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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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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 percent and 23.95 percent 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.

JEL Codes: 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).

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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, 2002; Roemer and Trannoy, 2016).

Following Roemer's conceptual framework for IOp (Roemer, 1998, 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 (Jusot *et al*., 2013; Carrieri and Jones, 2018). 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 (Jusot *et al*., 2013; Carrieri and Jones, 2018; Davillas and Jones, 2020).

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 percent of the population, and this is projected to reach 491.5 million (36.5 percent 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 percent to 14 percent), 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, Smith, *et al*., 2014). 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 (Tang *et al*., 2008; Baeten *et al*., 2013). 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*., 2008, 2011; Rossouw *et al*., 2018). Furthermore, 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*., 2008, 2011; 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 (Rosa Dias, 2009; Carrieri and Jones, 2018; Davillas and Jones, 2020), 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 percent 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 percent 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 percent and 95 percent 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 percent to 22 percent 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 percent and 23 percent 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 and Jones, 2018; Carrieri *et al.*, 2020; 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

[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.

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, Rosa Dias, 2009; Davillas and Jones, 2020), 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:

$$y_i = h\left(C_i, E\left(C_i, v_i\right), u_i\right) \tag{1}$$

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 (Fleurbaey and Schokkaert, 2009; Fleubaey and Peragine, 2013; 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 (Fleubaey and Peragine, 2013; Fajardo-Gonzalez, 2016; Ramos and Van de gaer, 2016; Davillas and Jones, 2020). 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 (Ferreira and Gignoux, 2011; Davillas and Jones, 2020).

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 $E(y_i \mid C_i)$ 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 (Ferreira and Gignoux, 2011; Davillas and Jones, 2020). 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 $\omega = 0$ (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:

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

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

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 (Shorrocks, 2013; Fajardo-Gonzalez, 2016). The main advantage of this decomposition technique is that it is path independent, that is, 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, that is, 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:

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

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:

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

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*., 2014). 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*., 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 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*., 2019; 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 percent), 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 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/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 (Seeman *et al*., 2004; McEwen, 2015; Davillas and Jones, 2020). 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.

3.4. *Circumstances*

Following the literature (e.g., Trannoy *et al*., 2010; Davillas and Jones, 2020; 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 (Zimmer and Kwong, 2004; Wu *et al*., 2015);
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., Barker, 1994; Alvarado *et al*., 2008; 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

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	≥200 mg/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	≥140 mm Hg
C-reactive protein (CRP)	Inflammation	Acute inflammation	>3 mg/L
White blood cell count (WBC)	Inflammation	Immune system activity	$\geq 11 \times 10^3/\mu L$
Creatinine	Excretory	Renal functioning	>1.4 mg/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	86.674	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	20.963	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

(Continues)

TABLE 2 (CONTINUED)

Variables	2011			2015			
	Mean/proportions	SD	Obs.	Mean/proportions	SD	Obs.	Mean diff.
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.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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 (Yang *et al.*, 2010; Yan *et al.*, 2012). 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).

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 percent to 93.3 percent for mothers and from 68.6 percent to 65.9 percent 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

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).
***$p < 0.01$.

(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 percent of the total inequality in AL, which is smaller than that in the UK (22 percent). 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 (Hu *et al*., 2011; Chen, Xia, *et al*., 2019).

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 percent for CRP to 23.95 percent 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 percent and 21.8 percent. 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 (Marnell *et al.*, 2005; Edes and Crews, 2017; Davillas and Jones, 2020). 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.

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 percent). These results are

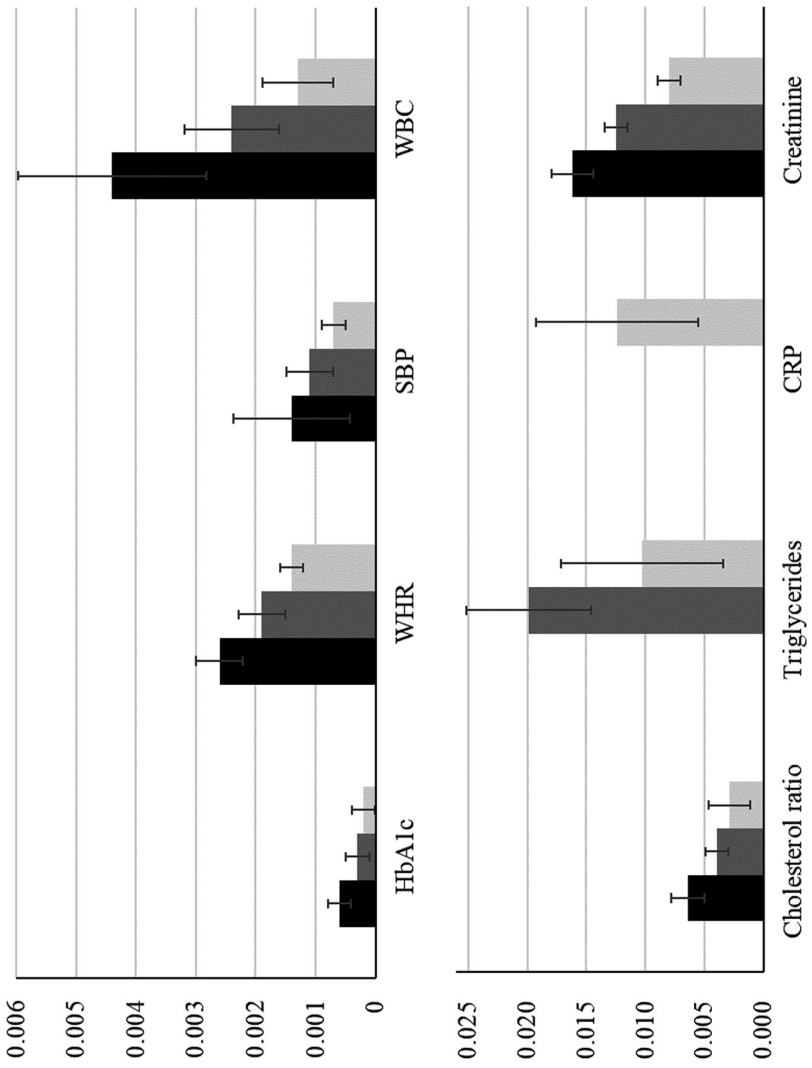

Figure 1. IOp in Health at Different Quantiles (MLD index).

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

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 percent). 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 percent and 4 percent, 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 percent), cholesterol ratio (56.50 percent), CRP (65.28 percent) and WBC (77.71 percent). 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 percent and 81.25 percent of the total IOp for biomarkers. Also household SES explains 0.96 percent-13.6 percent of the total IOp. And 0.69 percent-7.9 percent 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 percent and 5.47 percent. The contributions of access to healthcare in childhood and experience of war to the total IOp in most biomarkers are negligible.

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 percent at the 25th quantile to 47.51 percent 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 percent at the 25th quantile, and then declines to 14.38 percent at the median and further to 9.06 percent 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 percent at the 25th quantile to 7.52 percent at the median and further to 26.22 percent 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

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.

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

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

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

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 percent (25th quantile) to 5.85 percent (75th quantile). We also observe similar patterns for parental health status and health behaviors (increasing from 2.58 percent at the 25th quantile to 7.29 percent at the 75th quantile) and access to healthcare in childhood (increasing from 0.17 percent at the 25th quantile to 3.32 percent 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 (Fu and George, 2015; Davillas and Jones, 2020). For instance, using data from 1997 to 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 percent at the 25th quantile to 41.20 percent at 75th quantile. This also applies to the cholesterol ratio (from 66.65 percent to 55.35 percent), WHR (from 28.37 percent to 17.59 percent) and WBC (from 73.69 percent to 67.51 percent). 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.

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 percent quantile, and CRP at the 25 percent 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 (Ferreira and Gignoux, 2014; Wendelspiess Chávez Juárez and Soloaga, 2014; Davillas and Jones, 2020). 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 percent and 26.84 percent (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 and 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 percent to 22.87 percent, 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 nonlinearity 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 percent and 23.95 percent 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 percent and 21.8 percent for the UK, and from 1 percent to 23 percent 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 percent in China vs. 19.5 percent in the UK; cholesterol ratio: 6.6 percent vs. 11.0 percent; AL: 4.0 percent vs. 21.8 percent). 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 percent). 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 wartime 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).

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 percent at the 25th quantile to 26.22 percent 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

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

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.

References

Alesina, A. and G. M. Angeletos, "Fairness and Redistribution," *American Economic Review*, 95, 960–80, 2005.

Alvarado, B. E., M. V. Zunzunegui, F. Béland, and J. M. Bamvita, "Life Course Social and Health Conditions Linked to Frailty in Latin American Older Men and Women," *Journals of Gerontology Series A: Biological Sciences*, 63, 1399–406, 2008.

Baeten, S., T. Van Ourti, and E. van Doorslaer, "Rising Inequalities in Income and Health in China: Who Is Left Behind?," *Journal of Health Economics*, 32, 1214–29, 2013.

Bago d'Uva, T., M. Lindeboom, O. O'Donnell, and E. van Doorslaer, "Slipping Anchor? Testing the Vignettes Approach to Identification and Correction of Reporting Heterogeneity," *Journal of Human Resources*, 46, 875–906, 2011.

Bago d'Uva, T., O. O'Donnell, and E. van Doorslaer, "Differential Health Reporting by Education Level and Its Impact on the Measurement of Health Inequalities among Older Europeans," *International Journal of Epidemiology*, 37, 1375–83, 2008.

Banister, J. and X. Zhang, "China, Economic Development and Mortality Decline," *World Development*, 33, 21–41, 2005.

Barker, D. J. P. M., Mothers *Babies and Disease in Later Life*, British Medical Journal Publishing Group, London, 1994.

Baum, C. L. and C. J. Ruhm, "Age, Socioeconomic Status and Obesity Growth," *Journal of Health Economics*, 28, 635–48, 2009.

Bleich, S. N., M. P. Jarlenski, C. N. Bell, and T. A. LaVeist, "Health Inequalities: Trends, Progress, and Policy," *Annual Review of Public Health*, 33, 7–40, 2012.

Brandt, M., C. Deindl, and K. Hank, "Tracing the Origins of Successful Aging: The Role of Childhood Conditions and Social Inequality in Explaining Later Life Health," *Social Science & Medicine*, 74, 1418–25, 2012.

Brenner, D. R., D. Scherer, K. Muir, J. Schildkraut, P. Boffetta, M. R. Spitz, L. Le Marchand, A. T. Chan, E. L. Goode, C. M. Ulrich, and R. J. Hung, "A Review of the Application of Inflammatory Biomarkers in Epidemiologic Cancer Research," *Cancer Epidemiology and Prevention Biomarkers*, 23, 1729–51, 2014.

Bricard, D., F. Jusot, A. Trannoy, and S. Tubeuf, "Inequality of Opportunities in Health and the Principle of Natural Reward: Evidence from European Countries," in P. R. Dias and O. O'Donnell (eds), *Health and Inequality*, Emerald Group Publishing Limited, Bingley, 335–70, 2013.

Burt, V. L., P. Whelton, E. J. Roccella, C. Brown, J. A. Cutler, M. Higgins, M. J. Horan, and D. Labarthe, "Prevalence of Hypertension in the US Adult Population: Results from the Third National Health and Nutrition Examination Survey, 1988–1991," *Hypertension*, 25, 305–13, 1995.

Carrieri, V., A. Davillas, and A. M. Jones, "A Latent Class Approach to Inequity in Health Using Biomarker Data," *Health Economics*, 29, 808–26, 2020.

Carrieri, V. and A. M. Jones, "Inequality of Opportunity in Health: A Decomposition-Based Approach," *Health Economics*, 27, 1981–95, 2018.

Chen, W., C. Xia, R. Zheng, M. Zhou, C. Lin, H. Zeng, S. Zhang, L. Wang, Z. Yang, K. Sun, H. Li, M. D. Brown, F. Islami, F. Bray, A. Jemal, and J. He, "Disparities by Province, Age, and Sex in Site-Specific Cancer Burden Attributable to 23 Potentially Modifiable Risk Factors in China: A Comparative Risk Assessment," *Lancet Global Health*, 7, e257–69, 2019.

Chen, X., E. Crimmins, P. Hu, J. K. Kim, Q. Meng, J. Strauss, Y. Wang, J. Zeng, Y. Zhang, and Y. Zhao, "Venous Blood-Based Biomarkers in the China Health and Retirement Longitudinal Study: Rationale, Design, and Results from the 2015 Wave," *American Journal of Epidemiology*, 188, 1871–7, 2019.

Cowell, F. A. and E. Flachaire, "Statistical Methods for Distributional Analysis," in A. B. Atkinson and F. Bourguignon (eds), *Handbook of Income Distribution*, Elsevier, Oxford, 359–465, 2015.

Cui, H., J. P. Smith, and Y. Zhao, "Early-Life Deprivation and Health Outcomes in Adulthood: Evidence from Childhood Hunger Episodes of Middle-Aged and Elderly Chinese," *Journal of Development Economics*, 143, 102417, 2020.

Davillas, A. and A. M. Jones, "Ex Ante Inequality of Opportunity in Health, Decomposition and Distributional Analysis of Biomarkers," *Journal of Health Economics*, 69, 102251, 2020.

Deutsch, J., M. N. Pi Alperin, and J. Silber, "Using the Shapley Decomposition to Disentangle the Impact of Circumstances and Efforts on Health Inequality," *Social Indicators Research*, 138, 523–43, 2018.

Edes, A. N. and D. E. Crews, "Allostatic Load and Biological Anthropology," *American Journal of Physical Anthropology*, 162, e23146, 2017.

Fajardo-Gonzalez, J., "Inequality of Opportunity in Adult Health in Colombia," *Journal of Economic Inequality*, 14, 395–416, 2016.

Fang, P., S. Dong, J. Xiao, C. Liu, X. Feng, and Y. Wang, "Regional Inequality in Health and Its Determinants: Evidence from China," *Health Policy*, 94, 14–25, 2010.

Ferreira, F. H. G. and J. Gignoux, "The Measurement of Inequality of Opportunity: Theory and an Application to Latin America," *Review of Income and Wealth*, 57, 622–57, 2011.

_____, "The Measurement of Educational Inequality: Achievement and Opportunity," *World Bank Economic Review*, 28, 210–46, 2014.

Firpo, S., N. M. Fortin, and T. Lemieux, "Unconditional Quantile Regressions," *Econometrica*, 77, 953–73, 2009.

Fleubaey, M. and V. Peragine, "Ex Ante Versus Ex Post Equality of Opportunity," *Economica*, 80, 118–30, 2013.

Fleurbaey, M. and E. Schokkaert, "Unfair Inequalities in Health and Health Care," *Journal of Health Economics*, 28, 73–90, 2009.

Fu, Q. and L. K. George, "Socioeconomic Determinants of Childhood Overweight and Obesity in China: The Long Arm of Institutional Power," *Sociology of Health & Illness*, 37, 805–22, 2015.

Gong, J., Y. Lu, and H. Xie, "The Average and Distributional Effects of Teenage Adversity on Long-Term Health," *Journal of Health Economics*, 71, 102288, 2020.

Gu, D., Z. Zhang, and Y. Zeng, "Access to Healthcare Services Makes a Difference in Healthy Longevity among Older Chinese Adults," *Social Science & Medicine*, 68, 210–19, 2009.

Gu, Z., D. Li, H. He, J. Wang, X. Hu, P. Zhang, Y. Hong, B. Liu, L. Zhang, and G. Ji, "Body Mass Index, Waist Circumference, and Waist-to-Height Ratio for Prediction of Multiple Metabolic Risk Factors in Chinese Elderly Population," *Scientific Reports*, 8, 385, 2018.

Hu, F. B., Y. Liu, and W. C. Willett, "Preventing Chronic Diseases by Promoting Healthy Diet and Lifestyle: Public Policy Implications for China," *Obesity Reviews*, 12, 552–9, 2011.

Jusot, F., S. Tubeuf, and A. Trannoy, "Circumstances and Efforts: How Important Is Their Correlation for the Measurement of Inequality of Opportunity in Health?," *Health Economics*, 22, 1470–95, 2013.
Kanbur, R. and A. Wagstaff, "How Useful Is Inequality of Opportunity as a Policy Construct," in K. Basu and J. Stiglitz (eds), *Inequality and Growth: Patterns and Policy*, Palgrave Macmillan, London, 131–50, 2016.
Kim, B., *Inequality of Opportunity for Healthy Aging in Europe*, KU Leuven Department of Economics, Discussion Paper Series DPS16.20, 2016.
Kinsella, K. and H. Wan, *An Aging World: 2008*, U.S. Government Printing Office, Washington, DC, 2009.
Li Donni, P., V. Peragine, and G. Pignataro, "Ex-Ante and Ex-Post Measurement of Equality of Opportunity in Health: A Normative Decomposition," *Health Economics*, 23, 182–98, 2014.
Marmot, M., S. Friel, R. Bell, T. A. J. Houweling, and S. Taylor, "Closing the Gap in a Generation: Health Equity through Action on the Social Determinants of Health," *Lancet*, 372, 1661–9, 2008.
Marnell, L., C. Mold, and T. W. Du Clos, "C-Reactive Protein: Ligands, Receptors and Role in Inflammation," *Clinical Immunology*, 117, 104–11, 2005.
McEwen, B. S., "Biomarkers for Assessing Population and Individual Health and Disease Related to Stress and Adaptation," *Metabolism*, 64, S2–10, 2015.
McEwen, B. S. and E. Stellar, "Stress and the Individual: Mechanisms Leading to Disease," *Archives of Internal Medicine*, 153, 2093–101, 1993.
Nie, P., L. Ding, and A. Sousa-Poza, "Obesity Inequality and the Changing Shape of the Bodyweight Distribution in China," *China Economic Review*, 58, 101348, 2019.
Niessen, L. W., D. Mohan, J. K. Akuoku, A. J. Mirelman, S. Ahmed, T. P. Koehlmoos, A. Trujillo, J. Khan, and D. H. Peters, "Tackling Socioeconomic Inequalities and Non-Communicable Diseases in Low-Income and Middle-Income Countries under the Sustainable Development Agenda," *Lancet*, 391, 2036–46, 2018.
Oksuzyan, A., P. K. Singh, K. Christensen, and D. Jasilionis, "A Cross-National Study of the Gender Gap in Health among Older Adults in India and China: Similarities and Disparities," *Gerontologist*, 58, 1156–65, 2017.
Pasqualini, M., D. Lanari, L. Minelli, L. Pieroni, and L. Salmasi, "Health and Income Inequalities in Europe: What Is the Role of Circumstances?," *Economics & Human Biology*, 26, 164–73, 2017.
Prospective Studies Collaboration, "Blood Cholesterol and Vascular Mortality by Age, Sex, and Blood Pressure: A Meta-Analysis of Individual Data from 61 Prospective Studies with 55000 Vascular Deaths," *Lancet*, 370, 1829–39, 2007.
Ramos, X. and D. Van de gaer, "Approaches to Inequality of Opportunity: Principles, Measures and Evidence," *Journal of Economic Surveys*, 30, 855–83, 2016.
Ratigan, K., "Disaggregating the Developing Welfare State: Provincial Social Policy Regimes in China," *World Development*, 98, 467–84, 2017.
Rawls, J., *A Theory of Justice*, Harvard University Press, Cambridge, MA, 1971.
Roemer, J. E., *Equality of Opportunity*, Havard University Press, Boston, MA, 1998.
_____, "Equality of Opportunity: A Progress Report," *Social Choice and Welfare*, 19, 455–71, 2002.
Roemer, J. E. and A. Trannoy, "Equality of Opportunity: Theory and Measurement," *Journal of Economic Literature*, 54, 1288–332, 2016.
Rosa Dias, P., "Inequality of Opportunity in Health: Evidence from a UK Cohort Study," *Health Economics*, 18, 1057–74, 2009.
Rossouw, L., T. Bago d'Uva, and E. van Doorslaer, "Poor Health Reporting? Using Anchoring Vignettes to Uncover Health Disparities by Wealth and Race," *Demography*, 55, 1935–56, 2018.
Seeman, T. E., E. Crimmins, M.-H. Huang, B. Singer, A. Bucur, T. Gruenewald, L. F. Berkman, and D. B. Reuben, "Cumulative Biological Risk and Socio-Economic Differences in Mortality: Macarthur Studies of Successful Aging," *Social Science & Medicine*, 58, 1985–97, 2004.
Shorrocks, A. F., "Decomposition Procedures for Distributional Analysis: A Unified Framework Based on the Shapley Value," *Journal of Economic Inequality*, 11, 99–126, 2013.
Song, Q. and F. Chen, "Living Arrangements, Offspring Migration, and Health of Older Adults in Rural China: Revelation from Biomarkers and Propensity Score Analysis," *Journal of Aging and Health*, 32, 71–82, 2020.
Tang, S., Q. Meng, L. Chen, H. Bekedam, T. Evans, and M. Whitehead, "Tackling the Challenges to Health Equity in China," *Lancet*, 372, 1493–501, 2008.
Tian, Q., "Intergeneration Social Support Affects the Subjective Well-Being of the Elderly: Mediator Roles of Self-Esteem and Loneliness," *Journal of Health Psychology*, 21, 1137–44, 2016.
Trannoy, A., S. Tubeuf, F. Jusot, and M. Devaux, "Inequality of Opportunities in Health in France: A First Pass," *Health Economics*, 19, 921–38, 2010.
United Nations, *World Population Prospects: The 2019 Revision*, United Nations, New York, 2019.

Vona, R., L. Gambardella, and E. Straface, "Gender-Associated Biomarkers in Metabolic Syndrome," in R. Rezzani and L. F. Rodella (eds), *Carotid Artery-Gender and Health*, IntechOpen, London, 85–101, 2018.
Wang, T. D., W. J. Chen, K. L. Chien, S. S. Y. Su, H. C. Hsu, M. F. Chen, C. S. Liau, and Y. T. Lee, "Efficacy of Cholesterol Levels and Ratios in Predicting Future Coronary Heart Disease in a Chinese Population," *American Journal of Cardiology*, 88, 737–43, 2001.
Wang, T. and R. Zeng, "Addressing Inequalities in China's Health Service," *Lancet*, 386, 1441, 2015.
Wendelspiess Chávez Juárez, F. and I. Soloaga, "Iop: Estimating Ex-Ante Inequality of Opportunity," *Stata Journal*, 14, 830–46, 2014.
WHO, *China Country Assessment Report on Ageing and Health*, World Health Organization, Geneva, 2015.
World Population Review, *Life Expectancy by Country 2019*. Available at https://worldpopulationreview.com/countries/life-expectancy-by-country/, 2019.
Wu, B., Y. Yue, and Z. Mao, "Self-Reported Functional and General Health Status among Older Respondents in China: The Impact of Age, Gender, and Place of Residence," *Asia Pacific Journal of Public Health*, 27, NP2220–31, 2015.
Yan, B., X. Chen, and T. M. Gill, "Health Inequality among Chinese Older Adults: The Role of Childhood Circumstances," *Journal of the Economics of Ageing*, 17, 100237, 2020.
Yan, S., J. Li, S. Li, B. Zhang, S. Du, P. Gordon-Larsen, L. Adair, and B. Popkin, "The Expanding Burden of Cardiometabolic Risk in China: The China Health and Nutrition Survey," *Obesity Reviews*, 13, 810–21, 2012.
Yang, W., J. Lu, J. Weng, W. Jia, L. Ji, J. Xiao, Z. Shan, J. Liu, H. Tian, Q. Ji, D. Zhu, J. Ge, L. Lin, L. i. Chen, X. Guo, Z. Zhao, Q. Li, Z. Zhou, G. Shan, and J. He, "Prevalence of Diabetes among Men and Women in China," *New England Journal of Medicine*, 362, 1090–101, 2010.
Zeng, Q., Y. He, S. Dong, X. Zhao, Z. Chen, Z. Song, G. Chang, F. Yang, and Y. Wang, "Optimal Cut-Off Values of BMI, Waist Circumference and Waist: Height Ratio for Defining Obesity in Chinese Adults," *British Journal of Nutrition*, 112, 1735–44, 2014.
Zhao, Y., Y. Hu, J. P. Smith, J. Strauss, and G. Yang, "Cohort Profile: The China Health and Retirement Longitudinal Study (CHARLS)," *International Journal of Epidemiology*, 43, 61–8, 2014.
Zhao, Y., J. P. Smith, and J. Strauss, "Can China Age Healthily?," *Lancet*, 384, 723–4, 2014.
Zhou, M., H. Wang, X. Zeng, P. Yin, J. Zhu, W. Chen, X. Li, L. Wang, L. Wang, Y. Liu, J. Liu, M. Zhang, J. Qi, S. Yu, A. Afshin, E. Gakidou, S. Glenn, V. S. Krish, M. K. Miller-Petrie, W. C. Mountjoy-Venning, E. C. Mullany, S. B. Redford, H. Liu, M. Naghavi, S. I. Hay, L. Wang, C. J. L. Murray, and X. Liang, "Mortality, Morbidity, and Risk Factors in China and Its Provinces, 1990–2017: A Systematic Analysis for the Global Burden of Disease Study 2017," *Lancet*, 394, 1145–58, 2019.
Zimmer, Z. and J. Kwong, "Socioeconomic Status and Health among Older Adults in Rural and Urban China," *Journal of Aging and Health*, 16, 44–70, 2004.

Supporting Information

Additional supporting information may be found in the online version of this article at the publisher's web site:

Table A1: Statistical Tests to Compare the Full Sample and Matched Samples

Table A2: Statistical Tests of Circumstances Variables: Differences in Sample Means

Table A3: Statistical Tests (*p*-Values) Between the Matched Sample With No Missing Circumstances (Full) and Analysis Samples

Table A4: Absolute IOp in Health: RIF Regressions (MLD Index)

Table A5: Total Inequality and IOp in Health: Mean-Based Regressions (Variance Share)

Table A6: Contributions of Circumstances to IOp in Health: Mean-Based Shapley Decomposition (Variance Share)

Table A7: Contributions of Circumstances to IOp in Health: RIF-Based Shapley Decomposition (Variance Share)