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

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Abstract

Using pooled data from the 2011 and 2015 waves of the China Health and Retirement Longitudinal Study (CHARLS) linked with the 2014 CHARLS Life History Survey, we analyse *ex ante* inequality of opportunity (IOp) in blood-based biomarkers among Chinese adults aged 60+. We apply a re-centered influence function approach and a Shapley-Shorrocks decomposition to partition the contributions of different sets of measured circumstances and find that these account for between 2.01% and 23.95% of total health inequality across the range of biomarkers. The decompositions show that spatial circumstances such as urban/rural and province of residence at birth are the dominant factors for most of the biomarkers. Distributional decompositions further reveal that the relative contributions of household socioeconomic status and health and nutrition in childhood increase in the right tails of the distribution, where the clinical risk is focused, for most of the biomarkers.

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

JEL classifications: D63; I12; I14

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1. INTRODUCTION

As one of the five 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). However, not all of these sources of health inequality are equally objectionable. As suggested by earlier studies (e.g., Alesina and Angeletos, 2005; Rosa Dias, 2009), health inequalities due to factors that reflect individual choices, such as lifestyles, might be more ethically acceptable and, to some extent, regarded as fair. In contrast, sources of health inequality such as family socioeconomic characteristics, that are beyond individuals' control, are typically regarded as illegitimate and a priority for policy interventions. 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 normative economics (Roemer, 1998; Roemer, 2002; Roemer and Trannoy, 2016).

Following Roemer's conceptual framework for IOp (Roemer, 1998; Roemer, 2002; Roemer and Trannoy, 2016), the literature partitions the factors associated with an outcome of interest (e.g., health) into two broad components: "efforts", for which to some extent individuals are held responsible, and "circumstances", which are beyond individual control (Carrieri and 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 and Jones, 2020).

Rawls's "*A Theory of Justice*" (Rawls, 1971), which is a precursor to Roemer's work, stipulates that justice requires a set of institutions that maximize the "primary goods" allocated to those who are worse off in the society after guaranteeing a system

maximizing civil liberties (Roemer and Trannoy, 2016). Since primary goods refer to those inputs required for the success of any life plan, equalizing bundles of primary-goods across individuals is a way of holding people responsible for their choice of life-plan. Based on Rawls' theory of justice, Roemer's conceptual framework for equity of opportunity critically requires freedom to be meaningful: important outcomes (so called "advantages") are distributed independently of circumstances and only be determined by individual choices (i.e. efforts). Thus, circumstances in IOp involve factors beyond individual controls, such as institutional environment, race or family background. In particular, childhood circumstances (our focus in this study) such as family socioeconomic status and parental educational attainments have become a primary source of unfair health inequality (Marmot et al., 2008) and constitute a vitally important dimension of circumstances. 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 and Jones, 2018; Davillas and Jones, 2020; Jusot et al., 2013).

China offers a relevant 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 and 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 exceeds 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 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 (WHO, 2015).

To address these issues, this study uses pooled 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 and may suffer from reporting bias (Bago d'Uva et al., 2011; Bago d'Uva et al., 2008; Rossouw et al., 2018). Further, 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 and 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 can be useful for reducing health inequality, and promoting healthy longevity for the 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 and 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 and Jones, 2020), which has been used as a comprehensive, multi-system measure of cumulative biological dysregulation across major physiological systems that are due to the accumulation of stressful exposures (McEwen and Stellar, 1993).

Third, we measure a comprehensive set of childhood circumstances spanning: early exposure to war; parental health and health behaviors; childhood health and nutrition; household SES; access to healthcare; and provincial and urban/rural residence at birth. 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 and 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 and Jones, 2020).

We find that the contribution of observed circumstances to total health inequality can be substantial and the findings are broadly in line with Davillas and Jones (2020) for the UK and Yan et al. (2020) for China. The mean-based Shapley-Shorrocks

decompositions show that rural/urban residence and province of residence at birth make the largest contribution to IOp for most biomarkers, in line with earlier studies that underscore the importance of region of residence in China (Fang et al., 2010). The RIF-based Shapley decompositions show that, relative to household SES, the contribution of residence at birth and joint contribution of age and gender and decrease towards the upper tail of the distribution of most biomarkers. Focusing solely on a mean-based decompositions would mask this finding when accounting for health inequalities in the right tail of distributions, where health risks are most pronounced.

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 and Jones, 2018; Davillas and 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 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 of UK Household Longitudinal Study, 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% to 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 waves of CHARLS linked with the 2014 CHARLS Life History Survey, 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

[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.

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 and Jones, 2018; Davillas and 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 and Wagstaff, 2016). Finally, as Davillas and Jones (2020) highlight, a limitation in most studies (including the previous work for China) 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 underlying 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. EMPIRICAL 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 and Jones, 2020; 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 conceptualise and quantify IOp, namely, the *ex ante* and *ex post* approaches (Fleubaey and Peragine, 2013; Fleurbaey and 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 and Schokkaert, 2009; Li Donni et al., 2014). These opportunity sets are equated with the distribution of outcomes within social types, who share the same set of circumstances, and the *ex ante* approach implies that all individuals have equal opportunity in health when there are no differences in the distribution of health due to differences in circumstances (Davillas and Jones, 2020; Fajardo-Gonzalez, 2016; Fleubaey and Peragine, 2013; Ramos and Van de gaer, 2016). Since IOp is defined by comparing the outcome distribution between types, the *ex ante* approach only requires the measurement of circumstances, efforts do not need to be observed. Thus, following previous research, we adopt an *ex ante* approach that emphasizes inequality in the distribution of health outcomes across social types.

We begin with a direct *ex ante* parametric approach using the mean-based regressions proposed by Ferreira and Gignoux (2011) and Ferreira and Gignoux (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 and Gignoux, 2011). We adopt parametric estimation, which does not suffer from the curse of dimensionality that may occur, especially for a rich set of circumstances, due to insufficient sample sizes for specific social types. Note that, given the presence of unobserved circumstances, our IOp measures can be interpreted as lower bound estimates of overall IOp (Davillas and Jones, 2020; Ferreira and Gignoux, 2011).

Assuming additive separability and linearity of the functions $h(\cdot)$ and $E(\cdot)$, and noting again that the vector of efforts does not have to be observable, we obtain a linear reduced form for health (Davillas and Jones, 2020):

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

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 our biomarker measures (Davillas and Jones, 2020; Ferreira and Gignoux, 2011). MLD belongs to the generalized entropy (GE) 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 and 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:

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

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

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., changing the order of circumstances in the decomposition does not affect the results. Additionally, it is also exactly additive, meaning that the different components sum up to the total IOp. 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 and Jones, 2020; Yan et al., 2020). As a robustness check, we also apply the Shapley-Shorrocks decomposition to the variance.

3.1.3 Unconditional quantile 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 and 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 and Jones, 2020). To relax the assumption of inequality neutrality within types, we use the 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. To do so, we regress the recentred influence function (RIF) for each quantile 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 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 and 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 different quantiles of the distribution.

3.2 Data and study population

The data are drawn from the CHARLS, administered by the National School of Development together with the Institute for Social Science Surveys at Peking University. CHARLS is 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. Three follow-up interviews were conducted in 2013, 2015, and 2018. 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., 2019b). 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., 2019b).

As shown in the Appendix, Figure A.1, we match the pooled sample of 2011 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 exclude observations with 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 full matched sample and the matched sample that excludes missing values of childhood circumstances (with the exception of age in both waves 2011 and 2015). We retain the largest sample possible for analysis of each of the health measures, so the number of observations for each differs slightly because of missing data for the individual health biomarkers. Our final analysis samples range from 2,593 to 3,239 in 2011 and 4,188 to 4,648 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. These are associated with major chronic conditions such as obesity, high blood pressure, diabetes and cardiovascular diseases (CVD) (Davillas and Jones, 2020). Specifically, our physical measurements are the waist to height ratio (WHR), defined as waist circumference (in cm) divided by height (in cm), a useful indicator to measure adiposity and to predict multiple metabolic risk factors (Gu et al., 2018), and systolic blood pressure (SBP), an indicator for hypertension. In addition to raw biomarkers, we also generate dummies based on clinical cut-offs of these biomarkers (Chen et al., 2019b; Wang et al., 2001; Zeng et al., 2014, see Table 1) and then take those dummies as anchoring variables to measure high-level risks of health outcomes. After that, we recalculate the IOp as a robustness check.

Following Edes and Crews (2017), we use six blood-based biomarkers, namely, glycated haemoglobin (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., 2019b), 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 CVD and mortality risks (Prospective Studies Collaboration, 2007). Triglycerides, measured in mg/dL by the Oxidase method (Chen et al., 2019b), 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/μL) 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 and 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 and Jones, 2020; McEwen, 2015; Seeman et al., 2004). Following Davillas and Jones (2020), we transform each of the nurse-collected and the blood-based biomarkers 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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Place Table 1 here

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3.4 Circumstances

Following the literature (e.g., Davillas and 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 at birth: including urban or rural residence (1 = rural, 0 = urban) and province of residence at birth. 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 and Kwong, 2004);

(4) Wars. 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 = at least one of parent being bedridden, 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 and nutrition 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 compared to other children of the same age 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 = 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 health care in childhood. Evidence in the health literature suggests that early-life access to health care services can 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 5.3, 134.6, 1.7, and 0.8, 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 30.0 in 2011 to 30.6 in 2015. Such an increase in AL may promote additional somatic damage and chronic disease as the outcome of stressors and allostatic response (Edes and 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 and Chen, 2020).

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Place Table 2 here

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With regards to circumstances, the mean age and the proportion of males is quite stable over time. It is interesting that, during 2011-2015, the parental illiteracy rate declines, from 94.4% to 93.3% for mothers and from 68.6% to 65.9% for fathers. This finding may reflect the fact that, through programs such as building schools and training teachers, China has shifted from an illiterate, uneducated country to one that provides basic education to a large majority of the population (Banister and Zhang, 2005). However, without controlling for any covariates, this possible explanation should be treated with caution.

4.2 *Mean-based measures of ex ante IOp*

4.2.1 AL

Table 3 displays the measures of *ex ante* IOp for AL and the specific biomarkers. Column [a] shows the total inequalities of the different health outcomes (measured by MLD) and column [b] shows the absolute level of IOp in health. Interestingly, the total inequality of AL in our study, 0.0075 (Panel A), is quite comparable to that of Davillas and Jones (2020) for the UK, with a value of 0.0074. Yet the relative IOp is about 4% of the total inequality in AL, which is smaller than that in the UK (22%). These results indicate that the relative contribution of circumstances to total health inequalities in China is much smaller compared to the UK. This might be attributable to the fact in China that with rapid economic and social development, individual efforts such as a sharp decline in physical activity, poor-quality diets featured as low in micronutrients and high in carbohydrates and salts, and smoking also substantially explain such inequalities in non-communicable chronic diseases that AL may capture (Chen et al., 2019a; Hu et al., 2011).

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Place Table 3 here

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4.2.2 Specific biomarkers

As for specific biomarkers, results from the mean-based *ex ante* IOp measures show that the contribution of observed circumstances to total health inequality ranges from 2.01% for CRP to 23.95% for creatinine (column [c] in Panel B), 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. Such results are in accordance with those of Davillas and Jones (2020) for

the UK. One possibility is that CRP values vary greatly between the healthy and less healthy groups leading to large overall inequalities (Davillas and Jones, 2020). In addition, CRP may reflect acute inflammation rather than chronic systematic process (Davillas and Jones, 2020; Edes and Crews, 2017; Marnell et al., 2005). It is also notable that IOp in individual biomarker is relatively higher than that in AL, perhaps suggesting that there exists non-negligible IOp in biomarkers associated with chronic diseases in China.

4.3 Distributional analysis of ex ante IOp

4.3.1 Allostatic Load

To explore potential heterogeneity in the contribution of circumstances to inequality, 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. Generally, we identify significant differences in IOp across the biomarker distributions. We find that IOp in AL slightly declines from 0.0006 at the 25th quantile to 0.0004 at both the median and 75th quantile (see Appendix Table A.4). In other words, health inequalities explained by observed circumstances decline towards the upper tail of the distribution of AL. This finding may imply that observed circumstances play a less important role in health inequality at the upper tail of AL distribution, where individuals have a higher health risk. Instead, individual efforts may explain more than circumstances for health inequalities among those at higher levels of health risks.

4.3.2 Specific biomarkers

Figure 1 illustrates the IOp in biomarkers across different quantiles. Regarding specific biomarkers, heterogeneity in contributions of circumstances to health inequalities is more obvious than that for AL. We find that there is significant IOp across different quantiles and it decreases towards the upper tail of the distributions for almost all of specific biomarkers: for example, IOp in creatinine decreases from

0.0162 (25th quantile) to 0.0125 (50th quantile) and to 0.0080 (75th quantile). 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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4.4 Shapley-Shorrocks decomposition of ex ante IOp

4.4.1 Mean-based decomposition of IOp

AL: we use the Shapley-Shorrocks decomposition to quantify the contribution of each observed circumstance to IOp in health. As can be seen from Panel A of Table 4, urban/rural and province of residence at birth disparities consistently make the largest contribution to IOp for AL (59.81%). These results are in accordance with previous studies on health inequality in China, which highlight the important role of the regions in health inequalities (see, for instance, Nie et al., 2019; Yan et al., 2020). Then the combination of gender and age comes second (18.08%). These results are consistent with the literature on the role of gender and age when explaining variations in health (Baum and Ruhm, 2009) and health disparities (Oksuzyan et al., 2017). Additionally, household SES and health and nutrition in childhood are also important contributors to IOp in AL (13.14% and 4%, respectively).

Specific biomarkers: for most of specific biomarkers, we also observe a similar pattern (see Panel B of Table 4). Specifically, region/province at birth is the first contributor for HbA1c (48.78%), cholesterol ratio (56.50%), CRP (65.28%) and WBC (77.71%). Besides regions/provinces at birth, gender and age come out as two relatively important contributors to IOp in biomarkers. A combination of gender and

age accounts for between 9.67% and 81.25% of the total IOp for biomarkers. Also household SES explains 0.96-13.6% of the total IOp. And 0.69-7.9% of IOp is explained by health and nutrition in childhood for biomarkers. Parental health and health behaviors make moderate contributions to the total IOp, with ranges between 0.76-5.47%. The contributions of access to healthcare in childhood and experience of war to the total IOp in most biomarkers are negligible.

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4.4.2 RIF-based decomposition of IOp

AL: Panel A of Table 5 shows the contribution of each of the observed circumstances to IOp in AL at different quantiles of their distributions. Heterogeneities in the contribution of each observed circumstance to IOp at different quantiles for health outcomes are discernable. Several findings are worth mentioning. First, as seen from Table 5, similar to the mean-based results, region/province at birth still accounts for the majority of the total IOp in AL. However, the contribution of residential region/province at birth to IOp decreases towards to the upper tail of the distribution for AL (from 63.10% at the 25th quantile to 47.51% at the 75th quantile).

Second, it is also worthwhile to mention that the relative contribution of gender and age to IOp in AL decreases in the upper tail of the distribution of the biomarkers, where individuals are most at risk of health problems: the combined contribution of age and gender for AL is 21.07% at the 25th quantile, and then declines to 14.38% at the median and further to 9.06% at the 75th quantile. Nonetheless, the contribution of household SES to the total IOp in AL increases towards the upper quantiles of the AL distribution: the relative contribution of household SES to IOp in AL grows from 7.62% at the 25th quantile to 7.52% at the median and further to 26.22% at the 75th quantile.

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, and household SES to the total IOp in biomarkers. More importantly, our unconditional quantile-based decomposition supports 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 and Jones, 2020, p.10).

Finally, also note that the relative contribution of health and nutrition in childhood slightly increases towards the right tail of the biomarker distribution for AL. The contribution of early-life health and nutrition conditions to the total IOp in AL increases from 4.37% (25th quantile) to 5.85% (75th quantile). We also observe similar patterns for parental health status and health behaviors (increasing from 2.58% at the 25th quantile to 7.29% at the 75th quantile) and access to healthcare in childhood (increasing from 0.17% at the 25th quantile to 3.32% at the 75th quantile). However, the contribution of exposure to war is relatively stable across the whole distribution of AL. These results highlight the important role of socioeconomic circumstances such as household SES, parental health status and health behaviors, childhood health and nutrition, and access to healthcare in childhood in shaping health inequality (i.e. IOp in health) at the upper tail of the health distribution. Furthermore, our findings here echo previous studies (Davillas and Jones, 2020; Fu and George, 2015). For instance, using data from 1997-2006 China Health and Nutrition Survey, Fu and George (2015) confirm a protective effect of parental employment on the high percentile of childhood distribution of BMI in China.

Specific biomarkers: regarding specific biomarkers, we observe a similar pattern (Panel B of Table 5): region/province at birth is the leading contributor for most biomarkers except for WHR, SBP and creatinine. Furthermore, the relative

contribution of region/province at birth to IOp in HbA1c declines from 67.40% at the 25th quantile to 41.20% at 75th quantile. This also applies to the cholesterol ratio (from 66.65% to 55.35%), WHR (from 28.37% to 17.59%) and WBC (from 73.69% to 67.51%). Yet the patterns of the relative contributions of combined gender and age, household SES, and health and nutrition in childhood across different quantiles differ by different biomarker. One possible explanation is that the composite health indicator of AL may capture the general health status whilst each biomarker only reflects one specific dimension of health outcomes, thereby leading to the discrepancy of relative contributions of circumstances to IOp in AL and the specific biomarkers. All decomposition results are also illustrated in Appendix Figures A.2 and A.3.

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4.5 Robustness checks

4.5.1 Using variance share to measure IOp in health

It should be noted that the MLD is scale invariant but not translation invariant, whereas the variance share is both scale and translation invariant. Additionally, there are some restrictions when using mean log deviation (MLD), for instance, the outcome variable should be positive. In our case, such restriction only occurs for triglycerides at 25% quantile, and CRP at the 25% and median quantiles. To rule out this problem, we also use the variance share to quantify IOp (see Appendix Tables A.5 and A.6). Specifically, the variance share is the share of total variance in our biomarkers explained by circumstances and is a relative IOp measure (Davillas and Jones, 2020). Thus, our robustness analysis addresses the possible differences because of different selections of inequality measures (Davillas and Jones, 2020; Ferreira and

Gignoux, 2014; Wendelspiess Chávez Juárez and Soloaga, 2014). The variance also satisfies path independent decomposability and has been used to quantify health inequality (Carrieri and Jones, 2018).

Appendix Table A.5 shows IOp using the variance share and the results for relative IOp in biomarkers are quite similar to these using the MLD index in Table 3. Specifically, the contribution of observed circumstances to the total health inequality ranges between 1.94% and 26.84% (Appendix Table A.5), which are quantitatively similar to those in Table 3. And the results of decomposition based on variance in Appendix Tables A.6 and A.7 show that the main findings are stable and not affected by our choice of variance share.

4.5.2 Using the 2015 wave

Considering that significant changes between 2011-2015 for most of the biomarker indicators might lead to biased estimates of inequality when pooling the two waves. Specifically, differences in health outcomes between the two waves may not change equally for everyone, thereby resulting in biases in calculating inequality. It should be noted that inequality indices such as MLD or variance are used in the case of scale invariant or translation invariant measures. Thus, we also use the latest wave from 2015 as a robustness check. Generally, results in Appendix Tables A.8-A.10 are quantitatively similar to those in Tables 3-5. Specifically, the relative IOp in total health inequalities ranges from 2.84% to 22.87%, and the contribution of region/province at birth is the leading contributor for almost all of biomarkers. Appendix Table A.10 shows the results from quantile-based decomposition. In general, we find that ill health is not simply a matter of gender and age inequalities, our set of circumstances such as household SES, parental health status and health behaviors, and health and nutrition conditions in childhood become much more relevant towards the right tails of most biomarker distributions.

4.5.3 Redefining the biomarkers

Given that the scales of different biomarkers might be arbitrary and non-linearity may exist in the association between raw biomarkers and health risks, we generate dummies based on clinical cut-offs of these biomarkers and then take those dummies as anchoring variables to measure high-level risks of health outcomes. After that, we recalculate the IOp as a robustness check. When performing Shapley decomposition of IOp for these binary health variables, our results are consistent with those using the raw biomarkers (see Appendix Tables A.11 and A.12).

4.5.4 Excluding the measure of wartime

Our study sample cannot include individuals who died because of the Japanese or civil wars, thereby leading to the non-random selection of the sample associated with the addition of the wartime dummies. To rule out this problem, we also perform an additional robustness check without the circumstance of being born during wartime and the results (see Appendix Table A.13) are similar to those with the wartime circumstance.

4.5.5 Excluding gender and age

Regarding demographics (i.e. gender and age), there is no consensus in the literature on IOp as to whether associated inequalities are illegitimate or not (Jusot et al., 2013). Therefore, we exclude gender and age from circumstances and check how conclusions change (see Appendix Tables A.14 and A.15). Without gender and age, the magnitudes of MLD indexes decline for all biomarkers, especially for triglycerides, WHR, SBP and creatinine. However, in general, statistically significant IOp still exists in each biomarker (see Table A.14). Table A.15 further shows the relative contributions of circumstances to IOp in health and our main findings are stable.

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 of allostatic load. 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 unconditional quantile regression 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 2.01% and 23.95% 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. However, although we introduce almost identical circumstances to those in Davillas and Jones (2020), IOp in most biomarkers is relatively smaller than that in the UK (e.g., HbA1C: 3.3% in China vs. 19.5% in the UK; cholesterol ratio: 6.6% vs. 11.0%; AL: 4.0% vs. 21.8%). Furthermore, the study of Yan et al. (2020), which focuses on IOp in cognitive health, mental health, physical health, self-rated health and mortality, also shows similar findings, except for the cognition of mathematics score (23%). Such findings may suggest that, relative to Western countries, IOp is relatively smaller in China. This also implies that besides observed circumstances, individual efforts such as physical activities, dietary patterns and smoking/alcohol drinking play a substantial role in shaping health inequalities in China (Hu et al., 2011).

Second, according to the mean-based Shapley-Shorrocks decomposition, we find that rural/urban and province of residence at birth make the largest contribution to the total IOp in most domains of biomarkers. This echoes earlier studies that underscore the importance of region of residence in explaining health disparities among elderly Chinese adults (Fang et al., 2010; Wang and Zeng, 2015). With rapid economic growth over the past four decades, there still exist prominent health inequalities between urban and rural areas and different regions in China due to disparities not only in wealth but also the distribution of health resources and primary health care services (Fang et al., 2010), as well as education and welfare programs (Ratigan, 2017). In particular, Ratigan (2017) shows that developmental provinces that have an export-led, labor-intensive economies are likely to be wealthier and more engaged with education over other types of social policy such as poverty alleviation. In contrast, those provinces that are less economically developed and aim at poverty alleviation (defined as social autocratic provinces) tend to prioritize social insurance, pensions, and healthcare to alleviate poverty. Provinces that are concerned with unrest (defined as minimalist provinces) seek to quell unrest through targeted, means-tested policies like housing subsidies.[3] 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 and Ruhm, 2009) and health disparities (Burt et al., 1995; Vona et al., 2018). Childhood health and nutrition, 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. These results are consistent with the existing evidence that uses a lifecourse approach to highlight the important role of childhood circumstances in shaping health in old adults (e.g., Brandt et al., 2012; Cui et al., 2020).

[3] A detailed discussion of developmental, social autocratic and minimalist provinces are available in Ratigan (2017).

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 contribution of age, gender and residential region/province at birth decreases towards the upper tail of the distribution of the AL, where clinical concerns are focused. Nonetheless, the relative contribution of household SES to IOp in AL increases from 7.62% at the 25th quantile to 26.22% at the 75th quantile. This is in line with evidence for the UK (Davillas and Jones, 2020). Such results suggest that health is not only associated with demographics and regions, but also more relevant to socioeconomc circumstances in childhood, particularly for those individuals at high levels of health risk. This also 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 for old adults.

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 and promoting individual healthy lifestyle and health literacy. Given the nonnegligible contributions of illegitimate circumstances to health inequalities, especially the dominant contribution of residential regions and provinces at birth to IOp in health, besides programs/interventions focusing on promoting individual healthy lifestyles and health literacy, the government should also focus on the implementation of disease control policies at the regional (urban/rural) and province levels such as developing an equitable health care system,

to mitigate regional health inequalities. The new *Basic Healthcare and Health Promotion Law* (implemented on June 1, 2020), establishes a nutrition monitoring system to 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 effective measures to promote childhood nutrition and health for socioeconomically disadvantaged families 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**	**High-risk definition**
Glycated haemoglobin (HbA1c)	Metabolism	Long-term glucose metabolism (past 30-90 days)	≥ 6.5%
Cholesterol ratio	Metabolism	Long-term atherosclerotic risk	> 5
Triglycerides	Metabolism	Important source of energy, high levels indicate cardiovascular risk	≥ 200mg/dl
Waist to height ratio (WHR)	Metabolism	Long-term energy metabolism and storage, higher ratios indicate greater adipose tissue distribution	≥ 0.5 for males and 0.48 for females
Systolic blood pressure (SBP)	Cardiovascular	Cardiovascular health	≥ 140mmHg
C-reactive protein (CRP)	Inflammation	Acute inflammation	> 3mg/L
White blood cell count (WBC)	Inflammation	Immune system activity	≥ 11×10^3/μL
Creatinine	Excretory	Renal functioning	> 1.4mg/dl

Source: Edes and Crews (2017). The cut-offs of high risks refer to Chen et al. (2019b), Wang et al. (2001) and Zeng et al. (2014).

TABLE 2

DESCRIPTIVE STATISTICS: HEALTH OUTCOMES AND CIRCUMSTANCES

Variables	2011			2015			
	Mean/ proportions	SD	Obs.	Mean/ proportions	SD	Obs.	Mean diff.
Biomarkers							
Allostatic load (AL)	30.026	3.819	2593	30.561	3.778	4188	0.535***
Glycated haemoglobin (HbA1c, %)	5.277	0.780	3239	6.067	1.033	4648	0.790***
Cholesterol ratio	4.181	1.585	3214	3.772	1.088	4632	-0.410***
Triglycerides (mg/dL)	134.607	100.852	3216	139.872	86.67	4632	5.265*
C-reactive protein (CRP, mg/L)	1.723	1.761	3064	2.033	1.872	4409	0.310***
Waist to height ratio (WHR)	0.543	0.085	2885	0.544	0.085	4547	0.001
Systolic blood pressure (SBP, mmHg)	134.849	22.114	2872	132.312	20.96	4545	-2.537***
White blood cell count (WBC, in thousands/μL)	6.197	1.856	3192	5.963	1.842	4590	-0.234***
Creatinine (mg/dL)	0.811	0.203	3211	0.855	0.346	4632	0.044***
Circumstances							
Gender (1=male, 0=female)	0.492		3239	0.504		4648	0.012
Age	67.426	6.083	3239	68.092	6.595	4648	0.666***
Urban/rural residence at birth (1=rural, 0=urban)	0.912		3239	0.899		4648	-0.013
War							
Born in the Japanese War era	0.403		3239	0.288		4648	-0.115***
Born in the Civil War era	0.289		3239	0.213		4648	-0.076***
Parental health status and health behaviors							
Parental health status	0.162		3239	0.174		4648	0.012
Mother's smoking	0.101		3239	0.108		4648	0.007
Father's smoking	0.475		3239	0.492		4648	0.016
Father's alcohol drinking	0.066		3239	0.063		4648	-0.003
Health and nutrition in childhood							
Self-reported health before age 15			3239			4648	
Much less healthy	0.056			0.049			-0.007
Somewhat less healthy	0.080			0.081			0.001
About average	0.508			0.507			-0.001
Somewhat healthier	0.195			0.204			0.009
Much healthier	0.161			0.159			-0.002
Experienced hunger before age 17	0.725		3239	0.774		4648	0.049***
Household SES in childhood							

Parental political status	0.072	3239	0.095	4648	0.023***
Mother's education	0.944	3239	0.933	4648	-0.011
Father's education	0.686	3239	0.659	4648	-0.027*
Household economic status		3239		4648	
A lot worse off than them	0.231		0.232		0.001
Somewhat worse off than them	0.152		0.153		0.001
Same as them	0.513		0.511		-0.002
Somewhat better off than them	0.089		0.092		0.003
A lot better off than them	0.015		0.012		-0.003
Access to healthcare in childhood	0.307	3239	0.303	4648	-0.004

Notes: Sampling weights are applied. $^{***}p$ <0.01, $^{**}p$ <0.05 and $^{*}p$ <0.1.

TABLE 3

TOTAL HEALTH INEQUALITY AND IOP IN HEALTH: MEAN-BASED MLD INDEX

Biomarkers	Total inequality [a]	IOp		Obs.
		Absolute IOp [b]	% of total inequality [c=b/a]	
Panel A: AL				
AL	0.0075***	0.0003***	4.00	6781
	(0.0002)	(0.0001)		
Panel B: Specific biomarkers				
HbA1c	0.0123***	0.0004***	3.25	7887
	(0.0005)	(0.0001)		
Cholesterol ratio	0.0440***	0.0029***	6.59	7846
	(0.0016)	(0.0005)		
Triglycerides	0.1567***	0.0105***	6.70	7848
	(0.0042)	(0.0015)		
CRP	0.3923***	0.0079***	2.01	7473
	(0.0069)	(0.0024)		
WHR	0.0164***	0.0022***	13.41	7432
	(0.0008)	(0.0002)		
SBP	0.0128***	0.0007***	5.47	7417
	(0.0003)	(0.0001)		
WBC	0.0407***	0.0017***	4.18	7782
	(0.0012)	(0.0003)		
Creatinine	0.0380***	0.0091***	23.95	7843
	(0.0022)	(0.0005)		

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

TABLE 4

CONTRIBUTIONS OF CIRCUMSTANCES TO IOP IN HEALTH: MEAN-BASED SHAPLEY DECOMPOSITION

Biomarkers	Gender	Age	Region/ province at birth	War	Parental health status and health behaviors	Health and nutrition in childhood	Household SES	Access to healthcare in childhood
Panel A: AL								
AL	5.85%***	12.23%***	59.81%***	0.64%	3.19%	4.00%	13.14%***	1.12%
Panel B: Specific biomarkers								
HbA1c	11.77%***	3.10%**	48.78%***	24.75%***	3.49%*	2.41%	4.95%	0.75%*
Cholesterol ratio	17.92%***	3.07%***	56.50%***	4.17%***	5.47%*	4.28%	8.51%**	0.07%
Triglycerides	42.50%***	4.15%***	38.46%***	0.53%	2.09%	4.60%**	7.43%*	0.24%
CRP	0.37%	9.30%***	65.28%***	4.44%*	2.77%	2.60%	13.60%	1.65%
WHR	52.13%***	0.49%***	39.41%***	0.08%	0.83%	4.00%***	2.51%	0.57%**
SBP	0.28%	41.93%***	36.43%***	2.53%	1.97%	7.90%	8.38%**	0.58%
WBC	16.63%***	0.05%	77.71%***	0.18%	2.10%	1.29%	1.55%	0.50%
Creatinine	74.12%***	7.13%***	15.99%***	0.28%	0.76%	0.69%	0.96%	0.06%**

Notes: Region and province include rural/urban residence and provinces at birth. War includes born in the 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 in childhood include self-reported health before age 15 and whether experiencing 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 5

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 in childhood	Household SES	Access to healthcare in childhood
Panel A: AL									
AL	Q25	5.78%***	15.29%***	63.10%***	1.09%	2.58%	4.37%*	7.62%*	0.17%
	Q50	5.89%***	8.49%***	68.47%***	0.70%	1.72%	7.18%	7.52%	0.02%
	Q75	3.78%**	5.28%***	47.51%***	0.75%	7.29%	5.85%	26.22%***	3.32%
Panel B: Specific biomarkers									
HbA1c	Q25	3.49%***	1.60%***	67.40%***	14.65%***	2.78%*	8.40%***	1.65%	0.04%
	Q50	7.60%***	9.10%***	47.57%***	22.49%***	0.68%	7.73%***	4.68%**	0.15%
	Q75	18.99%***	11.30%***	41.20%***	10.85%***	5.15%	5.63%	6.25%	0.62%
Cholesterol ratio	Q25	16.00%***	0.99%	66.65%***	1.65%**	3.01%*	6.42%***	4.71%	0.57%
	Q50	16.35%***	2.71%**	58.85%***	3.57%***	8.83%***	3.01%	6.59%	0.08%
	Q75	7.37%***	3.68%***	55.35%***	9.75%***	8.00%***	3.29%	12.24%***	0.32%
Triglycerides [a]	Q25	-	-	-	-	-	-	-	-
	Q50	44.43%***	3.10%**	36.08%***	0.18%	4.27%***	3.62%**	8.19%***	0.12%
	Q75	35.67%***	3.84%**	35.90%***	0.46%	1.62%	13.26%***	8.22%	1.05%
CRP [b]	Q25	-	-	-	-	-	-	-	-
	Q50	-	-	-	-	-	-	-	-
	Q75	2.16%	4.11%**	63.55%***	2.59%	6.55%	4.18%	14.06%	2.79%
WHR	Q25	62.32%***	0.13%*	28.37%***	0.07%	1.21%	4.18%***	3.66%**	0.05%
	Q50	72.68%***	0.61%***	20.59%***	0.23%	1.58%	1.77%*	2.03%	0.50%**
	Q75	70.48%***	2.16%***	17.59%***	0.49%	1.36%	3.99%***	3.21%**	0.73%*
SBP	Q25	0.32%	35.67%***	34.42%***	2.21%	0.97%	14.59%	11.02%**	0.80%
	Q50	0.16%	44.51%***	33.67%***	3.06%	1.71%	7.95%	8.90%**	0.03%
	Q75	1.12%***	39.46%***	39.74%***	2.24%	5.15%	5.91%	5.94%	0.44%
WBC	Q25	10.46%***	0.03%	73.69%***	0.45%	7.14%	3.08%	4.54%	0.62%
	Q50	13.53%***	0.25%	68.89%***	0.91%	2.51%	7.41%**	6.29%**	0.21%
	Q75	22.69%***	0.10%	67.51%***	0.51%	2.59%	2.79%	3.62%	0.20%
Creatinine	Q25	80.48%***	4.87%***	11.47%***	0.29%	1.14%	0.37%	1.31%	0.06%

Q50	80.63%***	4.82%***	11.70%***	0.30%	0.41%	0.93%	1.15%	0.07%
Q75	66.18%***	6.70%***	23.29%***	0.25%	0.50%	2.03%***	0.83%	0.23%

Notes: Region and province include rural/urban residence and provinces at birth. War includes born in the 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 in childhood include self-reported health before age 15 and whether experiencing 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. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

[a] As discussed in Figure 1, given that MLD measures inequality of positive values, we only show absolute IOp at the 50% and 75% quantiles.

[b] As discussed in Figure 1, given that MLD measures inequality of positive values, we only show absolute IOp at the 75% quantile.

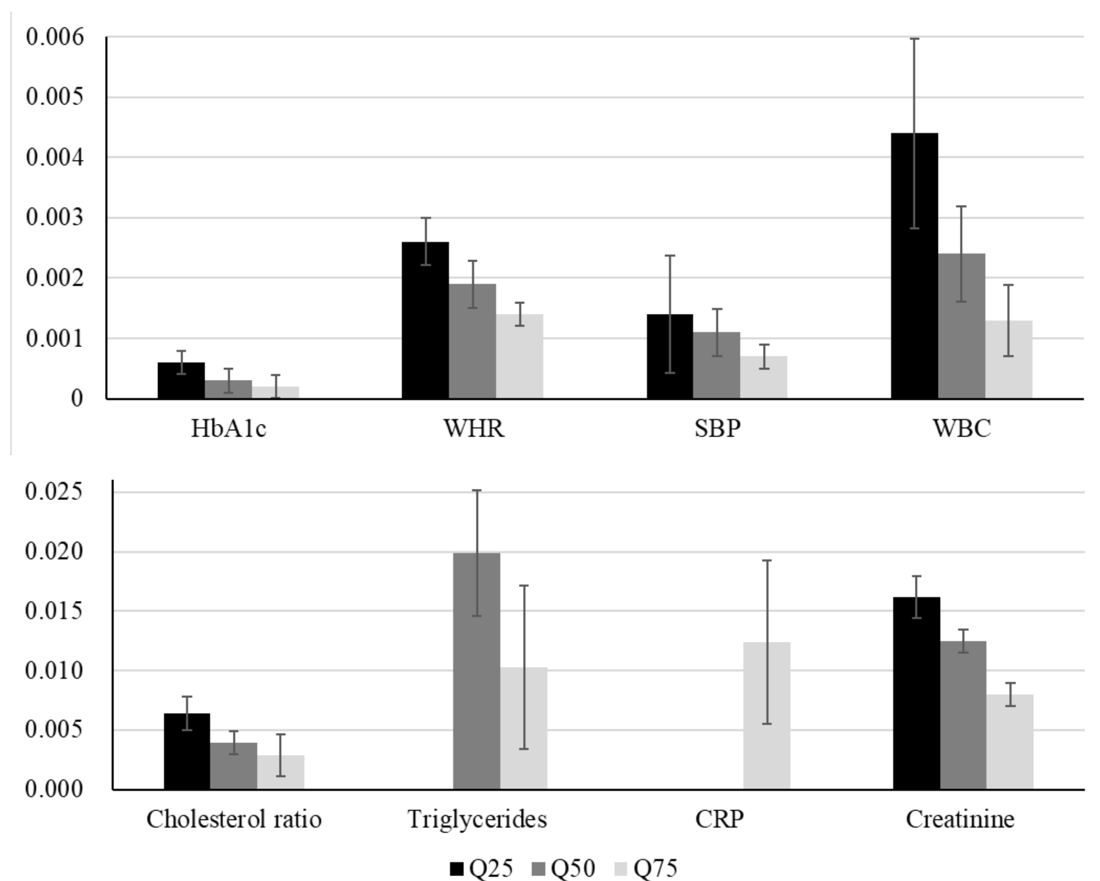

Figure 1 IOp in Health at Different Quantiles (MLD index)

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

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
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	0.509	0.498	-0.011	0.505	0.495	-0.010
Age	66.962	67.585	0.623^{***}	67.693	68.074	0.381^{***}
Urban/rural residence at birth	0.938	0.934	-0.003	0.933	0.930	-0.004
Born in the Japanese War era	0.391	0.386	-0.006	0.275	0.281	0.006
Born in the Civil War era	0.309	0.296	-0.014	0.227	0.223	-0.004
Parental health status	0.179	0.191	0.012	0.191	0.199	0.008
Mother's smoking	0.104	0.104	0.000	0.109	0.107	-0.002
Father's smoking	0.476	0.469	-0.007	0.490	0.488	-0.003
Father's alcohol drinking	0.065	0.068	0.002	0.062	0.063	0.001
Self-reported health before age 15						
Much less healthy	0.047	0.055	0.007	0.048	0.054	0.006
Somewhat less healthy	0.077	0.077	0.001	0.079	0.082	0.003
About average	0.526	0.526	0.000	0.514	0.512	-0.002
Somewhat healthier	0.188	0.189	0.002	0.194	0.194	0.000
Much healthier	0.162	0.153	-0.010	0.164	0.157	-0.007
Having enough food before age 17	0.248	0.254	0.006	0.211	0.218	0.007
Parental political status	0.074	0.067	-0.008	0.093	0.090	-0.003
Mother's education	0.951	0.954	0.002	0.942	0.943	0.001
Father's education	0.705	0.721	0.016	0.681	0.690	0.009
Household SES						
A lot worse off than them	0.237	0.260	0.023	0.239	0.260	0.021
Somewhat worse off than them	0.154	0.155	0.001	0.160	0.158	-0.002
Same as them	0.519	0.499	-0.020	0.513	0.496	-0.017
Somewhat better off than them	0.079	0.076	-0.003	0.080	0.078	-0.002
A lot better off than them	0.012	0.010	-0.001	0.009	0.009	0.000
Access to healthcare in childhood	0.304	0.297	-0.007	0.289	0.291	0.002

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
Panel A: 2011									
Gender	0.965	0.970	0.971	0.833	0.807	0.841	0.974	0.940	0.718
Age	0.992	0.930	0.913	0.763	0.578	0.478	0.964	0.922	0.219
Urban/rural residence at birth	0.869	0.974	0.967	0.969	0.357	0.293	0.589	0.982	0.217
Born in the Japanese War era	0.926	0.982	0.993	0.975	0.892	0.824	0.985	0.986	0.783
Born in the Civil War era	0.958	0.907	0.894	0.931	0.849	0.965	0.946	0.884	0.854
Parental health status	0.979	0.913	0.930	0.958	0.820	0.783	0.985	0.875	0.800
Mother's smoking	0.838	0.698	0.692	0.612	0.605	0.687	0.930	0.676	0.848
Father's smoking	0.984	0.995	0.996	0.860	0.903	0.928	0.896	0.977	0.828
Father's alcohol drinking	0.996	0.938	0.943	0.861	0.872	0.822	0.877	0.930	0.915
Self-reported health before age 15									
Much less healthy	0.877	0.927	0.931	0.919	0.841	0.810	0.972	0.920	0.890
Somewhat less healthy	0.917	0.893	0.925	0.948	0.943	0.895	0.820	0.902	0.993
About average	0.985	0.932	0.933	0.933	0.986	0.953	0.981	0.941	0.795
Somewhat healthier	0.938	0.844	0.854	0.734	0.996	0.964	0.853	0.830	0.833
Much healthier	0.965	0.779	0.771	0.624	0.890	0.863	0.982	0.766	0.514
Having enough food before age 17	0.867	0.963	0.974	0.800	0.824	0.708	0.950	0.997	0.546
Parental political status	0.994	0.924	0.929	0.810	0.979	0.982	0.797	0.915	0.919
Mother's education	0.981	0.983	0.978	0.805	0.782	0.620	0.755	0.990	0.359
Father's education	0.925	0.977	0.986	0.891	0.859	0.996	0.921	0.974	0.900
Household SES									
A lot worse off than them	0.980	0.855	0.867	0.959	0.757	0.683	0.906	0.825	0.787
Somewhat worse off than them	0.960	0.881	0.889	0.789	0.791	0.791	0.909	0.868	0.713
Same as them	0.981	1.000	0.979	0.832	0.800	0.752	0.852	0.991	0.683
Somewhat better off than them	0.990	0.917	0.923	0.884	0.844	0.805	0.999	0.908	0.910
A lot better off than them	0.845	0.965	0.944	0.939	0.645	0.659	0.989	0.940	0.464
Access to healthcare in childhood	0.953	0.987	0.974	0.842	0.912	0.817	0.871	0.985	0.723
Panel B: 2015									
Gender	0.975	0.957	0.957	0.852	0.906	0.807	0.969	0.957	0.848
Age	0.954	0.966	0.966	0.447	0.650	0.851	0.922	0.966	0.182
Urban/rural residence at birth	0.985	0.949	0.949	0.876	0.978	0.951	0.889	0.949	0.952
Born in the Japanese War era	0.962	0.913	0.913	0.765	0.865	0.985	0.886	0.913	0.748
Born in the Civil War era	0.969	0.937	0.937	0.762	0.861	0.908	0.906	0.937	0.676
Parental health status	0.986	0.987	0.987	0.959	0.979	0.950	0.949	0.987	0.785
Mother's smoking	0.980	0.987	0.987	0.978	0.973	0.994	0.944	0.987	0.965
Father's smoking	0.976	0.988	0.988	0.920	0.884	0.901	0.836	0.988	0.614
Father's alcohol drinking	0.985	0.912	0.912	0.954	0.868	0.967	0.999	0.912	0.774
Self-reported health before age 15									
Much less healthy	0.974	0.927	0.927	0.809	0.972	0.946	0.966	0.927	0.811
Somewhat less healthy	0.983	0.975	0.975	0.856	0.928	0.964	0.996	0.975	0.874
About average	0.977	0.981	0.981	0.888	0.760	0.907	0.943	0.981	0.865
Somewhat healthier	0.972	0.989	0.989	0.831	0.987	0.983	0.971	0.989	0.748
Much healthier	0.997	0.938	0.938	0.964	0.756	0.851	0.970	0.938	0.549
Having enough food before age 17	0.990	0.997	0.997	0.916	0.903	0.952	0.913	0.997	0.770
Parental political status	0.982	0.976	0.976	0.823	0.992	0.927	0.969	0.976	0.754
Mother's education	0.986	0.941	0.941	0.956	0.952	0.983	0.902	0.941	0.770

Father's education	0.978	0.976	0.976	0.954	0.926	0.844	0.725	0.976	0.566
Household SES									
A lot worse off than them	0.987	0.952	0.952	0.845	0.896	0.965	0.970	0.952	0.748
Somewhat worse off than them	0.975	0.993	0.993	0.824	0.969	0.976	0.987	0.993	0.863
Same as them	0.977	0.963	0.963	0.967	0.939	0.956	0.962	0.963	0.891
Somewhat better off than them	0.983	0.975	0.975	0.888	0.977	0.941	0.944	0.975	0.922
A lot better off than them	0.917	0.929	0.929	0.829	0.906	0.998	0.872	0.929	0.725
Access to healthcare in childhood	1.000	0.970	0.970	0.943	0.866	0.951	0.876	0.970	0.908

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 Absolute IOp in health: RIF regressions (MLD index)

Biomarkers	Q25	Q50	Q75
Panel A: AL			
AL	0.0006***	0.0004***	0.0004***
	(0.0001)	(0.0001)	(0.0001)
Panel B: Specific biomarkers			
HbA1c	0.0006***	0.0003***	0.0002**
	(0.0001)	(0.0001)	(0.0001)
Cholesterol ratio	0.0064***	0.0039***	0.0029***
	(0.0007)	(0.0005)	(0.0009)
Triglycerides [a]	-	0.0199***	0.0103***
	-	(0.0027)	(0.0035)
CRP [b]	-	-	0.0124***
	-	-	(0.0035)
WHR	0.0026***	0.0019***	0.0014***
	(0.0002)	(0.0002)	(0.0001)
SBP	0.0014***	0.0011***	0.0007***
	(0.0005)	(0.0002)	(0.0001)
WBC	0.0044***	0.0024***	0.0013***
	(0.0008)	(0.0004)	(0.0003)
Creatinine	0.0162***	0.0125***	0.0080***
	(0.0009)	(0.0005)	(0.0005)

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 in triglycerides 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 in CRP at the 75% quantile.

Table A.5 Total inequality and IOp in health: Mean-based regressions (variance share)

Biomarkers	IOp (% of total inequality)	Obs.
Panel A: AL		
AL	3.9903***	6781
	(0.6265)	
Panel B: Specific biomarkers		
Glycated haemoglobin	3.4594***	7887
	(0.5973)	
Cholesterol ratio	7.0446***	7846
	(1.1732)	
Triglycerides	7.3334***	7848
	(0.9291)	
C-reactive protein	1.9375***	7473
	(0.6222)	
Waist to height ratio	10.9943***	7432
	(0.8366)	
Systolic blood pressure	5.6268***	7417
	(0.9296)	
White blood cell count	4.2280***	7782
	(0.6261)	
Creatinine	26.8392***	7843
	(1.2721)	

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). *** $p < 0.01$.

Table A.6 Contributions of circumstances to IOp in health: mean-based Shapley decomposition (variance share)

Biomarkers	Gender	Age	Region/ Province at birth	War	Parental health status and health behaviors	Health and nutrition in childhood	Household SES	Access to healthcare in childhood
Panel A: AL								
AL	5.85%***	12.22%***	59.89%***	0.64%	3.19%	4.00%	13.08%***	1.12%
Panel B: Specific biomarkers								
HbA1c	11.77%***	3.08%**	48.89%***	24.70%***	3.49%*	2.41%	4.92%	0.75%*
Cholesterol ratio	17.87%***	3.12%***	56.77%***	4.19%***	5.47%*	4.23%	8.28%**	0.07%
Triglycerides	42.79%***	4.20%***	38.24%***	0.52%	2.14%	4.55%**	7.31%*	0.25%
CRP	0.36%	9.07%***	66.10%***	4.30%*	2.74%	2.61%	13.19%	1.63%
WHR	51.89%***	0.48%***	39.74%***	0.08%	0.82%	3.96%***	2.47%	0.56%**
SBP	0.27%	41.73%***	36.44%***	2.55%	1.97%	8.01%	8.44%**	0.58%
WBC	16.68%***	0.05%	77.65%***	0.18%	2.09%	1.29%	1.56%	0.50%
Creatinine	74.23%***	7.06%***	15.94%***	0.28%	0.76%	0.70%	0.97%	0.06%**

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

Table A.7 Contributions of circumstances to IOp in health: RIF-based Shapley decomposition (variance share)

Biomarkers	Quantile	Gender	Age	Region/ Province at birth	War	Parental health status and health behaviors	Health and nutrition in childhood	Household SES	Access to healthcare in childhood
Panel A: AL									
AL	Q25	8.32%***	11.22%***	62.91%***	0.55%	3.99%	4.21%	8.43%	0.35%
	Q50	10.89%***	4.53%***	63.60%***	0.47%	1.81%	6.35%	12.11%	0.25%
	Q75	14.78%***	3.32%*	45.54%***	0.21%	6.30%	3.28%	23.62%	2.96%
Panel B: Specific biomarkers									
HbA1c	Q25	2.57%***	2.14%**	66.19 %***	19.93 %*	0.70%	5.69%	2.75%	0.04%
	Q50	8.54%***	9.18%	37.57%***	31.28%	1.51%	5.11%	6.70%	0.11%
	Q75	20.65%***	11.68%	35.90%***	13.38%	2.36%*	6.21%	9.45%	0.37%
Cholesterol ratio	Q25	20.48%***	0.88%	64.10%***	0.32%	3.84%	3.67%**	6.54 %	0.17%
	Q50	13.63%***	3.88%	62.09%***	2.45%	7.18%	3.05%	7.54%	0.18%
	Q75	7.44%***	5.31%	56.31%***	5.66%	5.30%	3.41%*	15.01%*	1.56%
Triglycerides	Q25	55.39%	2.34%	32.95%	0.31%	2.48%	1.55%	4.76%	0.22%
	Q50	49.36%***	3.45%	34.41%***	0.68%	2.97%	2.03%	6.94%	0.16%
	Q75	33.07%***	8.02%	38.30%***	2.37%	3.04%	3.99%**	10.38%	0.82%
CRP	Q25	0.47%	9.86%	57.02%	4.62%	13.50%	2.45%	10.14%	1.93%
	Q50	3.60%	11.99%	49.33%	9.67%	6.43%	8.46%	8.43%	2.10%
	Q75	2.09%	9.31%***	52.69%***	6.67%	15.90%	2.58%	6.71%	4.06%
WHR	Q25	66.07%***	0.09%	27.15%***	0.17%	1.01%	2.93%*	2.49%	0.07%
	Q50	73.72%***	0.23 %	21.67%***	0.11%	0.62%	1.43%*	1.89%	0.33%*
	Q75	73.10%***	0.75%***	21.73%***	0.31%	0.50%	1.96%	1.29%	0.36%
SBP	Q25	1.00%	41.27%***	41.99%***	6.54%**	2.24%	3.55%	2.77%	0.64%
	Q50	0.99%*	48.76%***	34.67%***	5.31%	2.01%	4.69%	3.50%**	0.06%
	Q75	4.34%***	39.14%***	40.22%	3.12%	2.72%*	6.33%	3.70%	0.42%
WBC	Q25	11.01%***	0.15%	77.62%***	0.16%	3.25%	**3.07%**	4.72%	0.02%
	Q50	7.59%***	1.53%	76.61%***	1.58%	2.84%*	5.18%	4.66%	0.01%
	Q75	15.17%***	0.13%**	75.55%***	0.99%	1.99%	1.38%	4.78%	0.01%
Creatinine	Q25	86.04%***	3.81%***	8.25%***	0.27%	0.62%	0.18%	0.77%	0.05%
	Q50	82.88%***	4.65%***	10.41%***	0.46%	0.49%	0.50%*	0.56%	0.05%
	Q75	68.88%***	7.84%***	19.95%***	0.41%	0.91%	1.31%***	0.45%***	0.26%

Notes: Region and province include rural/urban residence and provinces at birth. War includes born in the 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 in childhood include self-reported health before age 15 and whether experiencing 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 A.8 Total health inequality and IOp in health: mean-based MLD index (2015 wave)

Biomarkers	Total inequality [a]	IOp		Obs.
		Absolute IOp [b]	% of total inequality [c=b/a]	
Panel A: AL				
AL	0.0073*** (0.0002)	0.0003*** (0.0001)	4.11	4188
Panel B: Specific biomarkers				
HbA1c	0.0109*** (0.0007)	0.0004*** (0.0001)	3.67	4648
Cholesterol ratio	0.0307*** (0.0018)	0.0023*** (0.0003)	7.49	4632
Triglycerides	0.1466*** (0.0040)	0.0107*** (0.0018)	7.30	4632
CRP	0.3761*** (0.0093)	0.0107*** (0.0036)	2.84	4409
WHR	0.0163*** (0.0009)	0.0029*** (0.0004)	17.79	4547
SBP	0.0125*** (0.0004)	0.0008*** (0.0002)	6.40	4545
WBC	0.0405*** (0.0016)	0.0028*** (0.0005)	6.91	4590
Creatinine	0.0446*** (0.0035)	0.0102*** (0.0006)	22.87	4632

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

Table A.9 Contributions of circumstances to IOp in health: mean-based Shapley decomposition (2015 wave)

Biomarkers	Gender	Age	Region/ province at birth	War	Parental health status and health behaviors	Health and nutrition in childhood	Household SES	Access to healthcare in childhood
Panel A: AL								
AL	1.28%	8.23%***	66.03%***	1.24%	2.87%	4.60%	15.58%**	0.17%
Panel B: Specific biomarkers								
HbA1c	14.50%***	1.12%	62.94%***	1.34%	1.71%	7.30%	10.80%	0.28%
Cholesterol ratio	17.69%***	0.55%	60.44%***	1.91%	6.66%**	2.08%	10.66%**	0.02%
Triglycerides	42.67%***	7.11%***	35.06%***	0.64%	1.48%	2.84%	9.79%	0.41%
CRP	0.17%	1.65%	67.26%***	0.59%	1.27%	8.17%	20.88%**	0.02%
WHR	36.25%***	0.11%	56.00%***	0.30%	1.52%	3.06%**	2.57%*	0.19%
SBP	0.99%	37.52%***	40.26%***	2.95%	2.54%	4.11%	11.40%***	0.23%
WBC	15.90%***	0.22%	75.68%***	0.63%	2.74%	0.64%	3.65%	0.53%
Creatinine	71.71%***	7.77%***	16.88%***	1.11%	0.68%	0.64%	1.00%	0.21%***

Notes: Region and province include rural/urban residence and provinces at birth. War includes born in the 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 in childhood include self-reported health before age 15 and whether experiencing 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 A.10 Contributions of circumstances to IOp in health: RIF-based Shapley decomposition (2015 wave)

Biomarkers	Quantile	Gender	Age	Region/ Province at birth	War	Parental health status and health behaviors	Health and nutrition in childhood	Household SES	Access to healthcare in childhood
Panel A: AL									
AL	Q25	2.82%**	8.90%***	65.88%***	2.55%	1.60%	4.94%	12.31%**	0.99%
	Q50	0.67%	7.26%**	73.13%***	1.28%	3.13%	4.08%	9.77%	0.69%
	Q75	0.33%	3.09%*	59.54%***	1.23%	6.12%	3.23%	24.88%***	1.58%
Panel B: Specific biomarkers									
HbA1c	Q25	9.94%***	1.37%	73.14%***	3.64%*	2.01%	7.19%**	2.69%	0.03%
	Q50	19.57%***	6.30%**	44.05%***	3.84%	5.93%	14.19%*	6.09%	0.04%
	Q75	15.05%***	1.97%	46.34%***	1.07%	4.91%	16.70%*	13.81%	0.14%
Cholesterol ratio	Q25	20.09%***	0.12%	64.14%***	1.18%	2.28%	5.61%**	6.27%***	0.30%
	Q50	12.40%***	0.85%	65.17%***	2.45%*	9.84%**	1.43%	7.78%	0.08%
	Q75	5.91%**	0.66%	61.23%***	4.71%**	9.57%**	2.23%	15.20%*	0.48%
Triglycerides [a]	Q25	-	-	-	-	-	-	-	-
	Q50	36.98%***	4.58%**	41.14%***	0.42%	3.17%	1.56%	12.12%***	0.03%
	Q75	35.15%***	6.11%**	42.19%***	0.81%	0.91%	4.32%	9.22%	1.29%
CRP [b]	Q25	-	-	-	-	-	-	-	-
	Q50	-	-	-	-	-	-	-	-
	Q75	0.07%	1.19%	63.29%***	0.73%	4.40%	3.74%	23.87%	2.72%
WHR	Q25	60.82%***	0.06%	26.63%***	0.19%	2.21%	4.80%***	5.20%***	0.08%
	Q50	69.35%***	0.78%**	22.72%***	0.36%	2.64%	1.10%	2.75%	0.29%
	Q75	64.48%***	1.69%**	21.67%***	1.22%	1.76%	4.47%**	3.99%**	0.71%
SBP	Q25	1.11%	31.53%***	44.86%***	2.82%	2.94%	6.88%	9.81%	0.04%
	Q50	0.85%	40.68%***	33.57%***	4.71%	2.33%	4.90%	12.89%**	0.07%
	Q75	0.66%	29.80%***	49.97%***	2.44%	4.17%	2.52%	10.36%	0.08%
WBC	Q25	6.26%***	0.02%	76.54%***	0.04%	8.73%*	1.65%	6.52%*	0.24%
	Q50	13.36%**	0.04%	74.27%***	0.56%	1.87%	3.67%	6.11%*	0.12%
	Q75	19.45%***	1.41%	68.30%***	1.89%	2.39%	3.41%	2.53%	0.63%*
Creatinine	Q25	84.60%***	4.75%***	7.87%***	0.53%	0.87%	0.36%	0.78%	0.23%
	Q50	78.17%***	5.63%***	12.22%***	1.45%	0.61%	0.64%	1.24%	0.04%
	Q75	61.46%***	9.92%***	23.31%***	0.82%	1.10%	1.49%	1.85%	0.06%

Notes: Region and province include rural/urban residence and provinces at birth. War includes born in the 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 in childhood include self-reported health before age 15 and whether experiencing 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. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

[a] As discussed in Figure 1, given that MLD measures inequality of positive values, we only show absolute IOp at the 50% and 75% quantiles.

[b] As discussed in Figure 1, given that MLD measures inequality of positive values, we only show absolute IOp at the 75% quantile.

Table A.11 IOp in biomarkers at high-level risks (using dissimilarity index)

Biomarkers	Pooled sample of 2011 and 2015 CHARLS	2015
HbA1c	0.1581***	0.1602***
	(0.0072)	(0.0116)
Cholesterol ratio	0.1758***	0.2278***
	(0.0199)	(0.0195)
Triglycerides	0.1846***	0.1843***
	(0.0174)	(0.0142)
CRP	0.1068***	0.1248***
	(0.0078)	(0.0110)
WHR	0.0852***	0.0864***
	(0.0105)	(0.0134)
SBP	0.1056***	0.1142***
	(0.0116)	(0.0150)
WBC	0.2812***	0.3330***
	(0.0031)	(0.0045)
Creatinine	0.4245***	0.4548***
	(0.0053)	(0.0091)

Notes: Sampling weights are applied. Bootstrapped standard errors in parenthesis (500 replications). When applying analysis to dummy variables, dissimilarity index is used to measure inequality (Wendelspiess Chávez Juárez and Soloaga, 2014). ***p <0.01.

Table A.12 Contributions of circumstances to IOp in biomarkers at high-level risks: Shapley decomposition (using dissimilarity index for pooled sample of 2011 and 2015 CHARLS)

Biomarkers	Gender	Age	Region/ province	War	Parental health status and health behaviors	Health and nutrition in childhood	Household SES	Access to healthcare in childhood
HbA1c	8.86%***	2.65%**	37.90%***	12.92%***	10.92%***	6.96%	16.16%***	3.63%
Cholesterol ratio	10.50%***	4.34%***	41.87%***	9.62%***	9.02%***	12.17%***	11.85%***	0.64%
Triglycerides	23.58%***	10.90%***	36.28%***	1.65%	5.17%**	11.73%***	9.19%**	1.39%
CRP	2.26%	6.10%***	46.54%***	7.48%**	13.28%**	4.11%	16.34%***	3.89%
WHR	69.75%***	0.49%	16.78%***	0.42%	2.20%	5.51%***	4.81%***	0.02%
SBP	0.32%	30.76%***	33.46%***	9.91%	3.51%	9.77%**	12.05%***	0.23%
WBC	5.01%	2.90%	47.87%***	0.63%	12.63%*	8.98%	19.62%	2.36%
Creatinine	13.61%***	12.18%***	51.23%***	5.01%***	2.43%	4.42%	10.21%***	0.85%

Notes: Region and province include rural/urban residence and provinces at birth. War includes born in the 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 in childhood include self-reported health before age 15 and whether experiencing 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 A.13 Contributions of circumstances to IOp in health: mean-based Shapley decomposition (without wartime)

Biomarkers	Gender	Age	Region/ Province at birth	Parental health status and health behaviors	Health and Nutrition in childhood	Household SES	Access to healthcare in childhood
Panel A: AL							
AL	5.84%***	12.50%***	60.11%***	3.21%	4.05%	13.16%***	1.13%
Panel B: Specific biomarkers							
HbA1c	16.25%***	3.19%***	64.78%***	4.00%*	3.28%	7.44%	1.06%
Cholesterol ratio	19.07%***	2.24%**	59.38%***	5.94%***	4.65%***	8.65%***	0.07%
Triglycerides	42.83%***	4.02%***	38.70%***	2.10%*	4.62%***	7.49%***	0.25%
CRP	0.40%	8.59%***	68.74%***	3.01%	2.74%	14.75%***	1.77%
WHR	52.15%***	0.51%**	39.43%***	0.83%	4.01%***	2.50%	0.56%**
SBP	0.27%	44.25%***	36.45%***	1.97%	7.97%***	8.52%***	0.57%
WBC	16.70%***	0.03%	77.88%***	2.11%	1.26%	1.54%	0.49%
Creatinine	74.21%***	7.28%***	16.01%***	0.76%***	0.70%	0.97%	0.06%*

Notes: Region and province include rural/urban residence and provinces at birth. 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 in childhood include self-reported health before age 15 and whether experiencing 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 A.14 IOp in health: mean-based MLD index

Biomarkers	All circumstances [a]	Excluding gender and age [b]	Obs.
Panel A: AL			
AL	0.0003***	0.0002***	6781
	(0.0001)	(0.00004)	
Panel B: Specific biomarkers			
HbA1c	0.0004***	0.0003***	7887
	(0.0001)	(0.0001)	
Cholesterol ratio	0.0029***	0.0023***	7846
	(0.0005)	(0.0005)	
Triglycerides	0.0105***	0.0058***	7848
	(0.0015)	(0.0012)	
CRP	0.0079***	0.0070***	7473
	(0.0024)	(0.0022)	
WHR	0.0022***	0.0011***	7432
	(0.0002)	(0.0002)	
SBP	0.0007***	0.0004***	7417
	(0.0001)	(0.0001)	
WBC	0.0017***	0.0014***	7782
	(0.0003)	(0.0002)	
Creatinine	0.0091***	0.0018***	7843

	(0.0005)	(0.0002)

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

Table A.15 Contributions of circumstances to IOp in health: mean-based Shapley decomposition (excluding gender and age)

Biomarkers	Region/ province	War	Parental health status and health behaviors	Health and nutrition in childhood	Household SES	Access to healthcare in childhood
Panel A: AL						
AL	73.87%***	0.98%	3.35%	4.92%	15.57%***	1.31%
Panel B: Specific biomarkers						
HbA1c	57.77%***	29.61%***	3.72%*	2.36%	5.77%	0.77%
Cholesterol ratio	71.95%***	3.92%***	7.17%***	5.90%***	11.04%***	0.04%
Triglycerides	71.17%***	0.89%	4.24%**	9.34%***	14.10%***	0.27%
CRP	74.03%***	3.88%	3.11%	2.76%	14.38%**	1.85%
WHR	83.21%***	0.25%	1.68%	8.53%***	5.61%	0.72%
SBP	56.67%***	7.78%***	3.68%	15.84%***	15.04%***	0.99%
WBC	93.48%***	0.23%	2.85%	1.15%	1.81%	0.48%
Creatinine	81.70%***	1.87%**	4.60%***	5.01%***	6.78%***	0.03%

Notes: Region and province include rural/urban residence and provinces at birth. War includes born in the 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 in childhood include self-reported health before age 15 and whether experiencing 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. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

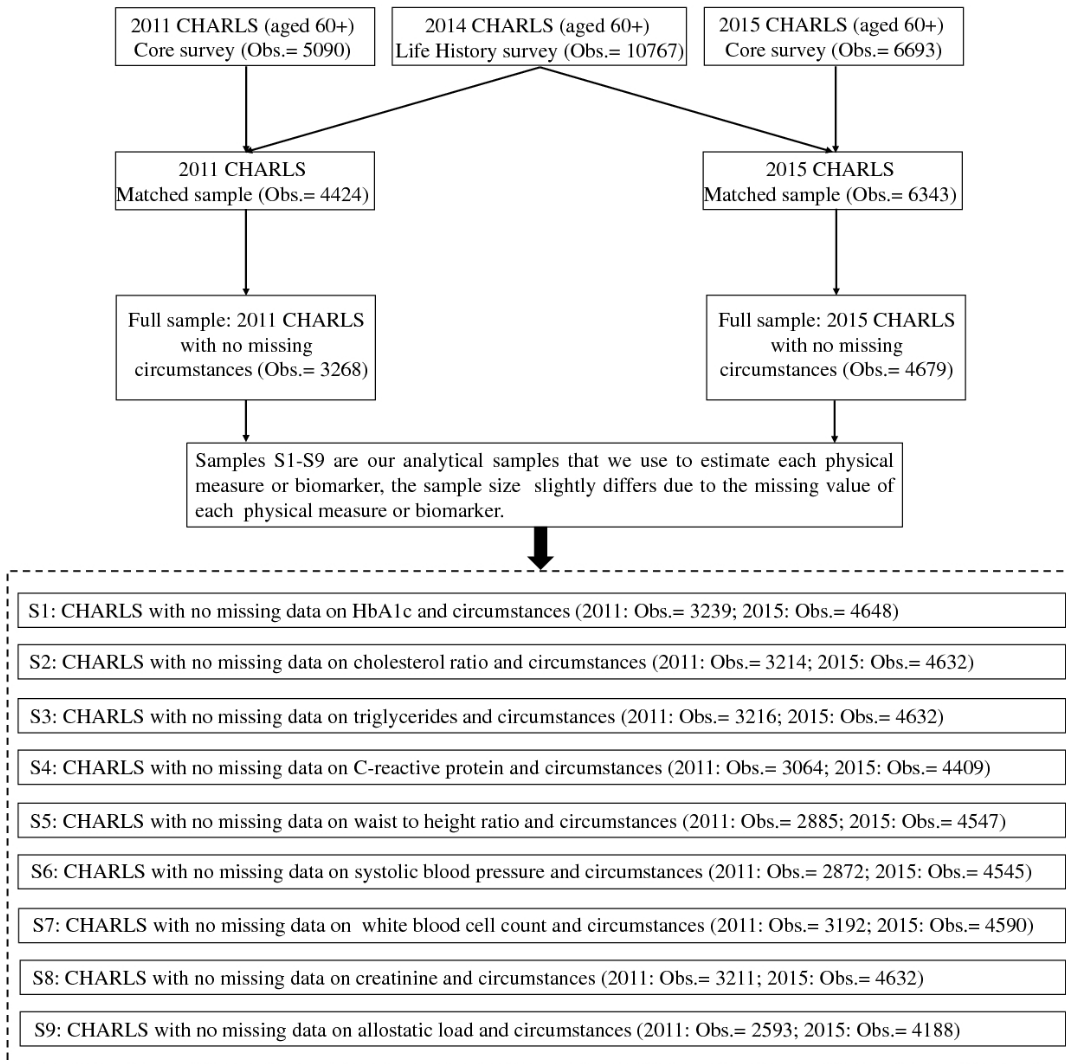

Figure A.1 Flow chart of study samples

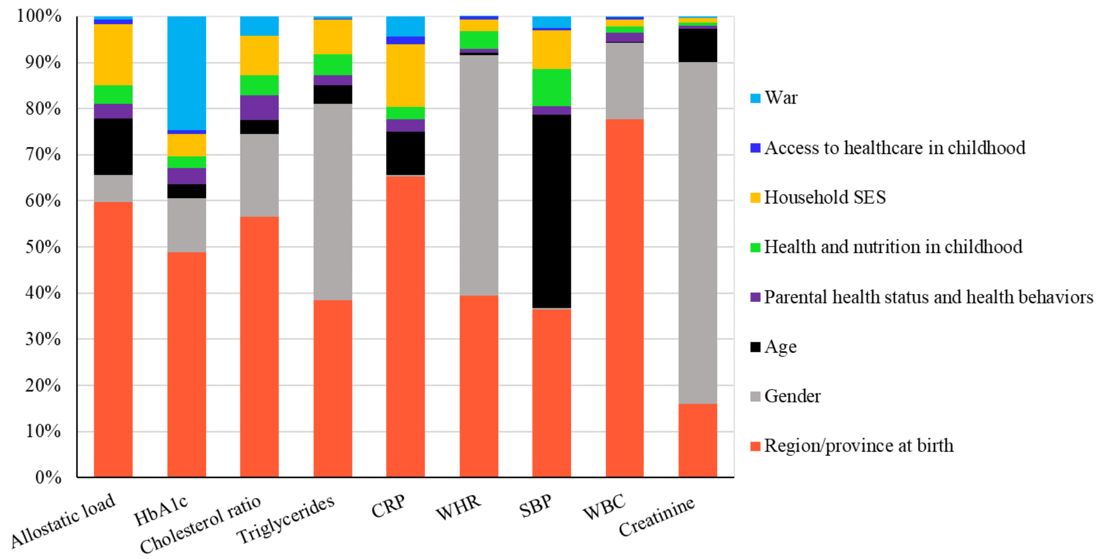

Figure A.2 Contributions of circumstances to IOp in health: mean-based Shapley decomposition

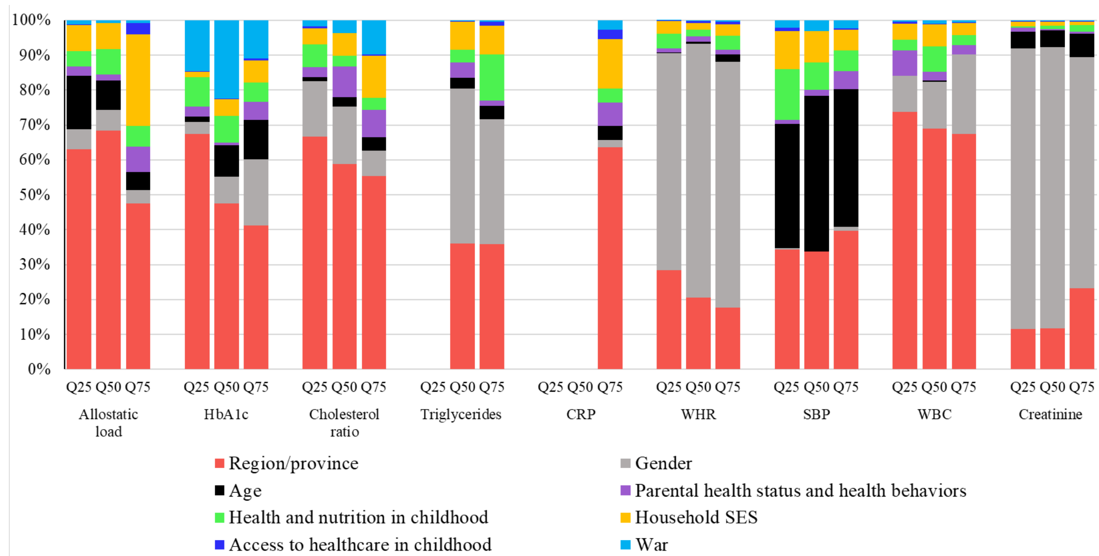

Figure A.3 Contributions of circumstances to IOp in health: RIF-based Shapley decomposition