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Ex ante inequality of opportunity in health, Decomposition and distributional analysis of biomarkers*

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Ex ante inequality of opportunity in health, decomposition and distributional analysis of biomarkers*

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Abstract

We use a set of biomarkers to measure inequality of opportunity (IOp) in health in the UK. Applying a direct *ex ante* IOp approach, we find that inequalities in health attributed to circumstances account for a non-trivial part of the total health variation. For example, observed circumstances account for 20% of the total inequalities in our composite measure of multi-system health risk, allostatic load. Shapley decompositions show that apart from age and gender, education and childhood socioeconomic status are sources of IOp. We propose an extension to the decomposition of *ex ante* IOp to complement the mean-based approach, analysing the contribution of circumstances across the quantiles of the biomarker distributions. This shows that, for most of the biomarkers, the percentage contribution of socioeconomic circumstances, relative to differences attributable to age and gender, increases towards the right tail of the biomarker distribution, where health risks are more pronounced.

Keywords: equality of opportunity; biomarkers; Shapley decomposition; Oaxaca decomposition; unconditional quantile regression

JEL codes: C1, D63, I12, I14.

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1 Introduction

Health inequality has many sources, not all of which are equally objectionable. The existing literature focuses on socio-economic inequalities in health and variations associated with differences in living conditions, access to health care, and health-related lifestyle (e.g., Contoyannis and Jones, 2004; Baum and Ruhm, 2009). This literature implicitly suggests a distinction between *legitimate* and *illegitimate* inequalities. Building on Roemer's (1998, 2002) influential formalisation of the concept of inequality of opportunity (IOp), the "egalitarian" framework does not necessarily indicate equality of the distribution of outcomes *per se* but emphasises the role of individual responsibility in defining a "fair" distribution (Fleurbaey and Schokkaert, 2009, 2012; Ramos and Van de Gaer, 2016; Roemer and Trannoy, 2016).

IOp has influenced the policy agenda in recent years (World Bank, 2005; NHS England, 2017) and a growing literature has addressed the measurement of IOp in health (e.g., Fleurbaey and Schokkaert, 2009; Garcia-Gomez et al., 2015; Jones et al., 2012, 2014; Jusot et al., 2013; Li Donni et al., 2014, 2015; Rosa Dias, 2009, 2010; Trannoy et al., 2010). However, most of the existing studies employ subjective self-reported health.[1] This was recently acknowledged by Carrieri and Jones (2018), who propose a semiparametric approach to decompose *ex post* IOp into the direct contribution of efforts and the direct and indirect contribution of circumstances, using blood-based biomarkers in the *Health Survey for England*.[2]

In this study, we use nationally representative UK data (*Understanding Society*) to provide a comprehensive analysis of *ex ante* IOp in health and its underlining sources using objective health indicators. We contribute to the literature in a number of ways. First, we use nurse-collected and blood-based biomarkers to measure health: spanning obesity, blood pressure, inflammatory biomarkers, blood glucose and cholesterol. These health measures are more objective than self-reports of health. As well as capturing different dimensions of health they are considered as "secondary" physiological responses to stress, reflecting the process through which adverse circumstances may get "under the skin" (Davillas et al., 2017; Turner et al., 2016). We use each biomarker separately and we also construct a composite score as a proxy measure of wear and tear on the body; similar composite health measures are often called the allostatic load.

[1] Self-reported measures may be subject to significant misreporting, with the reporting bias varying systematically with individual's socioeconomic characteristics, posing significant implications for the robustness of earlier IOp studies (e.g., Bago d'Uva et al. 2008). Some studies have used mortality as the outcome (Balia and Jones, 2011; Garcia-Gomez et al., 2016). This avoids the use of self-reported outcomes but it focuses on length rather than quality of life.

[2] As will be discussed later, there are two approaches to IOp: the *ex-ante* and the *ex-post* approach (eg., Fleurbaey and Schokkaert, 2009; Fleurbaey and Peragine, 2013; Li Donni et al., 2014). 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 their efforts and outcomes being realised. The *ex-post* approach seeks equality of outcomes among people who have exerted the same degree of effort, regardless of their circumstances.

Second, we use these objective health measures to estimate both absolute measures of the level of IOp and measures that express IOp as a fraction of the overall health inequality. We adopt the direct *ex ante* parametric approach proposed by Ferreira and Gignoux (2011). The advantage of the parametric approach is that, unlike nonparametric tests for IOp (e.g., Lefranc et al., 2009; Rosa Dias, 2009), it does not suffer from a curse of dimensionality, due to insufficient sample sizes for social types (groups of people sharing identical circumstances).[3] Moreover, even in the presence of unobserved circumstances, our IOp measures can be interpreted as the lower-bound estimates of overall IOp, i.e., of the inequality due to all circumstances, not only those that are observed (Ferreira and Gignoux, 2011).

Third, we decompose the direct *ex ante* measure of IOp in health into its sources. Shapley-decomposition techniques allow us to identify which circumstances are more relevant to shaping IOp in health. Given that age and gender are the main drivers of variations in health, Oaxaca-type decompositions are then used to analyse IOp in health differentials by gender and across the adult lifespan. Our decomposition analysis explores whether these IOp differences are attributed to differences in the distribution of circumstances *per se* (composition) or to differences in the relationship between circumstances and health (association) across age groups and by gender[4].

Finally, we relax the assumption of inequality neutrality within types, that is implied by the conventional parametric approach, and extend the literature on the decomposition of *ex ante* IOp, capitalising on the continuous nature of our health outcomes. We use the recentered influence function (RIF) approach to distributional analysis (Firpo et al., 2009), to explore how the contribution of circumstances may vary across the distribution of biomarkers. Shapley decompositions are implemented at different quantiles of the biomarker distribution to explore the underlying sources of these inequalities, with a particular focus on the right tails, where clinical concerns are typically focused. We also apply Oaxaca-type decomposition techniques to analyse the contribution of circumstances by gender and age at different biomarker quantiles, spanning the whole distribution of our health measures.

2 Methods

Roemer (1998) assumes a responsibility cut by which factors associated with individual attainments can be partitioned into: a) *effort* factors, for which individuals should be held partially responsible, and b) *circumstances* which are beyond individuals' control.

[3] Maintaining a reasonable number of observations within each social type is a challenging issue given the usual sample sizes of social-science datasets and the relatively large number of circumstances that empirical researchers wish to use to partition the population by types (Ferreira and Gignoux, 2011; Carrieri and Jones, 2018).

[4] For example, it has been shown that the association between education and health may follow heterogeneous patterns by age and gender (e.g., Davillas et al., 2017; Baum and Ruhm, 2009). We extend this literature by exploring whether the observed age and gender differences in IOp in health may be driven by this heterogeneity or whether other sources may be more relevant.

Following the IOp literature (Ferreira and Gignoux, 2011; Jusot et al., 2013; Rosa Dias, 2010; Carrieri and Jones, 2018), a generalised health production function for the health outcome (y_i) for each individual (i) can be defined as a function of a vector of circumstances (C_i) and of efforts (E_i). Assuming that circumstances are not affected by efforts, while efforts may be influenced by circumstances (Bourguignon et al., 2007; Ferreira and Gignoux, 2011; Roemer, 1998, 2002), we can write:

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

where v_i and u_i are unobserved error terms which capture the random variation in the realised outcomes, sometimes labelled as 'luck' in the IOp literature (Lefranc et al., 2009; Lefranc and Trannoy, 2017).[5] To be specific, v_i represents random variation in effort that is independent of C and u_i represents random variation in the outcome that is independent of C and E.

In principle, the structural form (1) can be used in an *ex post* framework to decompose the direct and indirect contribution of circumstances and efforts. Here we adopt an *ex ante* approach and are interested in measuring overall IOp as a share of total inequality. Then, assuming additive separability and linearity of $h(.)$ and $E(.)$, a linear reduced form can be derived:

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

where the coefficients ψ reflect the total contribution of circumstances and include both the direct effect of circumstances on health, and the indirect effect of circumstances through efforts.

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 regardless of their circumstances and prior to the realisation of effort and the outcomes. The *ex ante* approach can be implemented empirically using information on observed circumstances and does not require measures of effort. These circumstances are used to measure the opportunity set for each individual (e.g., Fleurbaey and Peragine, 2013; Aaberge et al., 2011). Two approaches have been adopted to do this:

i. The first uses the mean of outcomes within types, $E(y_i|C_i)$. This corresponds to the approach suggested by Roemer (1998, 2002) and has been termed "utilitarian reward". This implies inequality neutrality within types. Jones et al. (2014) note the equivalence between the mean and the area to the left of the distribution function, $F(y_i|C_i)$, and they

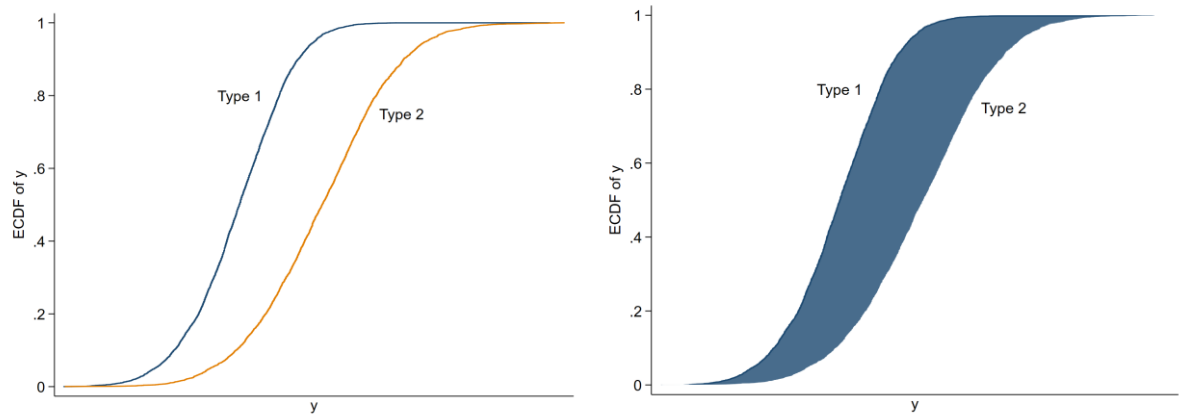
[5] In the Roemerian framework, the partial correlations between C and E should also be treated as circumstances, embodying the indirect effect of the unjust circumstances on health that is channelled through effort (see Ferreira and Gignoux, 2011; Rosa Dias, 2009). This is embodied in the reduced form coefficients that capture both direct and indirect effects. However, the ethical stance of the Roemer concept is open to debate. Examples of empirical methods to compare the Roemer view with other more liberal perspectives are available elsewhere (Jusot et al., 2013).

therefore use this as their criterion for health policy evaluation. This can therefore be considered as a 'mean-based' approach, where equality of opportunity corresponds to equality of mean outcomes across types (e.g., Lefranc et al., 2009; Ferreira and Gignoux, 2011).

ii. The second approach uses a more general definition that interprets the full type-specific conditional outcome distribution $F(y_i|C_i)$ as the opportunity set (e.g., Ramos and Van de Gaer, 2016, Lefranc et al., 2009; Lefranc and Trannoy, 2017). This goes beyond the mean-based approach, focusing on differences in distributions across types, and allows for the possibility of inequality aversion within types such that, for example, more significance is attached to inequalities across types at worse levels of health outcomes. The implications of this second approach are explored using a distributional regression approach that is described below.

Figure 1 illustrates these concepts for the case where there are just two values of circumstances, represented by types 1 and 2. The *ex ante* approach compares the distribution of outcomes conditional on type, as shown in the left-hand panel, and interprets these distributions as the opportunity set for each type. In particular, the mean-based approach focuses on differences in means across types, given by the area to the left of the distribution functions and hence, in this case, shown by the dark shaded area in the right-hand panel. Differences in means is regarded as a weak test for IOp. A stronger test takes account of the shape of the distribution within types and, depending on the degree of inequality aversion within types, may give more weight to horizontal differences between the distributions at different levels of the outcome[6]. This motivates our analysis of the contribution of circumstances at different points of the biomarker distribution.

Figure 1. *Ex ante* IOp and distribution functions.



[6] In the context of our application to biomarkers the notion of inequality aversion within types may be motivated by the fact that these are measured in physical units, y_i, which may not correspond to their social value, say $\omega(y_i)$. For example, rather than being linear, the function $\omega(.)$ may give different weight to outcomes above or below the clinical risk thresholds that are associated with some of the biomarkers.

We begin with the mean-based framework. The direct approach, as in Ferreira and Gignoux (2011), measures inequality in a counterfactual in which all inequalities are attributable to circumstances. This involves defining a smoothed distribution from the distribution of (health) outcomes (y_i) and a partition of ($k = 1,2..K$) types by replacing each individual health outcome y_i^k with the relevant type-specific mean (μ_i^k) and, then, using inequality indexes to measure IOp (Ferreira and Gignoux, 2011).[7] In practice, the mean-based direct parametric approach to measure *ex ante* IOp is based on using predictions of $E(y_i|C_i)$ from the reduced form as the counterfactual outcome:

$$\widetilde{y_i} = C_i\hat{\psi} \tag{3}$$

where $\hat{\psi}$ represents the OLS estimates of the coefficients in equation (2) (Checci and Peragine, 2010; Rosa Dias, 2010; Trannoy et al., 2010; Ferreira and Gignoux, 2011, Li Donni et al., 2014; Abatemarco, 2015). The predicted health outcomes are the same for all individuals with identical circumstances (Ferreira and Gignoux, 2011).Thus, IOp can be estimated using an inequality measure ($I(.)$) applied to $\widetilde{y_i}$:

$$\theta_a = \mathrm{I}(\widetilde{y_i}). \tag{4}$$

A relative measure of IOp, expressing IOp as a fraction of the overall health inequality ($I(y_i)$), can be obtained by:

$$\theta_r = \frac{\mathrm{I}(\widetilde{y_i})}{I(y_i)}. \tag{5}$$

Following Ferreira and Gignoux (2011), we use the mean logarithmic deviation (MLD) inequality index as our measure of inequality I(.). This is because of its path-independent decomposability properties (Ferreira and Gignoux, 2011; Ramos and Van de Gaer, 2016; Wendelspeiss Chávez Juárez and Soloaga, 2014).[8] The MLD is zero when there is no inequality, and takes on larger positive values as ill-health is distributed more unequally. It should be explicitly noted here that our analysis does not account for unobserved circumstances that are not available in the dataset. However, it has been shown that

[7] The indirect approach (as in, for example, Bourguignon et al., 2007) uses the difference between inequality in actual outcomes and a counterfactual in which there is no IOp, calculated using a reference level of circumstances. We have opted for the direct approach in our analysis. Parametric estimation shows that the direct and indirect approaches result in similar, but not exactly identical, results (Ferreira and Gignoux, 2011); this is typical, given the functional form assumptions that are relevant to parametric estimation models.

[8] I(.) needs to satisfy the path-independent decomposability axiom in addition to other typical axiomatic properties relevant to the measurement of inequality literature, i.e., symmetry, transfer principle, scale invariance, population replication, and additive decomposability. This restricts the eligible "path-independent decomposable" class of inequality measures to a single measure, the MLD (Ferreira and Gignoux, 2011). Alternatively, under these axiomatic properties, one may argue for the use of the variance as a measure of inequality. However the MLD is more appropriate, given the ratio-scale nature of our health variables (Wendelspeiss Chávez Juárez and Soloaga, 2014).

equations (4)-(5) can be interpreted at least as the lower-bound estimates of inequality due to all predetermined circumstances (Ferreira and Gignoux, 2011).

Shapley and Oaxaca Decompositions of IOp

We use the Shapley decomposition to explore the contribution of each of the circumstances to the total IOp in health (Shorrocks, 2013; Wendelspeiss Chávez Juárez and Soloaga, 2014; Fajardo-Gonzalez, 2016). Specifically, inequality measures (MLD) for all possible permutations of the circumstance variables are estimated and, then, the average marginal effect of each circumstance variable on the total IOp is calculated.[9]

Given that age and gender are the main sources of variation in health, we then use an Oaxaca-type decomposition to further analyse gender and age differentials in IOp.[10] This Oaxaca-type decomposition involves two steps (Wendelspeiss Chávez Juárez and Soloaga, 2014): i) we estimate IOp separately for each population sub-group (i.e., by gender and across age groups); ii) counterfactual IOp measures of one population sub-group (e.g., males, if targeting gender differences) are then estimated using the coefficients for circumstances from the other group (females). Comparison of counterfactuals with the original IOp measures allows us to explore whether IOp differences are attributed to differences in the distribution of circumstances (composition) and/or to the heterogeneous relationship between circumstances and health across the lifespan or by gender (association).

Using distributional regressions to relax inequality neutrality within types

The methods described so far measure and decompose overall IOp in health using linear parametric regression specifications and a counterfactual based on the conditional mean. As noted above, this implies inequality neutrality within types. In our context this may be too restrictive and, for example, 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 greater risk of developing chronic health problems.

To assess the implications of relaxing inequality neutrality we propose a method of decomposing the contribution of circumstances to the overall IOp at different points in the distribution of the outcome. This makes use of unconditional quantile regression (UQR) based on the RIF approach (Firpo et al., 2009) to decompose the contribution of circumstances at specific quantiles of the biomarker distributions.

The RIF method works by providing a linear approximation of the unconditional quantiles of each biomarker. Subsequently, the law of iterated expectations is applied to the approximated quantile and used to estimate the marginal effect of circumstances through

[9] The key advantage of the Shapley-decomposition, unlike other decomposition methods, is that it is both path independent and exactly additive, with the different components sum up exactly to the total IOp (Wendelspeiss Chávez Juárez and Soloaga, 2014).

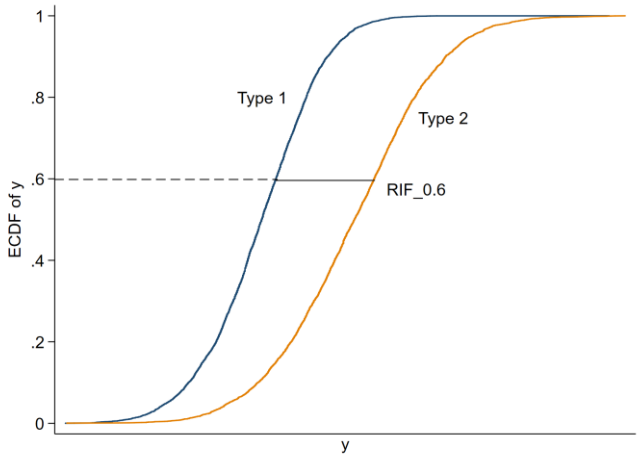
[10] A stated by Wendelspeiss Chávez Juárez and Soloaga (2014), the Oaxaca-type decomposition technique works for absolute measures of IOp. For the relative IOp measures such decompositions do not make sense, as the difference might be also due to the total inequality. However, correcting for that would bring us back the case of the absolute measure.

a regression of the RIF on the circumstance variables. The total contribution of circumstances, at each quantile q_τ, can be then obtained by:

$$RIF(y_i; q_\tau) = C_i \alpha^\tau + \varepsilon_i^\tau \quad (6)$$

where α^τ are the coefficients at different quantiles and ε_i^τ stands for the error term. This is illustrated by Figure 2, which shows how the RIF regressions aim to capture differences attributable to circumstances at specific quantiles of the distribution, represented here by the horizontal line at the 60th percentile.

Figure 2. *D*istributional regressions.



Then the counterfactuals used in the direct approach are given by:

$$\widetilde{y_i^\tau} = C_i \widehat{\alpha^\tau} \quad (7)$$

The variation in these fitted values, which capture the role of circumstances since counterfactuals ($\widetilde{y_i^\tau}$) are the same for all individuals with identical circumstances (in line with the concept of the direct *ex ante* IOp), can be summarized using an inequality index (here we again use the MLD, as in equation 4). As the RIF equations are additive and linear, the Shapley and Oaxaca-type decompositions can be then applied to this index to explore the contribution of each circumstance variable as well as differentials in their contribution by gender and age at different quantiles of biomarker distribution.

3 Data

The data come from *Understanding Society (UKHLS)*, a longitudinal, nationally representative study of the UK. We use the General Population Sample (GPS) component of UKHLS, a random sample of the general population. As part of wave 2 (2010-2011), nurse-measured and non-fasted blood-based biomarkers were collected for the GPS. The

wave 2 nurse visits included 15,632 respondents, while blood-based biomarkers impose further restrictions on the sample since they require the successful collection and processing of blood samples.[11] Exclusion of missing data on covariates reduces the potential sample to a maximum of 14,068 and 9,005 individuals with valid nurse-collected measurements and blood-based biomarkers, respectively.

Biomarkers

We focus on physical measurements and blood-based biomarkers that are associated with major chronic conditions such as obesity, diabetes and coronary heart disease. Our nurse-collected measurements are the waist-to-height ratio (WHR), defined as waist circumference over height, to measure adiposity and systolic blood pressure (SBP). Our blood-based biomarkers reflect 'fat in the blood', 'sugar in the blood' and markers for inflammation. The cholesterol ratio, the ratio of total cholesterol (TC) over high-density lipoprotein (HDL), is our 'fat in the blood' biomarker. Glycated haemoglobin (HbA1c) is a standard diagnostic test for diabetes. C-reactive protein (CRP) is our inflammatory biomarker. CRP rises as part of the immune response to infection and mainly indicates systemic inflammation. We exclude CRP values over 10mg/L, as they may reflect acute rather than chronic infections (Davillas et al., 2017).

In addition to each of the specific markers, we also combine them in a composite measure, which gives an overall assessment of a respondent's physiological condition. We construct an index of multi-system risk, often called *allostatic load* (e.g., Davillas and Pudney, 2017). Specifically, our composite measure combines all six nurse-collected and blood-based biomarkers considered in our study: WHR, SBP, HbA1c, CRP, TC and HDL cholesterol. HDL cholesterol, considered as the "good" cholesterol, is converted to negative values to reflect ill health, to be consistent with the other biomarkers. We then transform each of these biomarkers into z-scores and sum them (Davillas and Pudney, 2017; Vie et al., 2014). Since our inequality measure is only defined for positive values of the outcome (Wendelspeiss Chávez Juárez and Soloaga, 2014), the resulting index (A) is rescaled as: $allostatic\ load = A - \min(A) + 1$. Higher values of allostatic load indicate worse health.

Circumstances

The choice of measured circumstance factors follows the recent empirical literature, informed by the normative framework for health equity and the UK policy and legal context (Carrieri and Jones, 2018; Rosa Dias, 2009, 2010; Jusot et al., 2013). Our circumstance variables embody the ethical position of the responsibility cut, defining illegitimate sources of health inequality[12].

Drawing on the socio-legal context in the UK, the Equality Act of 2010 defines protected characteristics that include age, sex and race. We treat sex and age (dummies for 10-year

[11] Respondents were eligible for nurse visits if they were aged 16+, lived in England, Wales, or Scotland, and were not pregnant. Blood sample collections were further restricted to those who had no clotting disorders and no history of fits.

[12] There is unlikely to be universal agreement on the choice of circumstance variables. An advantage of the parametric approach to decomposition is that, given the assumptions made, the contribution of each of the variables can be identified separately.

intervals between 16 and 75 and a dummy for 75+) as circumstances (Carrieri and Jones, 2018).[13] Nationality and linguistic background is proxied by a dummy for speaking English at home during childhood.

The Equality Act does not directly encompass socioeconomic status (SES) among its protected characteristics but this has been a concern of the existing literature on IOp. Childhood SES is regarded as an important source of IOp in health, being beyond individual's control and exerting a lasting effect on individual's adult health (Jusot et al., 2013; Rosa Dias, 2009, 2010). We use both parental occupational status and education to proxy childhood SES. The occupational status of the respondent's mother and father, when the respondent was aged 14, is measured using two categorical variables (one for each parent) with six categories: not working (reference category), four occupation skill levels and a category for missing data.[14] Given the high correlation between mother's and father's education, we combine them creating a measure capturing the highest parental education level (Kenkel et al., 2006). This is a five category variable measured as: left school with no/some qualification (reference category), post-school qualification/certificate (e.g., an apprenticeship), degree (university or other higher-education degree) and a missing data category.[15]

The legal and policy context in the UK also frames the notion of an age of responsibility. This age varies across different dimensions such as criminal responsibility and age of consent. Young people aged over 18 are treated as an adult by the law. Here we make the normative assumption that the level of secondary schooling achieved by age 18 is beyond individual's responsibility, influenced by parental and environmental factors during individual's earlier life, and therefore individuals' own education constitutes a circumstance (Jones et al., 2012; Carrieri and Jones, 2018). Education is measured as: no/basic qualification (reference), O-Level, A-Level/post-secondary and degree. Descriptive statistics for circumstances and biomarkers are available in Tables A1 and A2 (Appendix).

4 Results

4.1. Mean-based measures of *ex ante* IOp

Table 1 presents inequality results for the different biomarkers and for allostatic load. Column [a] shows the total inequality, measured by the MLD. Observed circumstances

[13] A recent policy report suggests actions to advance equality of opportunity in health, particularly relevant to patient's age and gender, characteristics that are "protected" under the Equality Act (NHS England, 2017).

[14] Occupational skill levels are based on the skill level structure of the Standard Occupational Classification 2010.

[15] Comparison of summary statistics for the biomarkers reveals similar results for our working sample and the sample restricted to non-missing parental information (Table A2, appendix), suggesting that the use of missing categories or the exclusion of missing data on parental characteristics should have limited implications for our analysis.

account for a non-trivial part of the total inequalities as our results from the mean-based *ex ante* IOp measures show (columns [b]-[c]). The contribution of measured circumstances to the total inequality is lowest for CRP (4%), it is higher for cholesterol ratio (11%) and waist-to-height ratio (17%) and around 20% for systolic blood pressure, HbA1c and allostatic load.[16]

Table 1. Total inequality and IOp (MLD indexes).

	Total inequality [a]	IOp		Sample size
		Absolute IOp [b]	% of total inequality [c=b/a]	
Waist-to-height ratio	0.0116*** (0.0001)	0.0020*** (0.00007)	16.9%	14,068
Systolic blood pressure	0.0087*** (0.0001)	0.0017*** (0.00007)	19.8%	11,865
Cholesterol ratio	0.0583*** (0.0010)	0.0064*** (0.0004)	11.0%	9,005
HbA1c	0.0153*** (0.0006)	0.0030*** (0.0002)	19.5%	8,468
CRP	0.4244*** (0.005)	0.0161*** (0.0020)	3.9%	8,311
Allostatic load	0.0547*** (0.001)	0.0111*** (0.0006)	20.2%	6,242

Bootstrapped standard errors in parenthesis (500 replications).
***P<0.01

We then explore the contribution of each of the circumstances to IOp using the Shapley-decomposition (Figure 3). Age and gender (in combination) account for the largest part of the IOp in almost all the biomarkers (except CRP), and age accounts for the dominant contribution; this is in line with literature on the role of age and gender on explaining variations in health (e.g., Baum and Ruhm, 2009). Individuals' education and parental occupational status are the second and third sources of IOp, while parental education is the fourth contributor. Respondents' education, parental occupation and parental education account for 12%, 7% and 6% of the total IOp in allostatic load, respectively.

Given that age and gender are the main sources of variation in health, an Oaxaca-type decomposition is used to explore differentials in the IOp in health between women and men and across age groups to better understand the underlying sources of these differences. Table 2 presents the Oaxaca-type decomposition of IOp in allostatic load by gender. The main diagonal represents IOp measures estimated separately by gender, while the remaining values are counterfactual IOp estimates; the upper right (lower left) value is the counterfactual estimate of the IOp for women (men) computed using the coefficients on circumstances estimated for men (women). In this case, variation in the counterfactual outcome within groups reflects all of the measured circumstances other than gender itself.

[16] Although different techniques and biomarkers are employed by Carrieri and Jones (2018), our results regarding HbA1c (the only biomarker in common) are comparable, with IOp accounting for 13-19% of the total (including the unexplained) inequalities in HbA1c in their analysis of the Health Survey for England.

Figure 3. Shapley decomposition of circumstances to IOp.

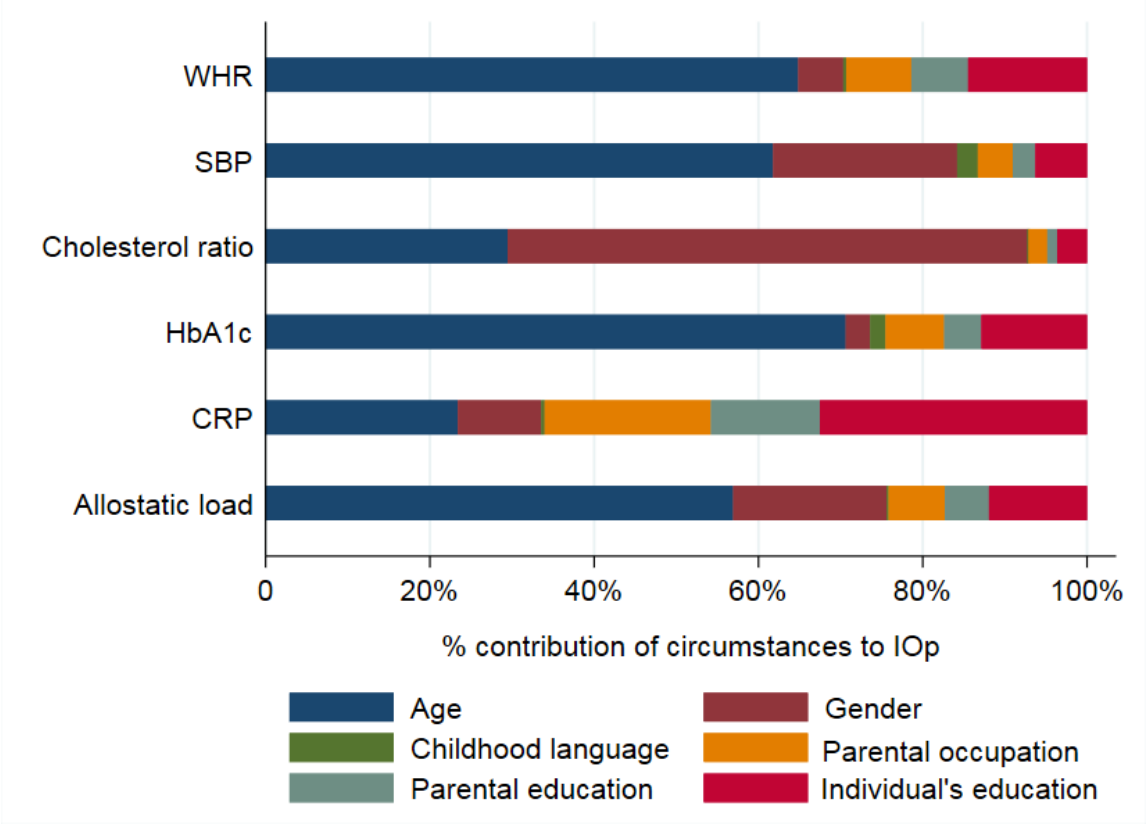


Table 2. Oaxaca-type decomposition of IOp (MLD) by gender: Allostatic load

	Coefficients for	
Distribution of circumstances	Women	Men
Women	**0.0135**	0.0060
Men	0.0127	**0.0059**

IOp in allostatic load is higher for women (MLD=0.0135) than for men (MLD=0.0059). Our counterfactual estimates suggest that these gender differences are mainly due to gender differences in the association between circumstances and allostatic load and to a lesser extent due to differences in the distribution of circumstances. For example, the counterfactual IOp estimate for men using the coefficients on circumstances for women (MLD=0.0127) differs substantially from the original IOp for men (MLD=0.0059) but is much closer to the IOp for women (MLD=0.0135), suggesting that the largest part of the IOp differential can be attributed to gender differences in the coefficients.

Table 3 presents the corresponding Oaxaca-type decomposition results of IOp in allostatic load by age group. We find that IOp in allostatic load varies substantially across the adult lifespan, being higher for the 26-35 and 36-45 age groups compared to younger and older ages. These results extend existing evidence, suggesting that cross sectional age-specific health inequalities increase with age up to a limit and then inequality begins to narrow most likely due to the age-as-leveller hypothesis (Baum and Ruhm, 2009; Davillas et al, 2017). As before, comparison of the counterfactual with the original IOp values for each age group shows that the observed IOp differences can be mainly attributed to association rather than to compositional differences due to differences in circumstances.

Table 3. Oaxaca-type decomposition of IOp (MLD) across the lifespan: Allostatic load

	Coefficient of age group						
Distribution of circumstances	16-25	26-35	36-45	46-55	56-65	66-75	76+
16-25	**0.0066**	0.0090	0.0072	0.0056	0.0023	0.0016	0.0013
26-35	0.0072	**0.0097**	0.0091	0.0072	0.0029	0.0016	0.0015
36-45	0.0072	0.0090	**0.0081**	0.0066	0.0026	0.0014	0.0014
46-55	0.0082	0.0086	0.0077	**0.0063**	0.0025	0.0013	0.0014
56-65	0.0078	0.0075	0.0071	0.0058	**0.0023**	0.0015	0.0013
66-75	0.0092	0.0068	0.0070	0.0058	0.0022	**0.0016**	0.0015
76+	0.0083	0.0064	0.0064	0.0056	0.0019	0.0016	**0.0013**

4.2. Distributional analysis of the contribution of circumstances

Unconditional quantile regression (UQR) models are estimated to measure the contribution of measured circumstances across the biomarker distribution and Shapley decomposition analysis is then used to explore the contribution of circumstances at each quantile (Table 4); a graphical illustration is presented in Figure A1 (Appendix).

Our results show the presence of systematic variation attributable to circumstances for all health outcomes across the whole distribution (as shown by the MLD indexes). The most striking result from the Shapley decomposition shows that the percentage contribution of socioeconomic circumstances, measured by parental occupation, education and individual's education, increases towards the right tail of the biomarker distribution for most of the biomarkers. For example, the contribution of parental occupation for allostatic load increases from 6% (25^{th} quantile) to 18.5% (95^{th} quantile). It is also notable that, in most cases, the relative contribution of age and sex declines, relative to that attributed to socioeconomic factors, in the right hand tails, where individuals are most at risk of health problems. For example, the joint contribution of age and gender for allostatic load at the 25th quantile is 82%, while socioeconomic circumstances (parental occupation, parental education and own education) account for 17%; the corresponding contributions are almost equal (around 50%) at the top quantiles (Q90, Q95).

Table 4. Contribution of circumstances (MLD) at different biomarker quantiles and Shapley decomposition.

Waist to height ratio	**Q25**	**Q50**	**Q75**	**Q90**	**Q95**
MLD index	0.0040***	0.0025***	0.0014***	0.0011***	0.0008***
		% contribution to IOp			
Age	68.89%	61.81%	52.93%	36.32%	34.00%
Gender	12.73%	7.75%	1.27%	0.55%	1.99%
Childhood language	0.40%	0.44%	0.35%	0.28%	0.27%
Parental occupation	5.64%	9.37%	12.77%	15.71%	15.41%
Parental education	5.29%	6.90%	7.69%	8.69%	8.90%
Individual's Education	7.07%	13.69%	24.98%	38.35%	39.31%
Systolic blood pressure	**Q25**	**Q50**	**Q75**	**Q90**	**Q95**
MLD index	0.0020***	0.0022***	0.0020***	0.0020***	0.0020***
		% contribution to IOp			
Age	41.87%	57.46%	73.00%	77.04%	77.38%
Gender	45.11%	29.58%	9.42%	3.12%	0.65%
Childhood language	4.19%	2.11%	1.66%	1.11%	0.80%
Parental occupation	2.79%	3.45%	5.49%	7.79%	7.32%
Parental education	1.74%	2.60%	3.17%	3.32%	2.79%
Individual's Education	4.29%	4.80%	7.25%	7.64%	11.11%
Cholesterol ratio	**Q25**	**Q50**	**Q75**	**Q90**	**Q95**
MLD index	0.0039***	0.0075***	0.0090***	0.0101***	0.0076***
		% contribution to IOp			
Age	34.28%	31.99%	29.98%	22.16%	25.27%
Gender	55.15%	59.30%	63.68%	70.73%	64.48%
Childhood language	0.03%	0.09%	0.12%	0.16%	0.01%
Parental occupation	3.71%	3.67%	2.30%	1.92%	4.01%
Parental education	3.38%	1.88%	0.84%	0.43%	0.89%
Individual's Education	3.43%	3.07%	3.05%	4.61%	5.34%
HbA1c	**Q25**	**Q50**	**Q75**	**Q90**	**Q95**
MLD index	0.0015***	0.0022***	0.0029***	0.0064***	0.0177***
		% contribution to IOp			
Age	81.01%	78.23%	71.19%	64.85%	55.94%
Gender	0.65%	0.68%	1.48%	3.88%	12.64%
Childhood language	1.04%	0.59%	1.14%	2.00%	3.43%
Parental occupation	6.63%	6.80%	7.07%	8.09%	7.63%
Parental education	5.20%	4.15%	4.28%	4.43%	3.14%
Individual's Education	5.40%	9.55%	14.91%	16.74%	17.21%
CRP	**Q25**	**Q50**	**Q75**	**Q90**	**Q95**
MLD index	0.0356***	0.0313***	0.0239***	0.0138***	0.0073***
		% contribution to IOP			
Age	46.10%	33.57%	20.79%	19.11%	14.43%
Gender	1.00%	7.70%	15.25%	12.72%	4.49%
Childhood language	0.27%	0.23%	0.72%	0.71%	0.70%
Parental occupation	13.11%	13.60%	23.99%	21.77%	34.50%
Parental education	14.43%	14.33%	11.65%	11.59%	15.21%
Individual's Education	25.09%	30.57%	27.59%	34.09%	30.67%
Allostatic load	**Q25**	**Q50**	**Q75**	**Q90**	**Q95**
MLD index	0.0323***	0.0121***	0.0059***	0.0045***	0.0034***
		% contribution to IOP			
Age	58.63%	55.02%	54.06%	49.98%	46.49%
Gender	23.78%	23.02%	13.57%	4.11%	3.78%
Childhood language	0.24%	0.20%	0.26%	0.74%	0.76%
Parental occupation	6.08%	5.78%	8.18%	12.28%	18.54%
Parental education	4.67%	4.47%	6.51%	7.93%	10.45%
Individual's Education	6.60%	11.52%	17.43%	24.97%	19.94%

Bootstrapped standard errors in parenthesis.
***P<0.01

Decomposition by gender and age

Figure 4 presents gender differentials in the contribution of circumstances for allostatic load, based on Oaxaca-type decompositions implemented at various quantiles using the RIF method. Figure 2 shows that the gender differentials at different quantiles of the distribution favour men; this echoes the analysis that uses estimates at the mean (Table 2). However, we find that these gender differentials decrease in magnitude towards the higher quantiles of the distribution of allostatic load, along with the absolute magnitude of the variation in outcomes across circumstances.

Figure 4. Gender differentials in IOp across the distribution of allostatic load.

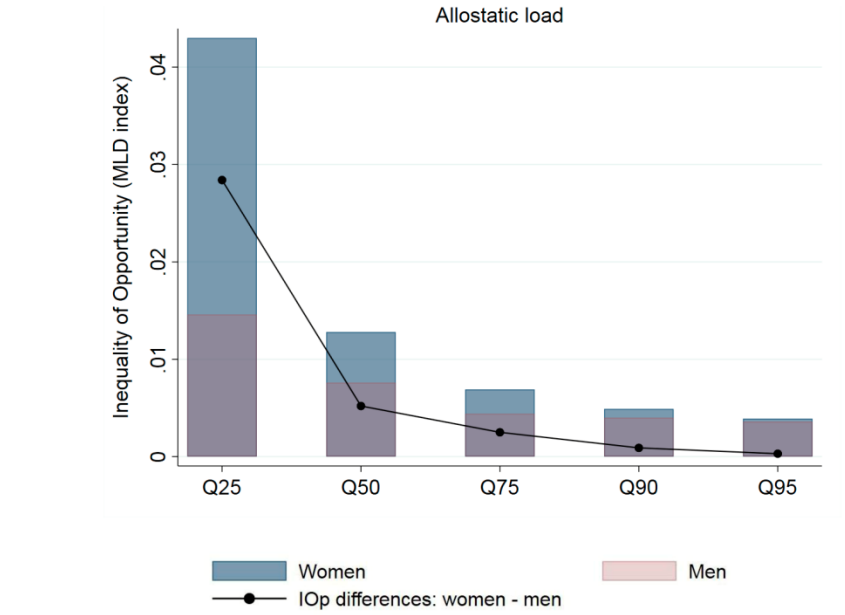


Table 5 presents the corresponding counterfactual decomposition estimates at different quantiles of the allostatic load. These results confirm our previous evidence (Table 2), revealing that, where gender differentials in IOp are evident, these differences can be attributed to differences in association rather than to gender differences in the composition of circumstances.

Table 5. Oaxaca-type decomposition of IOp (MLD) by gender across the allostatic load distribution.

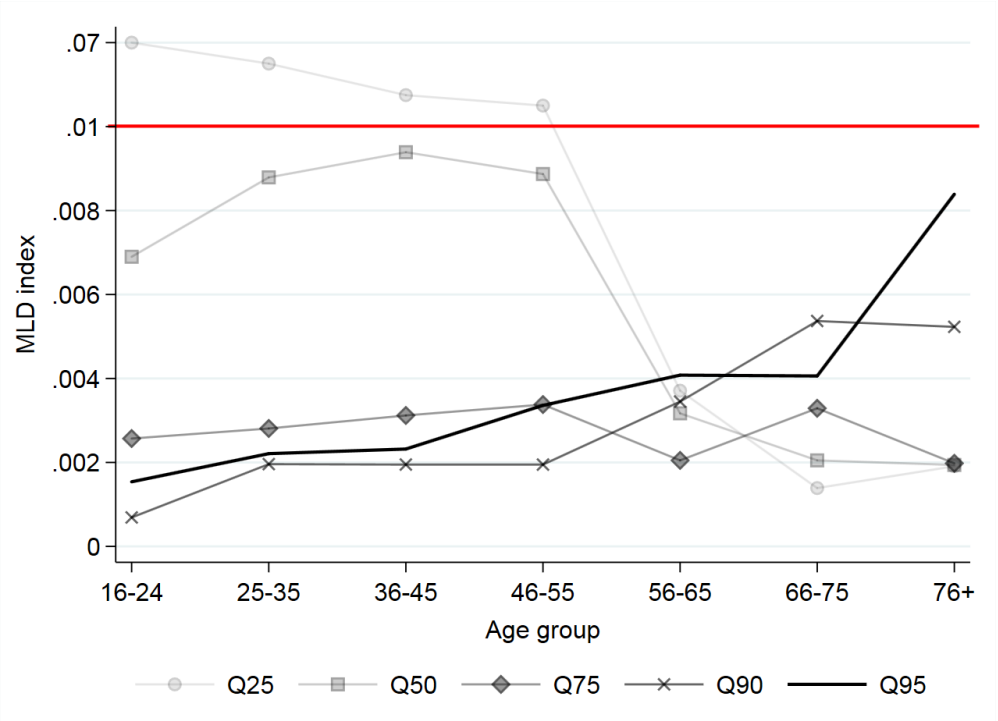
	Q25		Q50		Q75		Q90		Q95	
	Coefficient for		*Coefficient for*		*Coefficient for*		*Coefficient for*		*Coefficient for*	
Distribution of circumstances	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men
Women	**0.0430**	0.0148	**0.0128**	0.0079	**0.0069**	0.0045	**0.0049**	0.0047	**0.0039**	0.0038
Men	0.0407	**0.0146**	0.0121	**0.0076**	0.0064	**0.0044**	0.0045	**0.0040**	0.0037	**0.0036**

Oaxaca-type decompositions of the contribution of circumstances by age are also implemented across quantiles of the distribution of allostatic load. Figure 5 presents the MLD indexes estimated separately for each age group using the fitted RIF values for each

quantile (equation 7). We find that moving to the right tails of the allostatic load distribution, the inverted U-shaped pattern of IOp by age (observed for our "mean-based" IOp analysis; Table 3) becomes less evident, with IOp gradually increasing with age. The cumulative advantage hypothesis (e.g., Kim and Durden, 2007), rather than the age-as-leveller, seems to exert the dominant role when the focus is on the right tail of the distribution, suggesting that adverse circumstances and health disadvantages accumulate over time, suggesting a more pronounced role of circumstances in health as people age.

As before, comparison of the counterfactual with the original IOp values for each age group reveals that the observed IOp differences can be mainly attributed to association effects rather than to composition effects due to differences in circumstances (Table A3, Appendix).

Figure 5. IOp by age groups at different quantiles of allostatic load.



Note: Red line indicates a scale break (y axis).

5 Conclusions

Using UK nationally representative data we explore *ex ante* IOp in health and its underlying sources using objective biomarkers. We find that IOp accounts for a non-trivial part of the total variation in health. For example, 20% of the total inequality in allostatic load is attributed to IOp. Shapley-decomposition techniques show that apart from age and

gender, parental education, parental occupational status and own educational attainment are important sources of IOp.

We propose an extension to the decomposition of *ex ante* IOp using the RIF method. This analysis allows us to decompose IOp and its sources across quantiles of the biomarker distribution. We find the presence of systematic contributions of circumstances for all biomarkers across the whole distribution. A mixed pattern is observed on how the contribution of circumstances evolves towards the right tails across different biomarkers, highlighting the importance of considering the multidimensional nature of health. In most cases, the contribution of age and sex declines relative to socioeconomic circumstances in the right tails, the part of the distribution where health risks are more pronounced.

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Appendix

Table A1. Circumstance variables used in the analysis.

	Mean
Age groups	
16-25	0.075
26-35	0.126
36-45	0.183
46-55	0.188
56-65	0.190
66-75	0.147
76+	0.091
Gender	
Male	0.432
Female	0.568
Language at home during childhood	
English at childhood	0.930
Other language at childhood	0.070
Mother occupation	
1(low-skilled)	0.144
2	0.258
3	0.084
4(high-skilled)	0.084
Missing	0.030
Not working (reference)	0.400
Father occupation	
1(low-skilled)	0.087
2	0.238
3	0.386
4(high-skilled)	0.146
Missing	0.089
Not working (reference)	0.054
Highest parental education	
No/some qualification (reference)	0.501
Post-school qualification/certificate	0.247
Degree	0.100
Missing	0.151
Educational attainment	
No/basic qualification (reference)	0.150
O-level	0.315
A-level/post-secondary	0.310
Degree	0.224

Table A2. Descriptive statistics for biomarkers for the full and restricted samples.

	Full sample			**Excluding missing parental data**		
	Mean	Std. err.	Sample size	Mean	Std. err.	Sample size
Waist-to-height ratio	0.561	0.001	14,068	0.560	0.001	11,119
Systolic blood pressure (mmhg)	126.17	0.155	11,865	126.00	0.161	9,450
TC/HDL	3.741	0.014	9,005	3.732	0.016	7,228
HbA1c (mmol/mol)	37.240	0.082	8,468	37.111	0.090	6,803
CRP (mg/L)	2.092	0.022	8,311	2.044	0.024	6,672
Allostatic load	9.740	0.039	6,242	9.665	0.043	5,040

Table A3. Oaxaca-type decomposition of IOp (MLD index) across the lifespan at different quantiles of the allostatic load distribution

Q25

Distribution of circumstances	Coefficient of age group						
	16-25	26-35	36-45	46-55	56-65	66-75	76+
16-25	**0.0709**	0.0547	0.0265	0.0174	0.0038	0.0017	0.0029
26-35	0.0620	**0.0613**	0.0334	0.0213	0.0046	0.0013	0.0028
36-45	0.0600	0.0550	**0.0302**	0.0195	0.0046	0.0015	0.0026
46-55	0.0720	0.0487	0.0281	**0.0186**	0.0041	0.0013	0.0020
56-65	0.0771	0.0390	0.0264	0.0163	**0.0037**	0.0013	0.0019
66-75	0.0964	0.0351	0.0252	0.0154	0.0037	**0.0014**	0.0020
76+	0.0917	0.0302	0.0246	0.0142	0.0035	0.0012	**0.0019**

Q90

Distribution of circumstances	Coefficient of age group						
	16-25	26-35	36-45	46-55	56-65	66-75	76+
16-25	**0.0007**	0.0025	0.0017	0.0018	0.0040	0.0042	0.0175
26-35	0.0008	**0.0020**	0.0020	0.0021	0.0039	0.0052	0.0168
36-45	0.0009	0.0019	**0.0020**	0.0021	0.0039	0.0050	0.0127
46-55	0.0011	0.0023	0.0019	**0.0020**	0.0036	0.0049	0.0108
56-65	0.0010	0.0021	0.0019	0.0022	**0.0035**	0.0056	0.0078
66-75	0.0011	0.0021	0.0020	0.0024	0.0038	**0.0054**	0.0075
76+	0.0011	0.0020	0.0019	0.0026	0.0031	0.0055	**0.0052**

Q50

Distribution of circumstances	Coefficient of age group						
	16-25	26-35	36-45	46-55	56-65	66-75	76+
16-25	**0.0069**	0.0075	0.0092	0.0086	0.0032	0.0029	0.0030
26-35	0.0075	**0.0088**	0.0103	0.0097	0.0036	0.0037	0.0032
36-45	0.0074	0.0084	**0.0094**	0.0095	0.0036	0.0029	0.0028
46-55	0.0089	0.0081	0.0087	**0.0089**	0.0033	0.0024	0.0022
56-65	0.0091	0.0070	0.0085	0.0083	**0.0032**	0.0022	0.0021
66-75	0.0100	0.0061	0.0086	0.0086	0.0031	**0.0021**	0.0021
76+	0.0098	0.0059	0.0082	0.0081	0.0029	0.0021	**0.0019**

Q95

Distribution of circumstances	Coefficient of age group						
	16-25	26-35	36-45	46-55	56-65	66-75	76+
16-25	**0.0015**	0.0020	0.0027	0.0030	0.0065	0.0025	0.0162
26-35	0.0019	**0.0022**	0.0027	0.0032	0.0053	0.0041	0.0124
36-45	0.0019	0.0021	**0.0023**	0.0033	0.0055	0.0040	0.0112
46-55	0.0024	0.0024	0.0023	**0.0034**	0.0048	0.0033	0.0107
56-65	0.0022	0.0022	0.0022	0.0044	**0.0041**	0.0041	0.0093
66-75	0.0024	0.0023	0.0023	0.0054	0.0046	**0.0041**	0.0097
76+	0.0024	0.0020	0.0020	0.0060	0.0040	0.0041	**0.0084**

Q75

Distribution of circumstances	Coefficient of age group						
	16-25	26-35	36-45	46-55	56-65	66-75	76+
16-25	**0.0026**	0.0037	0.0029	0.0030	0.0020	0.0034	0.0022
26-35	0.0033	**0.0028**	0.0035	0.0039	0.0029	0.0043	0.0026
36-45	0.0033	0.0029	**0.0031**	0.0038	0.0026	0.0036	0.0024
46-55	0.0037	0.0030	0.0028	**0.0034**	0.0023	0.0034	0.0025
56-65	0.0033	0.0028	0.0026	0.0033	**0.0021**	0.0034	0.0022
66-75	0.0037	0.0027	0.0025	0.0034	0.0018	**0.0033**	0.0022
76+	0.0041	0.0026	0.0022	0.0032	0.0017	0.0032	**0.0020**

Figure A1. Contribution of circumstances (MLD index) at different biomarker quantiles and Shapley decomposition results.