high prevalence of infectious diseases to a nation with a rapidly ageing population affected by non-communicable chronic diseases (Song & Chen, 2020).

With regards to circumstances, the mean age increases from 67 in 2011 to 68 in 2015 and the proportion of males is quite stable over time (50%). It is interesting that the prevalence of reporting experience of hunger before age 17 declined from 27% in 2011 to 22% in 2015, reflecting China's successful experience in combating hunger and nutrition promotion due to programs aimed at poverty alleviation, social safety nets for disadvantaged villagers, agricultural development and land reforms (Bryce *et al.*, 2008).

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Table 2 about here

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4.2 Mean-based measures of *ex ante* IOp

Table 3 displays *ex ante* IOp in the different biomarkers and for allostatic load. Column [a] shows the total inequalities of different health outcomes (measured by MLD) and column [b] shows the absolute level of IOp in health. Results from the mean-based *ex ante* IOp measures show that, the contribution of observed circumstances to the total health inequality ranges from 4.21% for CRP to 29.57% for creatinine 2011 (Panel A, column [c]). In the 2015 wave, the contribution of measured circumstances to the total inequality ranges between 3.75% and 24.14% (Panel B, column [c]), which is in line with the results of Davillas and Jones (2020) for the UK, with a range between 3.9% and 21.8%. It is worth noting that the inequality in CRP is the largest but its IOp is smallest. One possibility is that CRP values vary greatly between the healthy and less healthy groups leading to large overall inequalities (Davillas & Jones, 2020). In addition, CRP may reflect acute inflammation rather than chronic systematic process (Davillas & Jones, 2020; Edes & Crews, 2017; Marnell *et al.*, 2005). Such results are in accordance with those of Davillas and Jones (2020).

From 2011 to 2015, except for WHR and WBC, the contribution of observed circumstances to total health inequality decreases, suggesting that health inequalities due to circumstances became less prominent by 2015, whereas individual efforts may play a more important role in health inequalities. Interestingly, the total inequality of AL in our study, 0.0077 in 2011 and 0.007 in 2015 respectively, is quite comparable to that of Davillas and Jones (2020) for the UK, with a value of 0.0074.

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Table 3 about here

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4.3 Distributional analysis of *ex ante* IOp

To explore potential heterogeneity in the contribution of circumstances, especially in the upper tail of the distribution of biomarkers, we also measure the *ex ante* IOp at different quantiles (25th, 50th and 75th) using the RIF quantile regressions (Table 4). Figure 1 illustrates the IOp in biomarkers at different quantiles in both 2011 and 2015. Generally, we identify significant differences in IOp across the biomarker distributions in both waves (with the exception for HbA1c in 2011 and 2015, and AL in 2015). In particular, IOp decreases towards the upper tail of the distributions for most of the biomarkers. For example, IOp in creatinine decreases from 0.0142 (25th quantile) to 0.0107 (50th quantile) and to 0.009 (75th quantile) in 2011. These findings suggest that heterogeneities in IOp across the whole distribution of the biomarkers would have been masked if the focus was solely on analysis at the mean.

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Table 4 about here

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Figure 1 about here

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4.4 Shapley-Shorrocks decomposition of *ex ante* IOp

4.4.1 Mean-based decomposition of IOp

We then use the Shapley-Shorrocks decomposition to quantify the contribution of each circumstance to IOp in health. As can be seen from Table 5 and Figure 2, urban/rural and province of residence disparities consistently make the largest contribution to IOp – in each of the biomarkers, specifically, 20.59% for creatinine, 37.88% for SBP, 39.15% for WHR, 60.79% for triglycerides, 65.96% for cholesterol ratio, 67.22% for AL, 68.49% for CRP, 72.86% for HbA1c and 78.38 for WBC, in 2011. This is also the case for the follow-up wave in 2015. And our results are in accordance with previous studies on health inequality in China (see, for instance, Nie *et al.*, 2019; Yan *et al.*, 2020). Besides regions/provinces, gender and age come out as two relatively important contributors to IOp in health. A combination of gender and age accounts for between 8.18% and 48.86% of the total IOp in 2011 (and explains between 1.91% and 33.48% in 2015). These results are consistent with the literature on the role of gender and age when explaining variations in health (Baum & Ruhm, 2009) and health disparities (Oksuzyan *et al.*, 2017).

Additionally, household SES and health and nutrition conditions in childhood are also important sources of IOp. Specifically, household SES explains 1.96-8.60% of the total IOp in 2011 (and accounts for 0.78%-18.53% in 2015). And in 2011, 0.59-9.53% (in 2015, 0.53-6.45%) of IOp is explained by health and nutrition conditions in childhood. Parental health and health behaviors make moderate contributions to the total IOp, with ranges between 0.5-7.59% in 2011, and 0.33-3.83% in 2015. The contributions of access to healthcare in childhood and experience of war to the total IOp in most of the biomarkers are negligible.

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Table 5 about here

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Figure 2 about here

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As a robustness check, we also use the variance share to quantify IOp (see Table A.4 in the Appendix). Specifically, the variance share is the share of total variance in our biomarkers explained by circumstances and is a relative IOp measure (Davillas & Jones, 2020). The MLD is a scale invariant but not translation invariant, whereas the variance share is both scale and translation invariant.[3] Thus, our robustness analysis may alleviate the possible biases because of different selections of inequality measures (Davillas & Jones, 2020; Ferreira & Gignoux, 2014; Wendelspiess Chávez Juárez & Soloaga, 2014). The variance also satisfies path independent decomposability and has been used to quantify health inequality (Carrieri & Jones, 2018).

According to the variance share of mean-based regressions in Table A.4, the results for relative IOp in biomarkers are quite similar to these based on the MLD index in Table 3. The contribution of observed circumstances to the total health inequality ranges between 4.16% and 29.89% in 2011, and between 3.78% and 28.18% in 2015, respectively.

4.4.2 RIF-based decomposition of IOp

Table 6 shows the contribution of each of the circumstances to IOp in the different biomarkers at different quantiles. Heterogeneities in the contribution of circumstances to IOp at different quantiles for most biomarkers are discernable. Several findings are worth mentioning. First, as seen from Table 6, similar to the mean-based results of the Shapley-Shorrocks decomposition, region/province still accounts for the majority of the total IOp in most biomarkers except for WHR, SBP and creatinine. However, the contribution of residential region/province to IOp decreases towards to the upper tail of the distribution for most biomarkers in 2011. For example, the contribution of

[3] Scale invariance means that health changes are distributionally neutral only if they occur in the same proportion for all individuals in the health distribution. Translation invariance means that health changes are distributionally neutral only if they occur in the same absolute amounts for all individuals in the health distribution (Chakravarty, 2007).

region/province for cholesterol ratio declines from 73.85% at the 25th quantile, to 66.93% at the median, and to 65.61% at 75th quantile. This also applies to HbA1c (from 85.81% to 70.95%), WHR (from 40.95% to 27.44%), SBP (from 39.27% to 30.01%), creatinine (from 22.99% to 21%) and AL (from 64.66% to 58.63%) (Panel A, Table 6). We also observe similar patterns in the follow-up wave of 2015, with the exception of SBP, and creatinine (Panel B, Table 6).

Second, it is also worthwhile to mention that, among seven of nine in 2015 (four of nine in 2011) health measures, the relative contribution of gender and age decreases in the upper tail of the distribution of the biomarkers, where individuals are most at risk of health problems. For instance, the combined contribution of age and gender for AL is 7.33% at the 25th quantile, and then declines to 4.52% at the median and further to 2.90% at the 75th quantile in 2015. Nonetheless, the contribution of household SES to the total IOp in health, in most cases, increases towards the upper quantiles of the biomarker distribution. For example, the relative contribution of household SES to IOp in AL grows from 8.22% at the 25th quantile to 13.55% at the 75th quantile in 2011 (from 10.85% to 14.96% in 2015). This observation echoes the findings of Davillas and Jones (2020) for the UK. This may also imply that the conventional mean-based Shapley-Shorrocks decomposition would mask the heterogeneous contributions of measured circumstances such as regions/provinces, age and gender to the total IOp in biomarkers. More importantly, our unconditional quantile-based decomposition support the conclusion that "ill health is not simply a matter of gender and age inequalities, with our set of socioeconomic circumstances become much more relevant towards the right tails of biomarkers distribution, where clinicians concerns are focused" (Davillas & Jones, 2020, p.10).

Finally, also note that the relative contribution of health and nutrition conditions in childhood increases towards the right tail of the biomarker distribution for most of our biomarkers. The contribution of early-life health and nutrition conditions, for instance,

to the total IOp in AL increases from 4.86% (25th quantile) to 7.94% (75th quantile) in 2011. However, the contributions of exposure to war and access to healthcare in childhood are relatively stable across the whole distribution of biomarkers.

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Table 6 about here

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Figure 3 about here

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5. Discussion

Using nationally representative survey data from CHARLS, we quantify absolute and relative *ex ante* IOp in health among Chinese adults aged 60+ and explore its underlying sources. We extend the existing literature by focusing on China, a country with the largest ageing population and fastest pace of ageing worldwide. In addition, we introduce objective physical measurements, blood-based biomarkers and a composite health indicator – allostatic load (AL). Such health measures are directly relevant to the risk of major chronic conditions for older adults, such as abdominal obesity, diabetes and CVD, and also avoid potential reporting bias of subjective health indicators, which are commonly used in the literature on IOp in health. Moreover, applying the RIF approach, we also perform a distributional analysis of IOp in health to assess how the contributions of observed circumstances differ across the distribution of the biomarkers.

The study yields several findings. First, we find that the contribution of observed circumstances to total health inequality can be substantial, ranging between 4.21% and 29.57% in 2011, and between 3.75% and 24.14% in 2015 across the different

biomarkers. This results are broadly in line with Davillas and Jones (2020) for the UK, and Yan *et al.* (2020) for China using the CHARLS data, with ranges between 3.9% and 21.8% for the UK, and from 1% to 23% for China, respectively.

Second, according to the mean-based Shapley-Shorrocks decomposition, we find that rural/urban residence and province of residence make the largest contribution to the total IOp in most domains of biomarkers. This is in accordance with earlier studies that underscore the importance of region of residence in explaining health disparities among elderly Chinese adults (Wu *et al.*, 2015; Zimmer & Kwong, 2004). In addition, gender and age play a relatively important role in IOp for most of biomarkers. This observation is broadly mirrored by the existing literature on the role of gender and age when explaining variations in health (Baum & Ruhm, 2009) and health disparities (Burt *et al.*, 1995; Vona *et al.*, 2018). Health and nutrition conditions in childhood, and household SES are also non-trivial contributors to IOp in health. Parental health and health behaviors also make moderate contributions to the total IOp, however, the contributions of access to healthcare early in life and being born during war-time to the total IOp are negligible for most biomarkers.

Finally, the results from the RIF-based Shapley decomposition show heterogeneities in the contributions of measured circumstances to IOp in biomarkers. Relative to household SES, the joint contribution of age and gender, in most cases, decreases towards the upper tail of the distribution of the biomarkers, where clinical concerns are focused. Nonetheless, the relative contribution of household SES to IOp in AL increases from 8.22% (25th quantile) to 13.55% (75th quantile) in 2011 (from 10.85% to 14.96% in 2015). This is in line with evidence for the UK (Davillas & Jones, 2020). This suggests that focusing solely on a mean-based decomposition would mask the important sources of household SES especially when accounting for health inequalities at the right tails of biomarker distributions, where health risks are more pronounced. Our results also confirm and extend previous literature on the long-term

impacts of early-life SES (Alvarado *et al.*, 2008) in the setting of the IOp in health in old age.

These results have potentially important policy implications. Given that IOp explains to what extent the illegitimate factors beyond individuals' control contribute to total health inequality, a comprehensive assessment of IOp in health among the elderly in China should be of particular importance for public policy aiming at effectively reducing health inequality in old age. Improving health equity has long been a government priority, and *Healthy China 2030* (Zhou *et al.*, 2019) includes justice and equity as one of its four core principles. Given the dominant contribution of residential regions and provinces to IOp in health, the government should promote the implementation of disease control policies at the regional (urban/rural) and province levels. The new *Basic Healthcare and Health Promotion Law* (to be implemented on June 1, 2020), establishes a nutrition monitoring system, implement nutrition intervention plans for under-developed regions and vulnerable populations, and nutrition improvement actions for minors and the elderly. The findings of our analysis indicate that measures that aim to promote childhood nutrition and health are highly advisable and could reduce IOp in lifecycle population health for the Chinese people.

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Tables and Figures

Table 1 Description of each physiological system contributing to the allostatic load index

Biomarkers	Physiological System	Function
Glycated haemoglobin (HbA1c)	Metabolism	Long-term glucose metabolism (past 30-90 days)
Cholesterol ratio	Metabolism	Long-term atherosclerotic risk
Triglycerides	Metabolism	Important source of energy, high levels indicate cardiovascular risk
Waist to height ratio (WHR)	Metabolism	Long-term energy metabolism and storage, higher ratios indicate greater adipose tissue distribution
Systolic blood pressure (SBP)	Cardiovascular	Cardiovascular health
C-reactive protein (CRP)	Inflammation	Acute inflammation
White blood cell count (WBC)	Inflammation	Immune system activity
Creatinine	Excretory	Renal functioning

Source: Edes and Crews (2017).

Table 2 Descriptive statistics: outcomes and circumstances

Variables	2011			2015			Mean diff.
	Mean/ proportions	SD	Obs.	Mean/ proportions	SD	Obs.	
Biomarkers							
Glycated haemoglobin (HbA1c, %)	5.276	0.775	3302	6.083	1.028	4937	0.807***
Cholesterol ratio	4.186	1.578	3277	3.791	1.017	4918	-0.395***
Triglycerides (mg/dL)	135.2	101.0	3279	141.2	86.43	4919	5.964*
C-reactive protein (CRP, mg/L)	1.722	1.757	3123	2.007	1.848	4684	0.285***
Waist to height ratio (WHR)	0.544	0.085	2937	0.547	0.084	4830	0.003
Systolic blood pressure (SBP, mmHg)	134.9	22.10	2924	132.1	21.05	4826	-2.837***
White blood cell count (WBC, in thousands)	6.181	1.852	3255	5.959	1.819	4874	-0.222***
Creatinine (mg/dL)	0.812	0.202	3274	0.852	0.334	4919	0.040***
Allostatic load (AL)	30.19	3.830	2643	30.78	3.740	4448	0.581***
Circumstances							
Gender (1=male, 0=female)	0.490	0.500	3302	0.501	0.500	4937	0.011
Age	67.47	6.107	3302	67.96	6.507	4937	0.493***
Urban/rural residence	0.570	0.495	3302	0.525	0.499	4937	-0.045**
War							
Born in the Japanese War era	0.401	0.490	3302	0.281	0.449	4937	-0.120***
Born in the Civil War era	0.289	0.453	3302	0.208	0.406	4937	-0.080***
Parental health status and health behaviors							
Parental health status	0.163	0.369	3302	0.176	0.381	4937	0.014
Mother's smoking	0.100	0.300	3302	0.104	0.306	4937	0.004
Father's smoking	0.472	0.499	3302	0.497	0.500	4937	0.025
Father's alcohol drinking	0.068	0.251	3302	0.062	0.241	4937	-0.006
Health and nutrition conditions in childhood							
Self-reported health before age 15			3302			4937	
Much less healthy	0.056	0.230		0.046	0.209		-0.010
Somewhat less healthy	0.080	0.271		0.086	0.281		0.007
About average	0.506	0.500		0.500	0.500		-0.006
Somewhat healthier	0.200	0.400		0.202	0.401		0.002
Much healthier	0.159	0.366		0.165	0.372		0.007
Experienced hunger before age 17	0.274	0.446	3302	0.221	0.415	4937	-0.053***
Household SES in childhood							
Parental political status	0.070	0.255	3302	0.104	0.305	4937	0.034***
Mother's education	0.944	0.230	3302	0.926	0.262	4937	-0.018***
Father's education	0.687	0.464	3302	0.640	0.480	4937	-0.047***
Household economic status			3302			4937	
A lot worse off than them	0.231	0.421		0.226	0.418		-0.005
Somewhat worse off than them	0.151	0.358		0.147	0.355		-0.004
Same as them	0.512	0.500		0.520	0.500		0.008
Somewhat better off than them	0.091	0.288		0.094	0.292		0.003
A lot better off than them	0.015	0.120		0.012	0.109		-0.003
Access to healthcare in childhood	0.309	0.462	3302	0.313	0.464	4937	0.004

Notes: Sampling weights are applied. The significance level is based on independent t-tests. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 Total health inequality and IOp in health: Mean-based regressions (MLD index)

Biomarkers	Total inequality [a]	IOp		Obs.
		Absolute IOp [b]	% of total inequality [c=b/a]	
Panel A: 2011				
HbA1c	0.0087***	0.0005***	5.88	3302
	(0.0006)	(0.0001)		
Cholesterol ratio	0.0583***	0.0054***	9.23	3277
	(0.0022)	(0.0013)		
Triglycerides	0.1705***	0.0168***	9.83	3279
	(0.0070)	(0.0041)		
CRP	0.4036***	0.0170***	4.21	3123
	(0.0107)	(0.0041)		
WHR	0.0163***	0.0026***	16.14	2937
	(0.0015)	(0.0004)		
SBP	0.0131***	0.0010***	7.59	2924
	(0.0004)	(0.0002)		
WBC	0.0404***	0.0022***	5.39	3255
	(0.0015)	(0.0004)		
Creatinine	0.0284***	0.0084***	29.57	3274
	(0.0014)	(0.0007)		
Allostatic load	0.0077***	0.0005***	6.59	2643
	(0.0003)	(0.0001)		
Panel B: 2015				
HbA1c	0.0108***	0.0004***	3.75	4937
	(0.0006)	(0.0001)		
Cholesterol ratio	0.0301***	0.0026***	8.70	4918
	(0.0016)	(0.0004)		
Triglycerides	0.1460***	0.0123***	8.41	4919
	(0.0041)	(0.0019)		
CRP	0.3693***	0.0149***	4.03	4684
	(0.0094)	(0.0039)		
WHR	0.0157***	0.0031***	19.56	4830
	(0.0009)	(0.0004)		
SBP	0.0128***	0.0008***	6.56	4826
	(0.0006)	(0.0003)		
WBC	0.0402***	0.0031***	7.60	4874
	(0.0015)	(0.0005)		
Creatinine	0.0426***	0.0103***	24.14	4919
	(0.0031)	(0.0007)		
Allostatic load	0.0070***	0.0004***	6.31	4448
	(0.0002)	(0.0001)		

Notes: Sampling weights are applied. Bootstrapped standard errors in parenthesis (500 replications). ***p <0.01.

Table 4 Absolute IOp in health: RIF regressions (MLD index)

Biomarkers	Q25	Q50	Q75
Panel A: 2011			
HbA1c	0.0007***	0.0006***	0.0007***
	(0.0001)	(0.0001)	(0.0003)
Cholesterol ratio	0.0138***	0.0090***	0.0069**
	(0.0023)	(0.0018)	(0.0031)
Triglycerides [a]	-	0.0313***	0.0191**
	-	(0.0055)	(0.0088)
CRP [b]	-	-	0.0321***
	-	-	(0.0098)
WHR	0.0027***	0.0031***	0.0020***
	(0.0003)	(0.0003)	(0.0002)
SBP	0.0025**	0.0015***	0.0012***
	(0.0012)	(0.0003)	(0.0003)
WBC	0.0060***	0.0036***	0.0022***
	(0.0014)	(0.0010)	(0.0005)
Creatinine	0.0142***	0.0107***	0.0090***
	(0.0013)	(0.0007)	(0.0007)
Allostatic load	0.0009***	0.0010***	0.0006***
	(0.0002)	(0.0003)	(0.0002)
Panel B: 2015			
HbA1c	0.0003***	0.0002***	0.0003***
	(0.0001)	(0.00005)	(0.0001)
Cholesterol ratio	0.0067***	0.0039***	0.0021***
	(0.0009)	(0.0006)	(0.0006)
Triglycerides [a]	-	0.0287***	0.0121***
	-	(0.0039)	(0.0032)
CRP [b]	-	-	0.0151***
	-	-	(0.0043)
WHR	0.0030***	0.0018***	0.0012***
	(0.0003)	(0.0002)	(0.0002)
SBP	0.0014***	0.0012***	0.0008***
	(0.0005)	(0.0002)	(0.0002)
WBC	0.0079***	0.0035***	0.0037***
	(0.0015)	(0.0006)	(0.0010)
Creatinine	0.0183***	0.0153***	0.0073***
	(0.0012)	(0.0008)	(0.0006)
Allostatic load	0.0007***	0.0006***	0.0007***
	(0.0001)	(0.0001)	(0.0002)

Notes: Sampling weights are applied. Bootstrapped standard errors in parenthesis (500 replications). ** $p < 0.05$, *** $p < 0.01$.

[a] The RIF regression can generate infeasible negative predictions for some individual observations (which occurs for triglycerides at 25% quantile). Given that MLD measures inequality of positive values, we only show absolute IOp at the 50% and 75% quantiles.

[b] The RIF regression can generate infeasible negative predictions for some individual observations (which occurs for CRP at the 25% and median quantiles). Given that MLD measures inequality of positive values, we only show absolute IOp at the 75% quantile.

Table 5 Contributions of circumstances to IOp in health: Mean-based Shapley decomposition

Biomarkers	Gender	Age	Region/ province	War	Parental health status and health behaviors	Health and nutrition conditions in childhood	Household SES	Access to healthcare in childhood
Panel A: 2011								
HbA1c	8.46%***	2.61%**	72.86%***	1.52%	7.59%**	0.59%	4.29%	2.07%
Cholesterol ratio	12.63%***	2.06%*	65.96%***	1.17%	3.74%	6.48%	7.85%*	0.12%
Triglycerides	24.84%***	1.07%	60.79%***	0.23%	1.56%	8.95%**	2.31%	0.26%
CRP	0.33%	7.85%**	68.49%***	0.63%	4.32%	5.26%	8.60%	4.52%
WHR	47.65%***	1.21%***	39.15%***	0.53%	1.41%	4.18%*	4.83%	1.03%*
SBP	5.42%***	33.31%***	37.88%***	2.92%	2.83%	9.53%	6.83%	1.28%
WBC	7.30%***	3.59%*	78.38%***	0.49%	4.02%	1.70%	4.30%	0.22%
Creatinine	71.27%***	3.97%***	20.59%***	0.33%	0.50%	1.19%	1.96%	0.20%
Allostatic load	10.24%***	9.09%***	67.22%***	1.27%	2.51%	3.08%	4.05%	2.56%
Panel B: 2015								
HbA1c	9.33%***	0.40%	67.64%***	0.93%	0.98%	3.95%	14.41%	2.36%
Cholesterol ratio	9.18%***	0.37%	70.07%***	2.04%*	3.65%*	3.27%	11.05%**	0.37%
Triglycerides	26.95%***	5.54%***	56.10%***	0.49%	1.34%	2.57%	6.53%	0.48%
CRP	0.01%	1.90%*	79.55%***	1.44%	1.50%	5.77%	9.55%	0.29%
WHR	33.11%***	0.12%*	61.44%***	0.18%	0.97%	1.87%	2.20%	0.09%
SBP	0.40%	33.08%***	33.97%***	3.32%	3.83%	6.45%	18.53%***	0.42%
WBC	23.10%***	0.30%	64.19%***	0.90%	3.61%	2.39%	5.11%*	0.41%
Creatinine	72.91%***	7.22%***	17.17%***	0.89%	0.33%	0.53%	0.78%	0.19%**
Allostatic load	0.03%	5.28%***	76.99%***	0.99%	1.91%	4.02%	10.46%**	0.31%

Notes: Region and province include rural/urban residence and provinces. War includes born in the Anti-Japan War era or in the Civil War era. Parental health status and health behaviors include parental health status and health behavior of mother's smoking, and father's smoking and drinking. Health and nutrition conditions in childhood include self-reported health before age 15 and whether experienced hunger before age 17. Household SES includes parental political status and education, and household social economic status. Access to healthcare in childhood is whether first visiting general/specialized hospital or township clinics when ill in childhood. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6 Contributions of circumstances to IOp in health: RIF-based Shapley decomposition

Biomarkers	Quantile	Gender	Age	Region/ province	War	Parental health status and health behaviors	Health and nutrition conditions in childhood	Household SES	Access to healthcare in childhood
Panel A: 2011									
HbA1c	Q25	3.61%***	1.88%**	85.81%***	1.66%*	1.25%	1.61%	3.51%	0.67%
	Q50	5.00%***	1.22%	87.91%***	1.25%	1.66%	1.54%	1.13%	0.29%
	Q75	9.45%***	0.19%	70.95%***	2.26%	4.19%*	7.73%	4.87%	0.36%
Cholesterol ratio	Q25	6.10%***	1.94%	73.85%***	2.01%	2.54%	7.54%**	5.21%	0.81%
	Q50	13.09%***	2.19%	66.93%***	2.25%	4.68%	4.49%	6.14%	0.22%
	Q75	4.67%***	0.75%	65.61%***	1.67%	4.00%	11.99%*	11.25%*	0.05%
Triglycerides [a]	Q25	-	-	-	-	-	-	-	-
	Q50	28.67%***	1.27%	59.13%***	0.28%	2.69%	4.88%	2.97%	0.10%
	Q75	15.88%***	1.59%	58.10%***	0.19%	0.93%	18.65%**	4.19%	0.48%
CRP [b]	Q25	-	-	-	-	-	-	-	-
	Q50	-	-	-	-	-	-	-	-
	Q75	0.72%	7.93%***	69.83%***	1.18%	2.57%	8.93%	7.90%	0.95%
WHR	Q25	49.23%***	0.23%	40.95%***	0.27%	2.35%	2.90%*	3.21%	0.86%
	Q50	59.84%***	0.25%	32.12%***	0.35%	0.92%	2.45%*	3.44%	0.63%*
	Q75	59.78%***	2.04%***	27.44%***	0.40%	1.06%	3.62%	5.30%	0.37%
SBP	Q25	0.05%	27.17%***	39.27%***	2.36%**	1.17%	16.65%	11.20%	2.12%
	Q50	1.82%*	33.67%***	32.80%***	5.82%	2.16%	12.32%	11.28%**	0.12%
	Q75	12.66%***	32.22%***	30.01%	3.64%	6.06%*	8.73%	5.80%	0.88%
WBC	Q25	8.12%***	0.12%	73.26%***	0.11%	4.99%	8.95%	3.58%	0.86%
	Q50	4.42%***	0.42%	67.95%***	0.27%	8.60%*	10.51%	7.21%	0.62%
	Q75	10.50%***	4.30%**	73.17%***	0.56%	2.55%	4.69%	3.71%	0.53%
Creatinine	Q25	66.65%***	3.58%***	22.99%***	0.48%	0.96%	2.03%	3.22%	0.09%
	Q50	78.26%***	2.63%***	12.82%***	0.22%	0.60%	2.86%*	2.32%	0.30%
	Q75	66.47%***	3.01%***	21.00%***	0.20%	0.67%	3.35%***	4.50%***	0.79%
Allostatic load	Q25	5.83%***	10.65%***	64.66%***	0.98%	3.87%	4.86%	8.22%	0.94%
	Q50	10.39%***	6.20%***	69.47%***	0.68%	1.12%	5.48%	6.36%	0.29%
	Q75	10.89%***	2.27%*	58.63%***	0.99%	3.52%	7.94%	13.55%	2.21%
Panel B: 2015									
HbA1c	Q25	11.53%***	0.96%	70.23%***	4.63%**	2.35%	5.17%	4.86%	0.26%
	Q50	16.21%***	3.61%**	60.08%***	2.06%	2.95%	7.03%	7.22%	0.84%
	Q75	10.02%***	0.75%	54.24%***	0.54%	3.41%	11.27%	16.86%	2.91%
Cholesterol ratio	Q25	14.13%***	0.08%	68.76%***	1.44%	1.95%	8.22%*	5.27%***	0.15%
	Q50	7.24%***	1.09%	72.63%***	3.54%***	4.92%*	2.46%	7.72%	0.39%

	Q75	2.50%*	0.55%	64.00%***	4.68%***	5.05%	5.97%*	14.89%**	2.36%*
Triglycerides [a]	Q25	-	-	-	-	-	-	-	-
	Q50	23.90%***	3.22%**	60.55%***	0.27%	2.04%	1.37%	8.17%	0.48%
	Q75	22.11%***	3.76%**	60.46%***	0.55%	1.91%	2.63%	8.34%	0.24%
CRP [b]	Q25	-	-	-	-	-	-	-	-
	Q50	-	-	-	-	-	-	-	-
	Q75	0.23%	1.25%	66.50%***	3.47%	4.33%	5.67%	17.95%**	0.60%
WHR	Q25	59.28%***	0.04%	32.50%***	0.22%	0.75%	2.96%	3.48%	0.79%*
	Q50	61.30%***	0.80%**	32.53%***	0.28%	1.95%	0.42%	2.54%	0.19%
	Q75	57.81%***	1.87%***	27.66%***	1.19%	1.12%	4.13%	5.88%	0.34%
SBP	Q25	0.86%	30.33%***	43.57%***	4.33%	3.61%	8.60%	8.69%	0.03%
	Q50	1.85%*	37.14%***	28.10%***	5.26%	2.77%	7.53%	17.24%***	0.11%
	Q75	1.49%	23.64%***	47.22%***	2.09%	4.21%	6.18%	15.02%*	0.16%
WBC	Q25	11.43%***	0.10%	71.55%***	0.32%	5.15%	2.33%	9.03%**	0.09%
	Q50	22.72%***	0.08%	60.85%***	0.80%	3.93%	5.41%	6.15%	0.07%
	Q75	21.78%***	1.43%	56.73%***	2.86%	2.08%	7.35%**	6.66%	1.12%*
Creatinine	Q25	82.79%***	4.40%***	10.82%***	0.39%	0.31%	0.67%	0.41%	0.21%
	Q50	78.74%***	4.54%***	13.57%***	1.00%	0.38%	0.54%	1.12%	0.11%
	Q75	64.79%***	9.00%***	21.09%***	1.14%	0.91%	1.71%	1.32%	0.04%
Allostatic load	Q25	0.09%	7.24%***	71.27%***	1.45%	0.73%	8.02%	10.85%*	0.34%
	Q50	0.33%	4.19%***	81.93%***	0.48%	2.63%	4.27%	5.99%	0.18%
	Q75	0.98%	1.92%*	66.63%***	1.07%	4.17%	9.30%	14.96%***	0.98%

Notes: Region and province include rural/urban residence and provinces. War includes born in the Japanese War era or in the Civil War era. Parental health status and health behaviors include parental health status and health behavior of mother's smoking, and father's smoking and drinking. Health and nutrition conditions in childhood include self-reported health before age 15 and whether experienced hunger before age 17. Household SES includes parental political status and education, and household social economic status. Healthcare Access to healthcare in childhood is whether first visiting general/specialized hospital or township clinics when ill in childhood. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[a] As discussed in Table 4, given that MLD measures inequality of positive values, we only show absolute IOp at the 50% and 75% quantiles.

[b] As discussed in Table 4, given that MLD measures inequality of positive values, we only show absolute IOp at the 75% quantile.

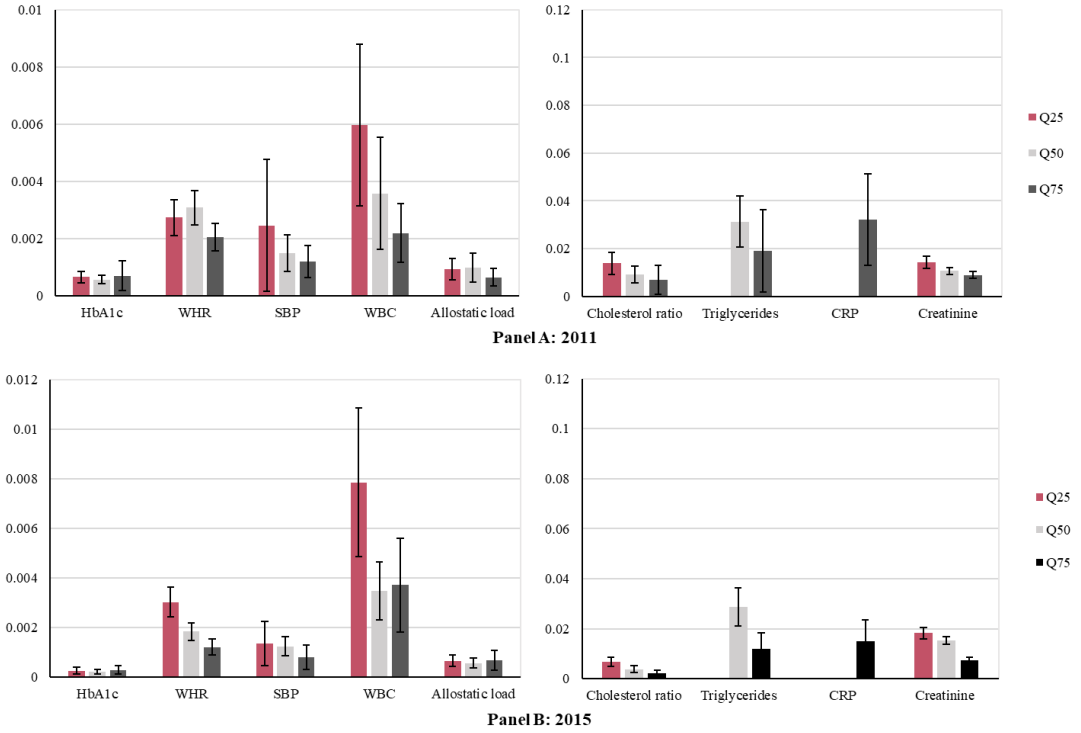

Figure 1 IOp (MLD index) in health at different quantiles: CHARLS 2011 and 2015

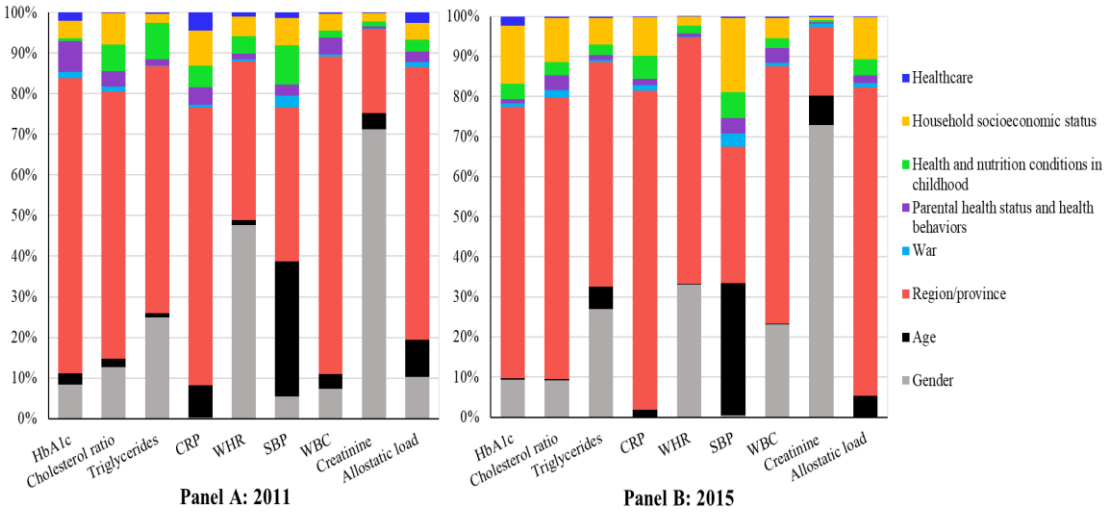

Figure 2 Contributions of circumstances to IOp in health: Mean-based Shapley decomposition

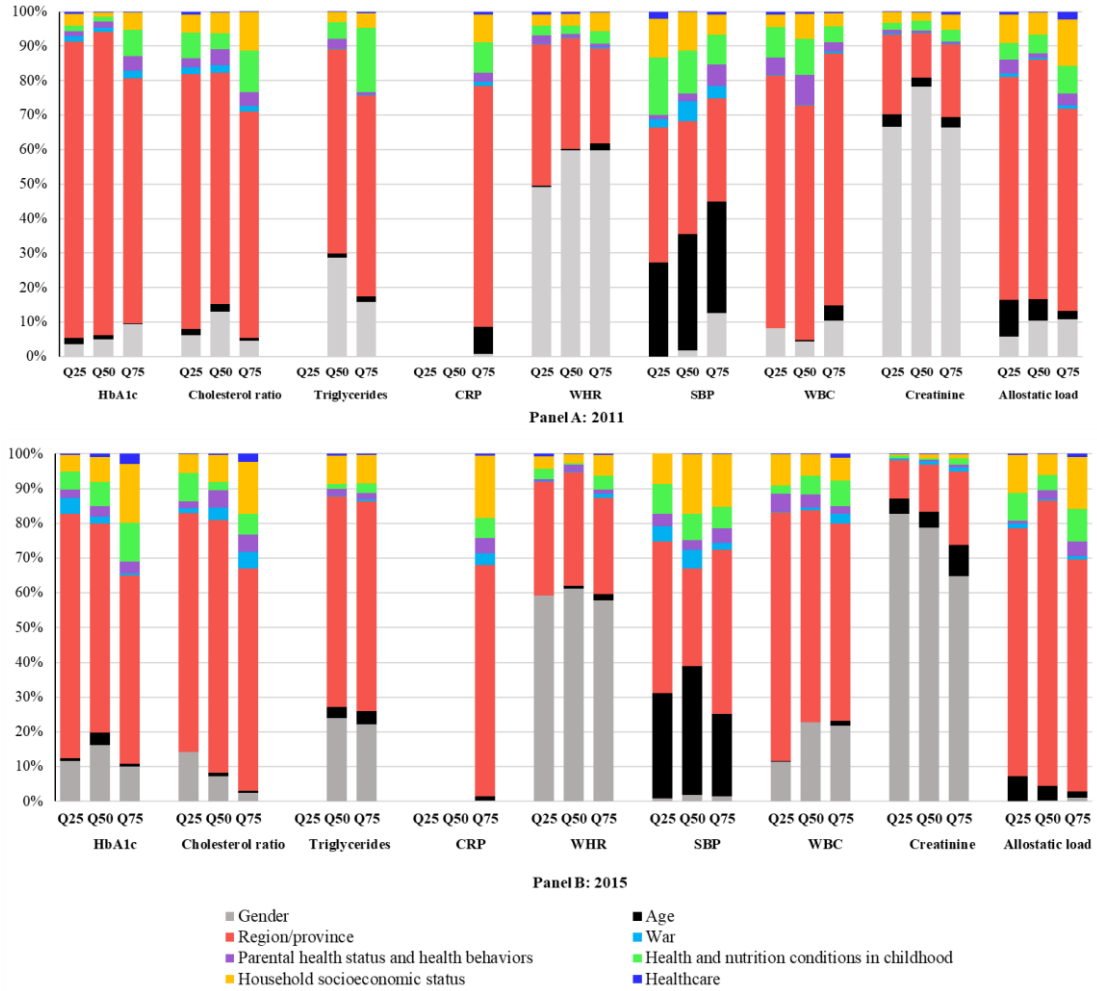

Figure 3 Contributions of circumstances to IOp in health: RIF-based Shapley decomposition

Appendix:

Table A.1 Statistical tests to compare the full sample and matched samples: differences in sample means

Variables	2011			2015		
	Matched	Full sample	Mean diff.	Matched	Full sample	Mean diff.
Gender	0.498	0.504	0.006	0.495	0.496	0.001
Age	67.59	67.95	0.369***	68.07	68.06	-0.013
Residence	0.668	0.649	-0.019	0.638	0.627	-0.011
Born in the Japanese War era	0.386	0.382	-0.004	0.281	0.279	-0.001
Born in the Civil War era	0.296	0.286	-0.010	0.223	0.222	-0.001
Obs.	4424	5090		6343	6693	

Notes: The matched sample is observations from the full sample that can be linked with the 2014 CHARLS Life History Survey. The significance is based on independent t-tests. *** $p < 0.01$.

Table A.2 Statistical tests of circumstances variables: differences in sample means

Variables	2011			2015		
	Matched sample with no missing circumstances	Matched sample	Mean diff.	Matched sample with no missing circumstances	Matched sample	Mean diff.
Gender	0.506	0.498	-0.008	0.502	0.495	-0.006
Age	66.97	67.59	0.611***	67.66	68.07	0.411***
Urban/rural residence	0.666	0.668	0.001	0.636	0.638	0.002
Born in the Japanese War era	0.390	0.386	-0.004	0.273	0.281	0.008
Born in the Civil War era	0.309	0.296	-0.014	0.227	0.223	-0.004
Parental health status	0.180	0.191	0.011	0.191	0.199	0.008
Mother's smoking	0.104	0.104	0.001	0.110	0.107	-0.003
Father's smoking	0.475	0.469	-0.006	0.490	0.488	-0.002
Father's alcohol drinking	0.067	0.068	0.001	0.063	0.063	0.000
Self-reported health before age 15						
Much less healthy	0.048	0.055	0.007	0.047	0.054	0.007
Somewhat less healthy	0.077	0.077	0.000	0.080	0.082	0.002
About average	0.524	0.526	0.002	0.512	0.512	0.000
Somewhat healthier	0.189	0.189	0.000	0.197	0.194	-0.002
Much healthier	0.161	0.153	-0.008	0.164	0.157	-0.007
Experienced hunger before age 17	0.246	0.254	0.008	0.210	0.218	0.009
Parental political status	0.074	0.067	-0.007	0.097	0.090	-0.006
Mother's education	0.951	0.954	0.002	0.939	0.943	0.004
Father's education	0.705	0.721	0.015	0.674	0.690	0.016
Household SES						
A lot worse off than them	0.238	0.260	0.022	0.237	0.260	0.023***
Somewhat worse off than them	0.154	0.155	0.001	0.160	0.158	-0.002
Same as them	0.517	0.499	-0.019	0.512	0.496	-0.016
Somewhat better off than them	0.079	0.076	-0.003	0.083	0.078	-0.005
A lot better off than them	0.011	0.010	-0.001	0.009	0.009	0.000
Access to healthcare in childhood	0.304	0.297	-0.007	0.292	0.291	-0.001

Notes: The matched sample is observations from the full sample that can be linked with the 2014 CHARLS Life History Survey. The significance is based on independent t-tests. *** $p < 0.01$.

Table A.3 Statistical tests (p-values) between the matched sample with no missing circumstances (Full) and analysis samples

Variables	Full vs. S1	Full vs. S2	Full vs. S3	Full vs. S4	Full vs. S5	Full vs. S6	Full vs. S7	Full vs. S8	Full vs. S9
2011									
Gender	0.967	0.974	0.975	0.820	0.751	0.782	0.969	0.944	0.638
Age	0.991	0.930	0.913	0.770	0.568	0.471	0.966	0.922	0.224
Urban/rural residence	0.848	0.875	0.847	0.736	0.381	0.271	0.566	0.916	0.117
Born in the Japanese War era	0.926	0.981	0.994	0.981	0.898	0.831	0.987	0.984	0.805
Born in the Civil War era	0.958	0.908	0.895	0.927	0.865	0.980	0.946	0.885	0.857
Parental health status	0.980	0.916	0.932	0.959	0.754	0.718	0.982	0.878	0.737
Mother's smoking	0.839	0.700	0.694	0.626	0.575	0.655	0.931	0.679	0.896
Father's smoking	0.985	0.993	0.994	0.853	0.869	0.963	0.899	0.979	0.856
Father's alcohol drinking	0.997	0.937	0.942	0.843	0.925	0.876	0.883	0.929	0.993
Self-reported health before age 15									
Much less healthy	0.880	0.927	0.931	0.953	0.855	0.824	0.970	0.920	0.890
Somewhat less healthy	0.918	0.895	0.926	0.963	0.944	0.895	0.821	0.904	0.996
About average	0.984	0.934	0.935	0.916	0.986	0.926	0.983	0.943	0.775
Somewhat healthier	0.938	0.844	0.853	0.734	0.963	0.997	0.858	0.830	0.844
Much healthier	0.964	0.778	0.770	0.609	0.895	0.868	0.979	0.765	0.491
Experienced hunger before age 17	0.866	0.960	0.972	0.814	0.873	0.755	0.947	1.000	0.592
Parental political status	0.995	0.926	0.931	0.816	0.999	0.962	0.795	0.917	0.938
Mother's education	0.981	0.983	0.978	0.815	0.761	0.602	0.757	0.990	0.350
Father's education	0.925	0.976	0.985	0.894	0.859	0.997	0.921	0.974	0.914
Household SES									
A lot worse off than them	0.979	0.858	0.870	0.916	0.758	0.684	0.909	0.828	0.817
Somewhat worse off than them	0.960	0.882	0.890	0.774	0.801	0.800	0.910	0.869	0.714
Same as them	0.980	0.999	0.978	0.849	0.784	0.736	0.855	0.990	0.682
Somewhat better off than them	0.989	0.917	0.923	0.871	0.885	0.846	1.000	0.909	0.859
A lot better off than them	0.845	0.964	0.945	0.939	0.649	0.662	0.988	0.940	0.464
Access to healthcare in childhood	0.953	0.987	0.974	0.848	0.874	0.781	0.872	0.985	0.700
2015									
Gender	0.976	0.959	0.959	0.851	0.899	0.787	0.966	0.959	0.830
Age	0.955	0.969	0.969	0.454	0.648	0.878	0.902	0.969	0.184
Urban/rural residence	0.976	0.965	0.965	0.846	0.970	0.860	0.682	0.965	0.637
Born in the Japanese War era	0.962	0.907	0.907	0.727	0.880	0.950	0.875	0.907	0.738
Born in the Civil War era	0.970	0.930	0.930	0.724	0.859	0.926	0.887	0.930	0.617
Parental health status	0.987	0.996	0.996	0.960	0.983	0.960	0.931	0.996	0.813
Mother's smoking	0.980	0.981	0.981	0.953	0.980	0.968	0.930	0.981	0.915
Father's smoking	0.977	0.988	0.988	0.888	0.906	0.939	0.867	0.988	0.668
Father's alcohol drinking	0.986	0.920	0.920	0.951	0.857	0.982	0.980	0.920	0.808
Self-reported health before age 15									
Much less healthy	0.975	0.931	0.931	0.835	0.978	0.976	0.972	0.931	0.861
Somewhat less healthy	0.984	0.970	0.970	0.874	0.948	0.958	0.988	0.970	0.873
About average	0.977	0.965	0.965	0.879	0.753	0.911	0.938	0.965	0.843
Somewhat healthier	0.972	0.998	0.998	0.807	0.955	0.967	0.995	0.998	0.717
Much healthier	0.997	0.933	0.933	0.952	0.762	0.862	0.945	0.933	0.520
Experienced hunger before age 17	0.991	0.995	0.995	0.913	0.907	0.963	0.914	0.995	0.766
Parental political status	0.982	0.957	0.957	0.809	0.995	0.906	0.952	0.957	0.747

Mother's education	0.986	0.950	0.950	0.972	0.965	0.991	0.891	0.950	0.777
Father's education	0.987	0.997	0.997	0.927	0.951	0.860	0.733	0.997	0.579
Household SES									
A lot worse off than them	0.988	0.945	0.945	0.830	0.915	0.992	0.970	0.945	0.773
Somewhat worse off than them	0.976	1.000	1.000	0.835	0.945	0.960	0.996	1.000	0.857
Same as them	0.977	0.949	0.949	0.926	0.957	0.974	0.971	0.949	0.876
Somewhat better off than them	0.983	0.969	0.969	0.863	0.953	0.914	0.935	0.969	0.865
A lot better off than them	0.922	0.935	0.935	0.862	0.921	0.991	0.885	0.935	0.785
Access to healthcare in childhood	0.999	0.995	0.995	0.977	0.820	0.912	0.868	0.995	0.980

Notes: The analytical sample of S1-S9, and the sample with no missing circumstances (i.e. Full) is explained in Figure A1. *p* values are reported.

Table A.4 Total inequality and IOp in health: Mean-based regressions (variance share)

Biomarkers	IOp	Obs.
	% of total inequality	
Panel A: 2011		
Glycated haemoglobin	6.4448***	3302
	(0.0108)	
Cholesterol ratio	9.6294***	3277
	(0.0213)	
Triglycerides	10.6011***	3279
	(0.0205)	
C-reactive protein	4.1616***	3123
	(0.0096)	
Waist to height ratio	13.2853***	2937
	(0.0144)	
Systolic blood pressure	7.6134***	2924
	(0.0168)	
White blood cell count	5.4617***	3255
	(0.0099)	
Creatinine	29.8930***	3274
	(0.0171)	
Allostatic load	6.6817***	2643
	(0.0127)	
Panel B: 2015		
Glycated haemoglobin	4.2183***	4937
	(0.0097)	
Cholesterol ratio	8.9918***	4918
	(0.0139)	
Triglycerides	9.0174***	4919
	(0.0129)	
C-reactive protein	3.7784***	4684
	(0.0105)	
Waist to height ratio	16.5482***	4830
	(0.0149)	
Systolic blood pressure	6.4545***	4826
	(0.0152)	
White blood cell count	7.7865***	4874
	(0.0109)	
Creatinine	28.1788***	4919
	(0.0167)	
Allostatic load	6.4367***	4448
	(0.0098)	

Notes: The variance share is defined as a relative measure of IOp in health, capturing the share of the total variation in each biomarker due to observed circumstances. Bootstrapped standard errors in parenthesis (500 replications). *** $p < 0.01$.

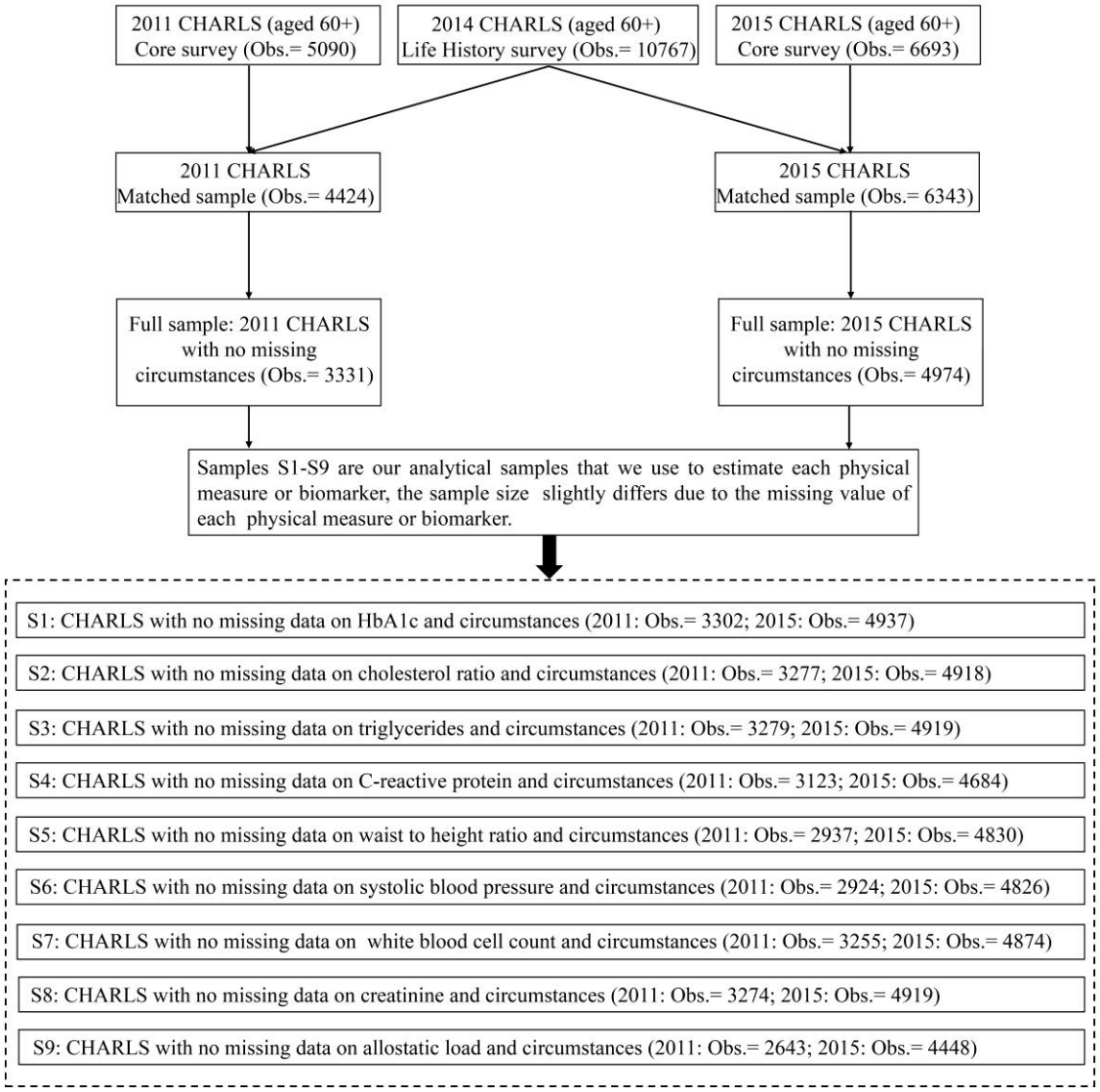

Figure A.1 Flow chart of study samples