HEDG

HEALTH, ECONOMETRICS AND DATA GROUP

WP 18/31

# Distributional analysis of the role of breadth and persistence of multiple deprivation in the health gradient measured by biomarkers*

Kompal Sinha; Apostolos Davillas; Andrew M Jones and Anurag Sharma

November 2018

http://www.york.ac.uk/economics/postgrad/herc/hedg/wps/

# Distributional analysis of the role of breadth and persistence of multiple deprivation in the health gradient measured by biomarkers*

Kompal Sinha†, Apostolos Davillas‡, Andrew M. Jones§, Anurag Sharma¶

November 8, 2018

**Abstract**

This paper analyses the relationship between health and socioeconomic status accounting for the role of breadth and persistence of multiple deprivation. Adopting a holistic approach to multidimensional deprivation, we construct measures of absolute and relative deprivation and use these measures along with a range of nurse measured and blood-based biomarkers for a distributional analysis of the relationship between socioeconomic status and health. Using data from the British Household Panel Survey and Understanding Society, our analysis finds the presence of systematic multidimensional deprivation gradient across the distribution of most of our biomarkers (BMI, waist circumference, heart rate, C-reactive protein and HbA1c) beyond income, with the size of this gradient to be substantially larger at higher tails of the biomarker distribution. Decomposition analysis of the contribution of components of deprivation to health suggests breadth of deprivation to dominate the contribution over persistence. Health policy prioritising health of people enduring deprivation across multiple domains, i.e., people who experience dual burden of deprivation across several domains and poor health, may be particularly effective at reducing the risk of falling into a health-deprivation trap.

**Keywords:** Health, biomarkers, multidimensional deprivation, relative deprivation.

**JEL classifications: C81, D13, I12, J1, J24, J26.**

*Andrew Jones acknowledges funding from the Leverhulme Trust Major Research Fellowship (MRF - 2016-004). Apostolos Davillas is grateful to the Economic and Social Research Council for financial support for this research via project: How can biomarkers and genetics improve our understanding of society and health? (award no. ES/M008592/1). The funders, data creators and UK Data Service have no responsibility for the contents of this paper.

†Department of Economics, Macquarie University. email: kompal.sinha@mq.edu.au ✉

‡Institute of Social and Economic Research, University of Essex. email: adavil@essex.ac.uk

§Department of Economics, University of York. email:andrew.jones@york.ac.uk

¶School of Public Health and Community Medicine, University of New South Wales. email: anurag.sharma@unsw.edu.au

# 1 Introduction

The association between socioeconomic status and health has been long established in the literature (Deaton and Paxson, 1998; Jones and Wildman, 2008; Jürges et al., 2013; Kim and Durden, 2007; Loucks et al., 2009; Van Doorslaer and Jones, 2003). Much of this literature has been largely limited to using subjective self reported measures of health and using income as a measure of socioeconomic status (SES). Both these measures have been subject to criticism as being partial measures of health and unidimensional measures of standard of living, respectively. First, self-reported health measures are often "coarse" (i.e., limited in sensitivity) and "noisy" (subject to measurement error). Despite their widespread use, the conventional self-reported health measures can – at best – be considered as only indirect indicators of underlying health, subject to significant misreporting, and associated with comparability problems at both the individual level and among countries (Bago d'Uva et al., 2008; Jürges, 2007, 2008). It has been shown that this reporting bias depends on socio-economic characteristics that are mostly used to explore the socioeconomic gradient; this raises significant concerns about the validity of studies based on self-reported health indicators (Dowd and Zajacova, 2010; Johnston et al., 2009). On the other hand, biomarkers are more objective measures of health that can capture different health dimensions, and are considered as more proximal outcomes in the process through which socioeconomic conditions get "under the skin" (e.g., Acabchuk et al., 2017).

Second, in the context of socioeconomic status, a single measure, such as income, may be an insufficient measure, especially for vulnerable sections of society (Sen, 1985; Stiglitz et al., 2010). The idea is that SES is broader than what can be captured by income alone and that an individual's SES also reflects individual's ability to achieve functioning in multiple life domains based on a broad range of non-monetary resources and their relative position in society (Cuesta and Budría, 2014). Recent studies have recognised the importance of including measures beyond income to quantify measurement of standards of living under the deprivation and social exclusion framework (Alkire and Foster, 2011; Nicholas et al., 2018).

This paper makes several contributions to the literature. First, we adopt a broad concept of multidimensional deprivation to explore the socioeconomic gradient in health. Following

Nicholas et al. (2018), we construct a dynamic multidimensional deprivation measure that is sensitive to both severity and persistence of deprivation by incorporating 29 dimensions spanning 10 years. The existing literature on the association between socio-economic status and various health outcomes is mainly based on either uni-dimensional or multiple static socioeconomic measures (e.g., Braveman et al., 2005, Carrieri and Jones, 2017, Contoyannis and Jones, 2004, Gruenewald et al., 2009, Johnston et al., 2009) or aggregate cumulative measures of SES (e.g., Kim and Durden, 2007, Loucks et al., 2009). Although cumulative socio-economic measures capture how disadvantage accumulates over the life course and its impact on health, they do not allow for a deep look into the "black box" of the aggregate SES scores. Specifically, these measures cannot differentiate subgroups that might have similar counts of deprivation but with a very different distribution of deprivation over time. Moreover, the unidimensionality of these measures does not account for different dimensions of SES, which is considered of key importance for health (Blázquez et al., 2014), but also how these different dimensions of deprivation may be distributed across individuals and over time. Our longitudinal dynamic multidimensional measures of deprivation allow us to account not only for the count of deprivations but also allows the identification of those who experience them across the widest variety of dimensions in a given period and those who experience them for the most periods in any given dimension. Capitalising on the decomposability of our dynamic multidimensional deprivation measure, we can disentangle the role of the breadth and duration of deprivation in shaping the observed socioeconomic gradient in health. In addition to the multidimensional deprivation measures, we also account for conventional income measures in our model specifications to explore the role multidimensional deprivation to explain its association with health over and above income.

Deprivation can also manifest through the tendency of humans to compare themselves with societal peers, thereby impacting individual's psychosocial health and resulting in poor health (Decancq and Lugo, 2012; Wilkinson and Pickett, 2011). Most of the existing studies aiming to explore the role of relative deprivation on health employ the Yitzhaki (1979) index of relative deprivation based solely on income (Jones and Wildman, 2008; Subramanyam et al., 2009). However, a recent review by Adjaye-Gbewonyo and Kawachi (2012) highlighted dimensions other than income when measuring relative deprivation; for example, they sug-

gested that consumption and non-income dimensions (such as household amenities or item ownership) can be used to measure relative deprivation. In this study, a measure of relative deprivation is also used in our analysis to identify the comparative role of relative versus absolute deprivation regarding health.

Third, unlike most of the previous literature on the SES-health gradient, we employ a set of nurse-collected and blood-based biomarkers most relevant to the growing threat of non-communicable diseases (i.e., adiposity measures, blood pressure, resting heart rate, inflammatory biomarkers, blood glucose and cholesterol ratio). Using biomarkers has several advantages as they: a) are objective measures of health compared to the conventional self-reported health measures; b) provide direct information on pre-disease mechanisms that are below the individual's threshold of perception or clinical diagnosis thresholds and, thus, allowing for a better understanding of the deprivation-health gradient when diseases have not yet become explicit; and c) are considered as "secondary" physiological responses to stress and, thus, they are more proximal outcomes in the process through which social and economic stressors get "under the skin" (Glei et al., 2013).

Fourth, we account for the fact that the relationship between health and SES would vary across the distribution of nurse collected and blood based biomarkers. Our analysis estimates the deprivation gradient at the mean and across quantiles of the distribution of biomarkers using unconditional quantile regression (UQR) techniques. While existing studies typically explore the effect of SES on the conditional mean of the health outcome of interest (for instance, Johnston et al., 2009; Jürges et al., 2013), analyses based solely on the mean might mask important information in other parts of the distribution (Carrieri and Jones, 2017). This is particularly important for our analysis given the greater burden of illness and possibly higher costs for the healthcare system at the higher tails of the biomarkers distribution. Hence, evaluating the potential heterogeneity of the deprivation gradients across the distribution of the health measures is of particular interest.

The paper's key results are as follows. First, for most of the biomarkers explored in our analysis (BMI, waist circumference, hear rate, CRP and HbA1c), there are systematic deprivation gradients over and above the role of income. Second, the deprivation gradients are larger in magnitude and systematic towards the higher quantiles of the biomarkers distribution,

where higher risk of illnesses are relevant. Third, the breadth of deprivation (i.e., number of dimensions deprived) is more relevant in shaping the observed deprivation gradients over duration of deprivation (i.e., number of years deprivated in a particular dimension) in our set of health measures. Finally, we find limited evidence that relative deprivation plays a role in our health measures.

# 2 Data

The data is the British Household Panel Survey (BHPS) sub-sample of the UK Household Longitudinal Survey (UKHLS), also known as Understanding Society. At UKHLS wave 2, the sample of the BHPS[1] was absorbed into the UKHLS. A distinguishing feature of this database is that for the BHPS respondents followed up in the UKHLS, a set of nurse-measured health indicators and non-fasted blood samples were collected after the UKHLS wave 3 main survey. These objective measures of health along with the detailed longitudinal information from BHPS (including employment status, housing conditions, income and wealth, social support, household demographics and residential mobility) makes an ideal database for the objectives of this paper. Contemporaneous information (such as individuals' demographic characteristics) from UKHLS wave 3 main survey are used as explanatory variables to model our health outcomes.

## 2.1 Nurse-collected health measures

Measures of adiposity, heart rate (HR) and blood pressure are used in our analysis. In addition to the Body Mass Index (BMI), we use waist circumference (WC) to capture central adiposity. BMI is calculated as body weight (in kilograms) over the square of height (in metres). Three repeated measurements of HR, systolic and diastolic blood pressure (SBP, DBP) were taken at intervals of one minute. We skip the first reading, believed to impose upward biases, and computed HR, SBP and DBP as the average of the second and third readings. Values of SBP (DBP) above 140 (90) mmHg are considered as hypertensive (e.g., Davillas and Pudney, 2017).

[1]The BHPS is widely used representative longitudinal UK study that covered the period between 1991 and 2009 (18 waves) up to the time it was incorporated in the UKHLS.

## 2.2 Blood-based biomarkers

We explore inflammatory, blood glucose and "fat in the blood" biomarkers. Two biomarkers of inflammation are examined: CRP and Fibrinogen. CRP is an acute phase protein that reflects chronic inflammation. CRP values over 5 mg/L are considered to be of high risk, while CRP above 10 mg/L is suggestive for severe acute infections (Ishii et al., 2012). Fibrinogen (in g/L) is a glycoprotein that stops bleeding by helping blood clots to form, also considered as an inflammatory biomarker. Glycated haemoglobin (HbA1c) is a validated diagnostic test for diabetes. HbA1c $\geq$ 48 mmol/mol is suggestive for diabetes ($>$ 42 for predictable risk), with higher levels capturing the severity of the condition (WHO, 2011). Cholesterol ratio, calculated as the ratio of total cholesterol over high density lipoprotein cholesterol, is our "fat in the blood" biomarker. A cholesterol ratio greater than 4 is suggestive for elevated atherosclerotic risk (Millán et al., 2009). Descriptive statistics of all health outcomes are presented in Table A1.

## 2.3 Measures of socio-economic status

We use three measures of socio-economic status: income, multidimensional deprivation and relative deprivation. The details of these measures are as follows.

### 2.3.1 Multidimensional deprivation

An important issue in the construction of the dynamic multidimensional deprivation index is the selection of dimensions (Alkire, 2002). In a report on measuring economic performance and social progress, Stiglitz et al. (2010) identified the following domains to shape individual well-being: material living standard (income, consumption and wealth); education; personal activities; political voice and governance; social connection and relationships; and insecurity (economic and physical). Following these recommendations and data availability, our measure of multidimensional deprivation considers deprivation across ten life domains comprising of a battery of 29 dimensions. These domains include education, economic activity, housing conditions, consumer goods, car ownership, affordable lifestyle, financial hardships, social engagement and environment and security. Appendix Table A2 contains a complete

description of these domains and dimensions.

The analysis of deprivation across multiple dimensions over time requires the use of a balanced sample covering the largest number of dimensions across the longest time period possible (Nicholas et al., 2018). Within this context, experimenting with different time frames we found a ten year time interval over 1999-2008 (BHPS waves 9 to 18) to be most suitable for constructing our long-run deprivation measure. Our working sample is created by merging the balanced panel of BHPS waves 9 to 18 with the UKHLS wave 3 followed up by a nurse visits for biomarker data. An advantage of this working sample is that we are using longitudinal information on SES indicators collected in years prior to the time of measuring our health outcome, which allows us to partially alleviate concerns about contemporaneous effect of health on SES.

### 2.3.2 Measure of relative deprivation

Along with absolute deprivation, another channel through which deprivation may affect health is in relative terms. Individuals could feel relatively deprived whenever they come across someone with more resources. To account for this form of deprivation we use our measure of multidimensional deprivation to construct a measure of relative deprivation following the approach proposed by Bossert et al. (2007). Specifically, we measure relative deprivation of an individual as a product of the share of people with fewer functional failures than that individual.

For analysis of relative deprivation it is important to consider the issue of reference group, that is, whom do individuals compare themselves to? There is no consensus in the literature on an ideal reference group, with the empirical literature using a range of reference groups aggregated at country level (Deaton, 2001; Jones and Wildman, 2008), regional level (Lorgelly and Lindley, 2008, Mangyo and Park, 2011) and individual characteristics (Ferrer-i Carbonell, 2005). For the present analysis we use region of residence as the reference group. That is, all the individuals living in that region who are better off (i.e., people who are either not deprived or less deprived).

### 2.3.3 Income data

Household income data available in the BHPS is used in our analysis. Income is transformed to natural logarithms to allow for the concavity of the health income association and skewness of income distribution (e.g., Contoyannis et al., 2004). To facilitate comparison over time and between households, household income is deflated using the Retail Price Index, to express income in January 2010 prices, and equivalised using the modified OECD scale. For consistency with our longitudinal multidimensional deprivation measure, we measure income as the within individual average income measured over BHPS waves 9-18 (i.e., 1999 - 2008).

## 2.4 Other covariates

The covariates (collected during the UKHLS wave 3) that are used to model our health outcomes over and above deprivation and income are presented in Table A3 (Appendix), along with summary statistics. A similar set of covariates to those employed by Contoyannis et al. (2004) and Carrieri and Jones (2017) are used in this analysis. Specifically, our estimation models include fifteen age dummies (age group dummies for five years intervals between 15 and 84 and a dummy for those over 84), gender and ethnicity (white vs non-white). We include marital status since it may affect household production of health and demand for health. Education is also accounted for given evidence on the positive association between schooling and health (Contoyannis et al., 2004). A set of household characteristics (household size and number of children in the household) and household composition dummies are also included in the health regression models. Finally, regional dummies are also added to capture regional variations.

# 3 Methods

## 3.1 Definition of the dynamic multidimensional deprivation measure

Recent literature on the measurement of deprivation has considered either an absolute measure of deprivation or a relative measure of deprivation. The absolute measure of deprivation has been extended to either incorporate a wider set of dimensions, following Amartya Sen's

capability approach (for example, Alkire and Foster, 2011); or incorporating a longer time period (for example, Bossert et al., 2013). However, these approaches by themselves would not serve our purpose of analysing the relationship between health and deprivation accounting for severity and persistence of deprivation. Instead, we use the methodology proposed by Nicholas et al. (2018), which is unique in constructing a dynamic measure of multidimensional deprivation that simultaneously accounts for severity and persistence of deprivation. This measure allows us to analyse how longitudinal histories of deprivation influence health.

Consider a randomly drawn individual from a population of $N$ individuals (where $i = 1, 2, ...I$), $J$ deprivation dimensions (where $j = 1, 2, ....J$) and $T$ equally spaced periods of time (where $t = 1, 2..., T$). For each individual $i$, $x_{ijt}$ is the achievement in dimension $j$ at time $t$. The overall achievement profile for individual $n$ is $\mathbf{A_n}$ such that,

$$\mathbf{A_n} = \begin{pmatrix} x_{n11} & \cdots & x_{n1t} \\ \cdots & \cdots & \cdots \\ x_{nJ1} & \cdots & x_{nJT} \end{pmatrix}$$

The population achievement profile is a vector $\rho = (\mathbf{A_1}, ..., \mathbf{A_n})$. We say that an individual $i$ is deprived in dimension $j$ at time $t$ when $x_{ijt} < F_j$, where $F_j$ is a deprivation cut-off that determines whether or not an individual is considered deprived in a particular dimension at a particular time and F the vector of such cut-offs. For example, for the dimension 'Education', $x$ is individual's level of education and $F_{education}$ will be the threshold, say Year 12, below which individual is considered deprived in education. Then, an index to measure poverty $g(\rho; \nu)$ is a function that produces a single non-negative real number for any observed vector $\rho$ and appropriately defined vector $\nu$. Vector $\nu$ is the identification vector to define an individual's deprivation status such that $v = (c_1, ..., c_N)$, where $c_n$ takes the value 1 if the individual is considered poor, and 0 otherwise. It is possible for $\rho$ to be transformed into the sample deprivation profile $\delta = (\mathbf{D_1}, ..., \mathbf{D_N})$, where $\mathbf{D_n}$ is the individual deprivation profile, a $J \times T$ matrix for which each element of $\mathbf{A_n}$ is transformed into deprivations defined as follows:

$$d^{\alpha}_{njt} = \begin{cases} (1 - \frac{x_{njt}}{F_j})^{\alpha} & \text{if } x_{njt} < F_j \forall j, t \\ 0 & otherwise \end{cases} \tag{1}$$

where $\alpha \geq 0$ is a sensitivity parameter. When achievement levels are ordinal in at least one dimension, it is common to restrict $\alpha = 0$ such that $d^{\alpha}_{njt} \in \{0,1\} \forall j,t$. The indicator function $c_n$ takes the form $c_n = \begin{cases} 1 & \text{if } \sum_{t=1}^{T}\sum_{j=1}^{J} d^{0}_{njt} \geq z \\ 0 & otherwise \end{cases}$ where $(J \times T) \geq z \geq 1$. These deprivations are counted both across dimensions and time to give a convex combination of deprivation due to severity and deprivation due to persistence represented as follows:

$$\Omega = \frac{1}{N}\sum_{n=1}^{N}\left(\delta\frac{1}{T}\sum_{t=1}^{T}\left(\frac{1}{J}\sum_{j=1}^{J} d_{njt}\right)^{\beta} + (1-\delta)\frac{1}{J}\sum_{j=1}^{J}\left(\frac{1}{T}\sum_{t=1}^{T} d_{njt}\right)^{\beta}\right) \times c_n \tag{2}$$

where $0 \leq \delta \leq 1$ and $\beta > 0$. The right hand side of Equation 2 is a convex combination of two components - the dimension measure and the dynamic measure respectively. The first component essentially measures the dimension component of overall deprivation, $\Omega^{dimension} = \frac{1}{N}\sum_{n=1}^{N}\left(\delta\frac{1}{T}\sum_{t=1}^{T}\left(\frac{1}{J}\sum_{j=1}^{J} d_{njt}\right)^{\beta}\right) \times c_n$; this component is calculated for each year separately and then averaged over all years. The second component forms the duration measure of deprivation $\Omega^{duration} = \frac{1}{N}\sum_{n=1}^{N}\left((1-\delta)\frac{1}{J}\sum_{j=1}^{J}\left(\frac{1}{T}\sum_{t=1}^{T} d_{njt}\right)^{\beta}\right) \times c_n$; this component is calculated for each dimension and then averaged over dimensions. The two parameters $\beta$ and $\delta$ account for dimensional convexity (i.e., giving more weight to individuals experiencing deprivation across multiple dimensions within the same period) and duration convexity (i.e., individuals experiencing deprivation across multiple years within the same dimension) respectively. As is common in these class of measures (Nicholas et al., 2018) we assume equal weight for dimensions and duration of deprivation (i.e., $\delta = 0.5$) and each individual's deprivation profile is squared to allow for sensitivity to the across-individual distribution (i.e., $\beta = 2$).

An important aspect of our deprivation measure (Equation 2), is that the contribution of each dimension to overall deprivation is a non-linear function of other dimensions, which does not allow direct decomposition of our deprivation measure into dimensions. However, following the Shapley method (Shorrocks, 2013), we are able to decompose the contribution of each dimension to overall deprivation and, then, decompose the dimensional contribution into: a) a part of deprivation due to distribution of breadth within individuals; and b) a part that is the proportion of deprivation score due to the distribution of length of depri-

vation across time for an individual (Nicholas et al., 2018). Accordingly, Equation 2 can be rearranged to yield three additive components as:

$$\Omega = \bar{\Omega} + \delta(\Omega^{dimension} - \bar{\Omega}) + (1-\delta)(\Omega^{duration} - \bar{\Omega}) = \Omega_A + \Omega_B + \Omega_C \tag{3}$$

where $\bar{\Omega} = \frac{1}{N}\sum^{N}{}_{n=1}(\frac{\sum_{t=1}^{T}\sum_{j=1}^{J} d_{njt}}{j*T})^{\beta}$. The first component, $\Omega_A$, is the sum of count of deprivations averaged over individuals and is the distribution insensitive component, i.e., it is not influenced by how deprivation is distributed across dimensions and across time. This indicates that a change in the pattern of deprivations for any individual has no impact on this component. The second component, $\Omega_B$, measures the distribution of breadth component across dimensions or prevalence of deprivation component. This would take the value of zero if the breadth of deprivation is same for each year for all individuals. The third component, $\Omega_C$, is distribution of the length component across dimensions or persistence of deprivation. This component will take the value of zero if the length of deprivation is same across each dimension for all individuals. The decomposition of overall deprivation into the contribution due to dimensions would be the sum $\Omega_A + \Omega_B$, and the contribution due to duration would be the sum $\Omega_A + \Omega_C$.

### 3.2 Definition of the relative deprivation measure

In addition to our measure of absolute deprivation, we also consider a measure of relative deprivation. In the spirit of the approach proposed by Bossert et al. (2007)[2], we measure relative deprivation for an individual as a measure of the difference between their deprivation status and the deprivation of each member of their reference group with a lower deprivation status. Specifically, considering region of residence as our reference group, with $N$ members and $i$ and $j$ as any two individuals then the measure of relative deprivation of each individual $i$ in a region is compared to that of any other individual $j$ who are better off (i.e., not deprived or less deprived). Formally, if $j$ has a deprivation status of $\Omega_j$ (i.e., $j$ is a member and $i \neq j$) lower than individual $i$'s deprivation status $\Omega_i$, then defining this set of individuals with

[2]The original Yitzhaki index (Yitzhaki, 1979) measures the difference between income of an individual and the average income in the reference group given that income is greater than the income of this individual. In the context of multidimensional deprivation, we consider the difference between deprivation of individual and average deprivation in the reference group given that deprivation is lower.

lower deprivation $B_i(\Omega) = \{j \in N | \Omega_j < \Omega_i\}$, a relative deprivation measure:

$$D_i(\Omega) = \begin{cases} 0 & \text{if} \quad B_i(\Omega) = 0 \\ \alpha_i \frac{|B_i(\Omega)|}{|N|^2} \sum_{j \in B_i(\Omega)} (\Omega_i - \Omega_j) & \text{if} \quad B_i(\Omega) \neq 0 \end{cases}$$

The term $\frac{\sum_{j \in B_i(\Omega)} (\Omega_i - \Omega_j)}{|N|}$ is the average difference in deprivation between individual $i$ and $j$ and the term $\frac{|B_i(\Omega)|}{|N|}$ is the proportion that are better off than this individual. In this sense, relative deprivation is directly proportional to the difference between $\Omega_i$ and $\Omega_j$. Since higher relative deprivation would mean that individual $i$ is worse off compared to peers in their reference group, the association between relative deprivation and poor health is expected to be positive (Eibner and Evans, 2005).

### 3.3 Estimation Strategy

The nurse-collected and blood-based biomarkers are initially modelled using linear regression model estimated by OLS. Distributional regression techniques are also applied to consider the entire distribution of each biomarker ($H_i$). We employ UQR models, allowing us to estimate unconditional quantile partial effects (Firpo et al., 2009). UQR models are based on the recentered influence function (RIF). The RIF can be estimated by computing sample quantiles of the health measure ($q_\tau$) and then estimating the density of the distribution of health measures at the quantiles using kernel density methods. That is,

$$RIF(H_i; q_\tau) = q_\tau + \frac{\tau - 1[H_i \leq q_\tau]}{f_H(q_\tau)}$$

where $q_\tau$ is the observed sample quantile, $1[H_i \leq q]$ is an indicator function taking the value of one if the observed value of health measure of interest is less than or equal to the observed quantile $q_\tau$ and zero otherwise; $f_H(q_\tau)$ is the estimated kernel density of the particular health measures at the $\tau^{th}$ quantile. The RIF is then regressed on our set of covariates using OLS. We use a bootstrap method with 500 replications to obtain unbiased estimates of the variance covariance matrix of the parameter estimates (Buchinsky, 1998).

### 3.4 Health model specification

We specify our health model using each biomarker as a function of measure of deprivation along with income and other covariates. Accordingly, three model specifications are estimated as follows.

Multidimensional deprivation: Each health outcome ($H_i$) is regressed on our long term income and the dynamic multidimensional deprivation measure along with other covariates. This is done at the mean using OLS and across quantiles (with 0.05 increments) using RIF regressions defined as follows:

$$RIF(H_i; q_\tau) = \beta_{0\tau} + \beta_{1\tau} ln(Inc_{iLT}) + \beta_{2\tau}\Omega_i + \beta'_{3\tau}\mathbf{x_i} + \epsilon_{i\tau} \tag{4}$$

where $Inc_{LT}$ is the long term income (calculated as an average income over BHPS wave 9 to wave 18) and $\beta_{1\tau}$ is the coefficient for income; $\Omega$, is our dynamic multidimensional measure and $\beta_{2\tau}$ is the corresponding coefficient at $\tau^{th}$ quantile. The vector $\mathbf{x}$ is the set of covariates, $\beta'_{3\tau}$ are the relevant coefficients and $\epsilon_{i\tau}$ is the error term at each quantile.

Dimension and duration deprivation: A unique feature of our measure of multidimensional deprivation is that this measure is decomposable into a deprivation due to breadth and length of deprivation. We exploit this feature to reestimate Equation 4 incorporating components to investigate how the gradient changes with breadth of deprivation vis-a-vis length of deprivation as follows:

$$RIF(H_i; q_\tau) = \theta_{0\tau} + \theta_{1\tau} ln(Inc_{iLT}) + \theta_{2\tau}\Omega_{iA} + \theta_{3\tau}\Omega_{iB} + \theta_{4\tau}\Omega_{iC} + \theta'_{5\tau}x_i + \epsilon_{i\tau} \tag{5}$$

where $\Omega_{iA}, \Omega_{iB}$ and $\Omega_{iC}$ are the three components of overall multidimensional deprivation ($\Omega_i$) as discussed in Equation 3.

A simple way to explore the relative contribution of breadth and duration of deprivation to each of the different biomarkers is to estimate, for each quantile $\tau$, a counterfactual as follows:

$$\widetilde{H}_i^t(q_\tau) = \hat{\theta}_{0\tau} + \hat{\theta}_{1\tau} ln(Inc_{iLT}) + \hat{\theta}_{2\tau}\Omega_{iA} + \hat{\theta}_{3\tau}\Omega_{iB} + \hat{\theta}_{4\tau}\Omega_{iC} + \hat{\theta}'_{5\tau}x_i \tag{6}$$

where $\hat{\theta}$ coefficients represent the estimated coefficients in Equation 5. As the RIF equations

are additive and linear, fitted values for each biomarker can be estimated using the RIF method at each quantile ($\widetilde{H}_i^t$), while the contribution of the three components is calculated as: $\hat{\theta}_{2\tau}\Omega_{iA}$, $\hat{\theta}_{3\tau}\Omega_{iB}$ and $\hat{\theta}_{4\tau}\Omega_{iC}$. The ratio of each of the latter to the total prediction ($\widetilde{H}_i^t$) shows the percentage contribution to each of the three components to the fitted biomarker values at quantile $\tau$.

Relative deprivation: The measure of relative deprivation computed assuming that the relative position of an individual in their reference group is based on how many individuals are less deprived than individual $i$ (Yitzhaki, 1979). The equation estimated using relative deprivation as the measure of socioeconomic status is as follows:

$$RIF(H_i^\star; q_\tau) = \eta_{0\tau} + \eta_{1\tau} ln(Inc_{iLT}) + \eta_{2\tau} RD_i + \eta'_{3\tau}\mathbf{x_i} + \epsilon_i \tag{7}$$

where $RD_i$ is the relative deprivation measure and $\eta$'s are the corresponding regression coefficients to be estimated.

# 4 Results

We start with a discussion of the results for Shapley decomposition of our dynamic multi-dimensional deprivation measure to identify the contribution of each dimension to overall deprivation. This is followed by a discussion of the results for the deprivation gradient in health and the role of breadth and length of deprivation in shaping this deprivation gradient. Finally, we discuss results for the role of relative deprivation.

## 4.1 Shapley decomposition

Table 1 presents the decomposition of overall deprivation into contribution of each dimension - Shapley decomposition results. These results allow us to identify which domains contribute the most to overall deprivation and within these domains how much of the contribution is explained by each component of deprivation. The proportional contribution of each of the ten domains to overall deprivation is presented in column (2); domainwise decomposition of the percentage contribution of the three components of overall deprivation are presented

in each row of columns (3) to (5), as in equation (3); column (6) showing the sum of each row of these columns adding up to 100%. The proportional contribution of each domain to overall prevalence of deprivation and persistence of deprivation is presented in column (7) and column (8), respectively. These results suggest that education, consumer goods, social engagement and housing conditions had the largest contribution to overall deprivation (column 1). For these domains the percentage contribution of deprivation across time is larger than that of prevalence of deprivation (column 3-5). Finally, these domains are also characterised by relatively higher values of percentage contribution to both $\Omega^{dimension}$ and $\Omega^{duration}$ in comparison to the other domains (column 7-8). Overall, these results highlight the role of persistence and prevalence of deprivation in explainining the overall deprivation in the UK.

### 4.2 Income and deprivation gradient in health

Figure 1 and Figure 2 present deprivation gradients estimated across quantiles (with 0.05 increments) of each of our set of biomarkers (UQR estimates); the corresponding coefficients at the mean are presented in Table A4 (Appendix). To explore the role of deprivation over and above income, we include income as an additional covariate (Equation 4).

Overall, the deprivation and income gradients are more pronounced and larger in magnitude towards the right tails of the biomarker distributions, where the greater burden of illness for individuals and higher costs for the healthcare system are evident. Specifically, regarding our adiposity measures, although no systematic associations at the mean (see Table A4) are observed, we find a steep increase in deprivation gradients after the $75^{th}$ percentile of the BMI (i.e., BMI $>$ 31.7 kg/$m^2$) and waist circumference (i.e., $>$ 106 cm) distribution (Figure 1); these correspond to BMI and waist circumference values close to the clinical threshold for elevated health risks, indicating stronger positive associations with higher deprivation levels. Regarding income, our UQR results also show that the OLS estimator masks notable differences in the income-adiposity gradient across the BMI and WC distributions. For example, we find that the negative income gradient peaks at around the $95^{th}$ percentile of the BMI distribution, which is about 5 times higher than the corresponding OLS coefficient. The evidence on the presence of gradient due to deprivation over and

above the effect of income suggests that income alone is not sufficient to account for the socioeconomic gradient in adiposity measures.

Turning to the results for blood pressure measurements, there are no systematic deprivation gradients both at the mean and across quantiles of their distribution. On the other hand, the deprivation gradient is much more pronounced, independent of income, for our cardiovascular fitness measure (heart rate) towards the right tail of its distribution (Figure 1). For example, analysis "beyond the mean" reveals that although there is a flat pattern in the deprivation gradient in heart rate across most of its distribution, there is a steep increase at the far right tails of the distribution; the deprivation gradient at the $95^{th}$ percentile is about 2.5 times higher than the OLS coefficient. A gradually increasing negative income gradient is also evident when moving to higher quantiles of the heart rate distribution.

Considering inflammatory biomarkers (CRP and fibrinogen), our analysis at the mean (Table A4) suggests presence of a systematic income gradients with the corresponding results for deprivation to be less pronounced. However, UQR estimates (Figure 2) paint a different picture, showing gradually increasing and statistically significant (at least the 5% level) deprivation gradients beyond the normal range of CRP (i.e., for CRP $> 3$). No systematic associations are observed for the very high CRP values, which mostly reflect non-systematic but recent infections (CRP $> 10$; Ishii et al., 2012). Similarly, we find increasing long-run income gradients towards the highest quartiles of the CRP distribution. On the other hand, generally flat, income and deprivation gradients are evident across the distribution of fibrinogen; the observed flat income gradients in fibrinogen are in line with previous evidence (Carrieri and Jones, 2017).

For our "blood sugar" biomarker (HbA1c), a biomarker for diabetes, we find a sharp increase in the positive deprivation gradient towards the right tail of the distribution (Figure 2). Specifically, we find a "saddle" point at around the $90^{th}$ percentile of the HbA1c distribution (corresponding to the clinical threshold of diabetes), with the relevant UQR coefficient being statistically significant at the 10% level.

For cholesterol ratio, a predictor of several heart diseases, we find no systematic associations with deprivation over and above the role of income. However, the long-run income gradients in cholesterol ratio remain fairly stable up to the $75^{th}$ percentile of the cholesterol ratio

distribution, which is very close to the high-risk threshold of 4 (Millán et al., 2009), and then gradually increases toward the far right tails of the distribution.

### 4.3 Decomposing the multidimensional deprivation in health into its sources

To explore the relative contribution of breadth and length of deprivation, we conduct a counterfactual analysis of the relative contribution of breadth and length of deprivation to each biomarker (Equation 6). Table 2 presents the percentage contribution of each of the these three components to the predicted counterfactual outcome for each biomarker estimated at the $10^{th}$, $25^{th}$, $50^{th}$, $75^{th}$, $90^{th}$ and $95^{th}$ quantile of the distribution using the RIF method. For each biomarker, the last two rows of Table 2 present the sum of the percentage contribution of $\Omega_A$ and $\Omega_B$, reflecting the breadth component, and $\Omega_A$ and $\Omega_C$ reflecting the duration component.

For any given biomarker, if the sign of the percentage contribution is positive (negative) means that the certain component results in increasing (decreasing) our health measures, indicating a positive (negative) association with ill health (given that our biomarkers increase to ill health). Overall, our results show that for the biomarkers for which systematic deprivation gradients are observed (sub-section 4.2), i.e., BMI, waist circumference, HR, CRP and HbA1c, the percentage contribution of the breadth of deprivation component $\Omega^{dimension}$, is positive and increasing in magnitude towards the right tails of the biomarker distribution. On the other hand, the percentage contribution of the duration of deprivation component $\Omega^{duration}$ seems, in most of these biomarkers, to be less evident in magnitude and often negative at higher quantiles of the distribution, contributing to shrinking the contribution of the breadth component and the overall deprivation gradient in health. For example, the percentage contribution of $\Omega^{dimension}$ to the fitted waist circumference using the fitted RIF method increases from 0.37% at the bottom to around 2.9% at the top of the distribution; less pronounced is the relevant contribution of $\Omega^{duration}$, being about 0.15% at the $95^{th}$ quantile of the waist circumference distribution. Taking HbA1c as another example, the contribution of breadth of deprivation increased from 1.1% at the bottom to 17% at the top of the distribution, while the duration component seems to exert a negative contribution at higher quantiles contributing to shrinking the contribution of the breadth of deprivation

component.

These results echo the relevant results from the three components of the breadth and duration of deprivation (i.e., $\Omega_A, \Omega_B, \Omega_C$). Specifically, the percentage contribution of the distributional-insensitive count of deprivation component ($\Omega_A$) is positive and large (relative to the sub-component $\Omega_B$). This explains the dominant role of the overall breadth of deprivation component of our multidimensional deprivation measure ($\Omega^{dimension}$) stated above. On the other hand, it seems that $\Omega_C$ (i.e, the distribution of the length component across dimensions or persistence of deprivation) has a negative contribution that increases in magnitude at the higher quantiles of biomarkers distribution. This may offset the contribution of $\Omega_A$ sub-component, offering an explanation on why the overall percentage contribution of the duration of deprivation $\Omega^{duration}$ (i.e., the sum of $\Omega_A$ and $\Omega_C$) seems, in most of the cases, to be relatively less evident and often negative at the highest quantiles of the biomarker distribution.

### 4.4 Gradient in health using relative deprivation

The results for relative deprivation gradients estimated at the mean and across quantiles of the distribution of health measures are presented in Table A5 (Appendix) and Figures 3 and 4. Overall, we find limited evidence of relative deprivation playing an important role over and above the effect of long run income (Equation 7). However, an exception is the case of waist circumference, for which relative deprivation gradients become steeper and statistically significant towards right tails of the distribution. Regarding HbA1c, although relative deprivation seems to exert a positive and statistically significant effect at the mean (Table A5), much less pronounced results are evident at higher quantiles of the distribution. These results are broadly in accordance with previous evidence suggesting a limited role of relative deprivation - based on income - on self reported health measures (Jones and Wildman, 2008) and extend this literature to the case of biomarkers and multidimensional relative deprivation measures.

# 5 Conclusion

In this paper we propose a new approach to analysing the relationship between health and socioeconomic status. While most of the existing literature adopts a static approach to analysing this relationship, we adopt a holistic approach by accounting for the role of breadth and persistence of deprivation across time in influencing health. Building on method of measuring multidimensional deprivation based on Nicholas et al. (2018) and Bossert et al. (2007) we develop measures of absolute and relative deprivation. Further decomposition of overall deprivation using the Shapley decomposition method allows us to conduct a detailed analysis to explore the role of breadth and duration of deprivation on shaping the deprivation gradient in health. Moreover, we employ UQR to conduct a distributional analysis of the gradient to understand how the gradient evolves for people with vulnerability in health. In contrast to the majority of existing studies, we use data for a range of objectively measured biomarkers, rather than self reported health measures taken from the UKHLS and BHPS databases.

The first finding is that the socioeconomic gradient in most of our health measures is not solely attributed to income and it is important to account for the level of multidimensional deprivation. Our second finding is the existence of a systematic deprivation gradient across the distribution of most of the biomarkers explored in our analysis, i.e., BMI, waist circumference, heart rate, CRP and HbA1c. The gradient becomes larger in magnitude and systematic at higher quantiles of the distribution of biomarkers, where higher health risks are evident. The third finding is that breadth of deprivation to be more relevant in shaping the observed deprivation gradients, indicating that ignoring the dynamic and multidimensional nature of deprivation would give an incomplete picture of the deprivation status in the UK. Design of health policy should aim at prioritising health of people enduring deprivation across multiple domains, i.e., people who experience dual burden of deprivation and poor health and thus, at risk of falling into a health deprivation trap.

Table 1: Shapley Decomposition of Dynamic Multidimensional Deprivation

| Domain | Dynamic deprivation | Percentage contribution of components | | | Total column (3)-(5) | Prevalence of deprivation | Persistence of deprivation |
|---|---|---|---|---|---|---|---|
| | ($\Omega$) | $\Omega_A$ | $\Omega_B$ | $\Omega_C$ | | ($\Omega^{dimension}$) | ($\Omega^{duration}$) |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Education | 11.36 | 52.75 | 0.11 | 47.14 | 100 | 18.69 | 11.45 |
| Economic activity | 9.99 | 31.53 | 0.63 | 67.84 | 100 | 10.00 | 10.01 |
| Housing conditions | 10.03 | 29.82 | 1.86 | 68.32 | 100 | 9.89 | 9.93 |
| Consumer goods | 12.84 | 69.86 | 0.07 | 30.08 | 100 | 27.96 | 12.95 |
| Car ownership | 9.30 | 19.78 | 0.38 | 79.84 | 100 | 5.84 | 9.35 |
| Affordable lifestyle | 9.24 | 17.14 | 1.11 | 81.75 | 100 | 5.25 | 9.22 |
| Financial hardship | 8.62 | 5.27 | 0.55 | 94.18 | 100 | 1.56 | 8.65 |
| Social Engagement | 9.96 | 28.96 | 1.72 | 69.32 | 100 | 9.52 | 9.88 |
| Environment | 9.30 | 17.68 | 1.43 | 80.89 | 100 | 5.54 | 9.25 |
| Security | 9.34 | 18.28 | 1.48 | 80.23 | 100 | 5.75 | 9.29 |
| Overall | 100.00 | 31.22 | 0.90 | 67.88 | 100 | 100.00 | 100.00 |

Note: Refer to Equation 2 and 3 in Section 3.1.

$\Omega_A$: Sum of count of deprivation averaged over individuals. This is the distribution sensitive component.

$\Omega_B$: Component of multidimensional deprivation due to distribution of breadth of deprivation.

$\Omega_C$: Component of multidimensional deprivation due to the distribution of length of deprivation.

$\Omega^{dimension} = \Omega_A + \Omega_B$

$\Omega^{duration} = \Omega_A + \Omega_C$

Figure 1: Income and deprivation gradient in nurse-collected health measures: unconditional quantile regression

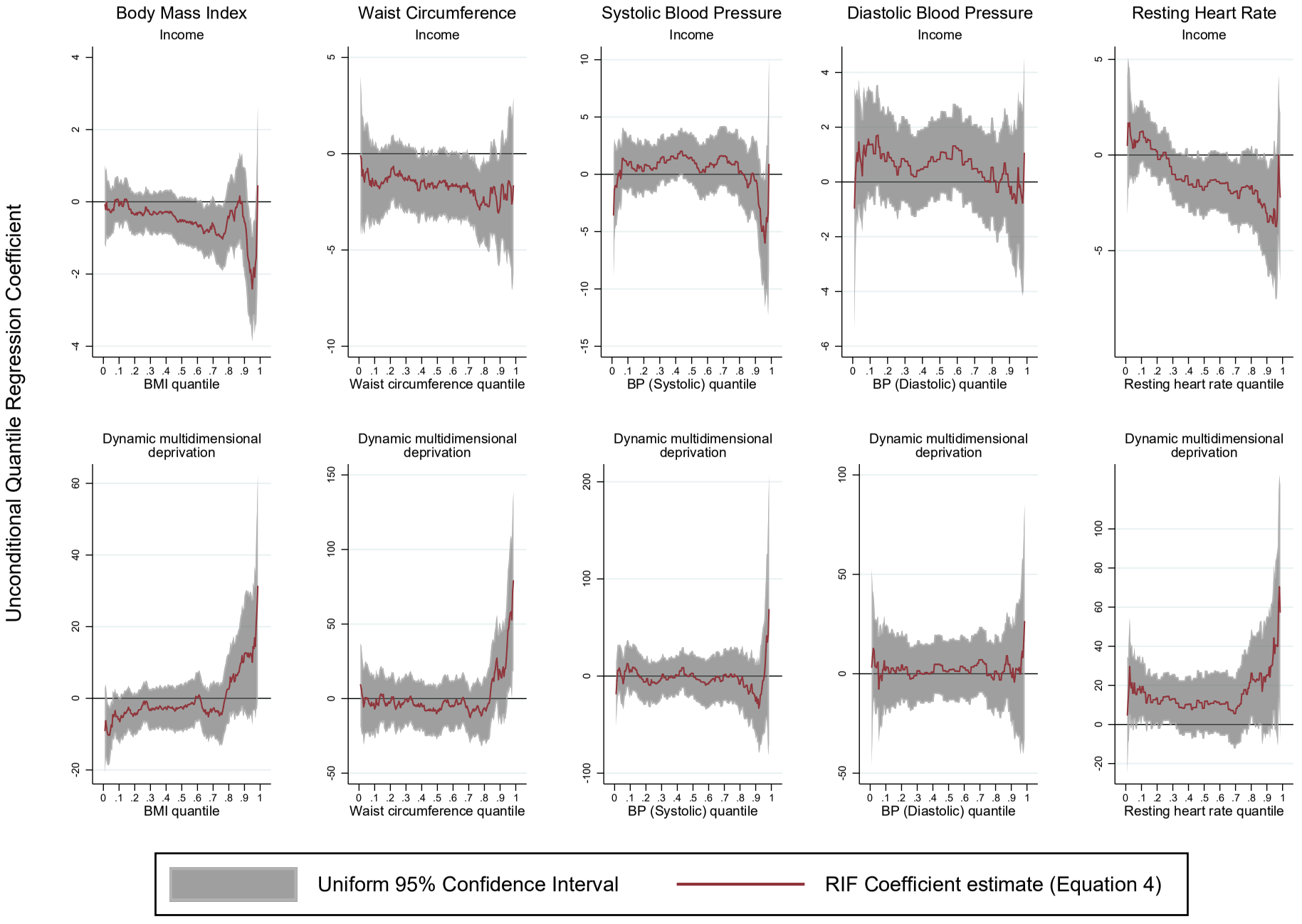

Figure 2: Income and deprivation gradients in blood-based biomarkers: unconditional quantile regression estimates

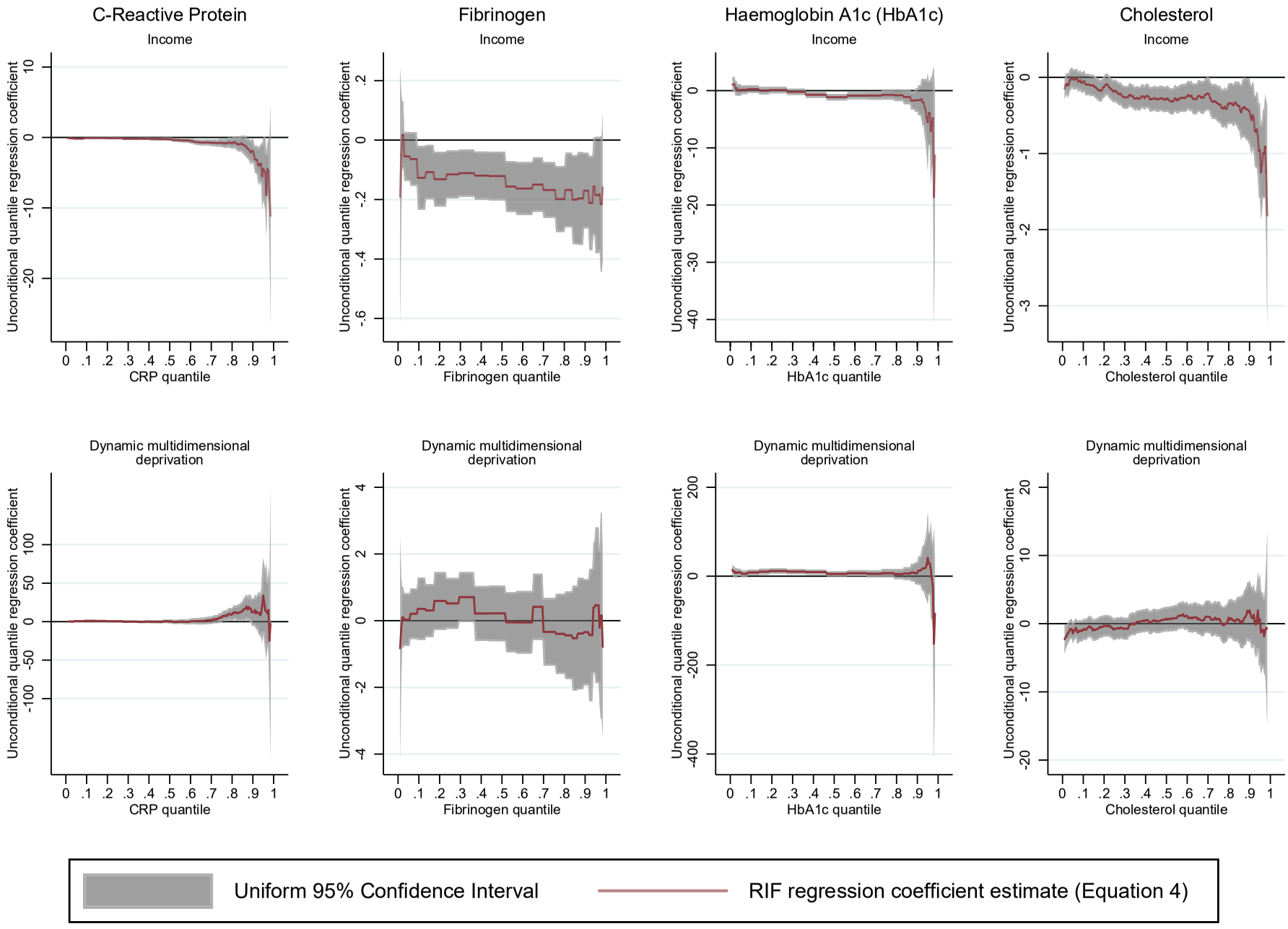

Figure 3: Income and relative deprivation gradients: nurse-collected biomarkers

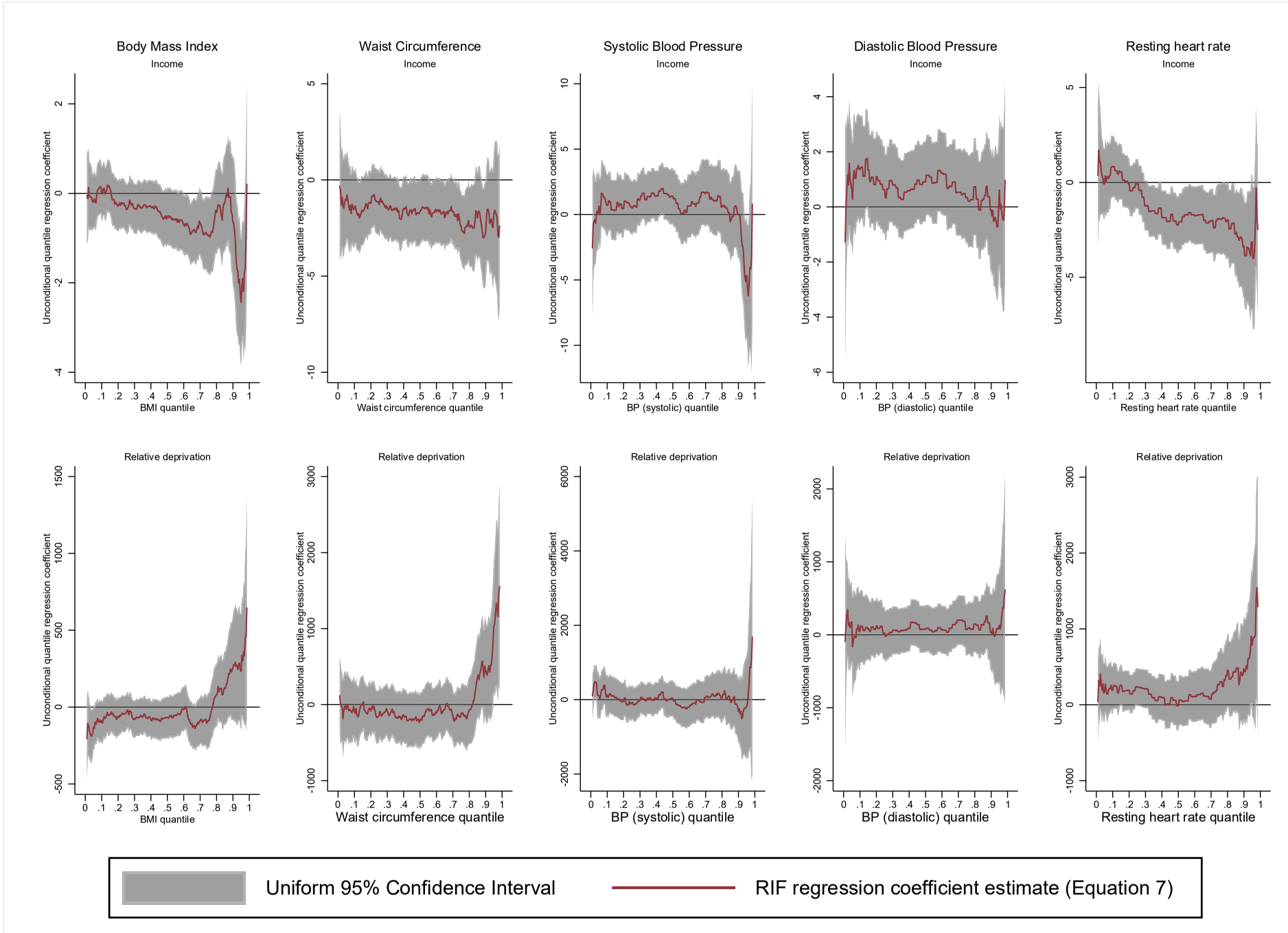

Figure 4: Income and relative deprivation gradients: blood-based biomarkers

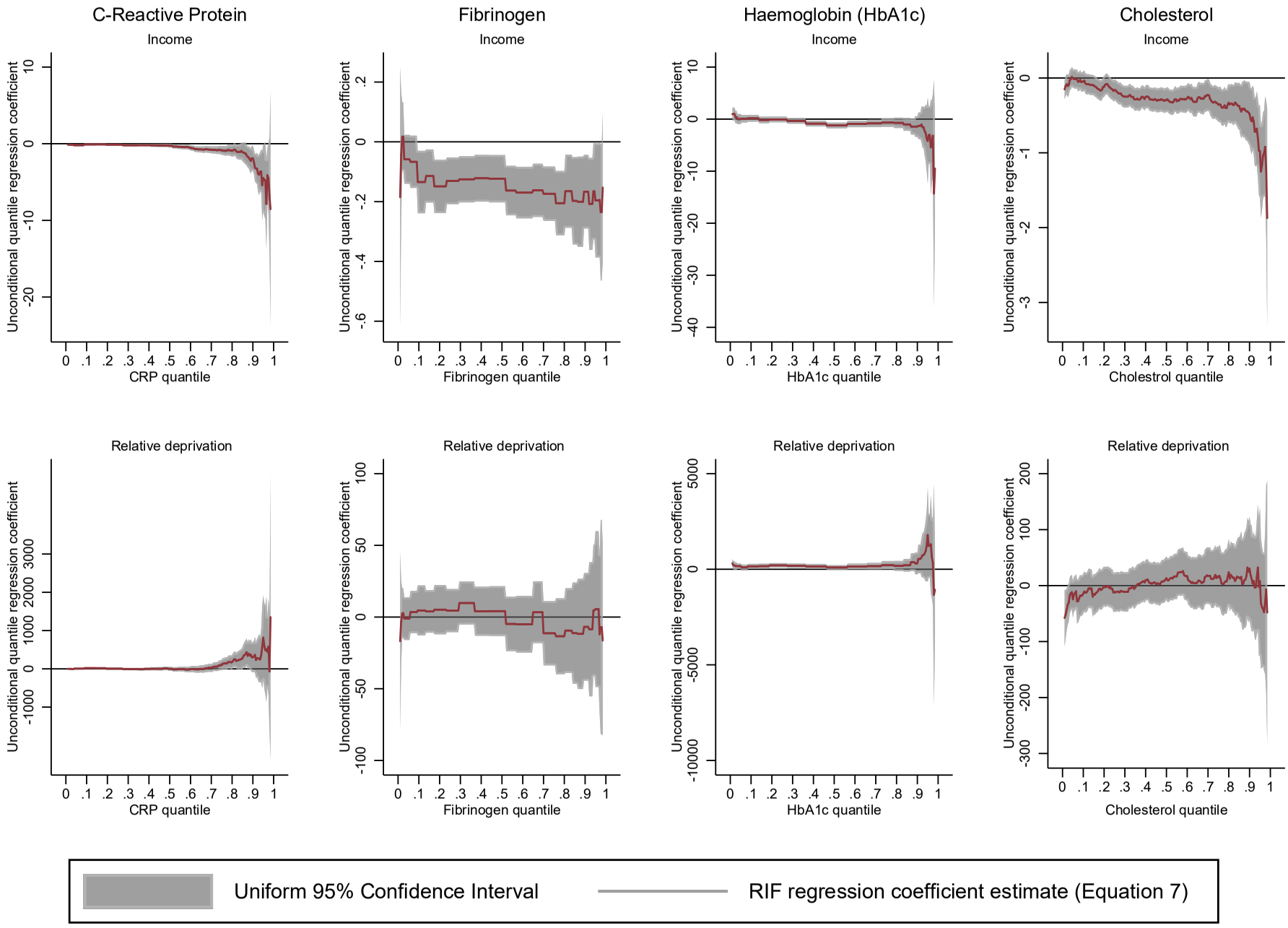

Table 2: Percentage contribution of components of deprivation to predicted biomarkers*

| | Deprivation Component | q(10) | q(25) | q(50) | q(75) | q(90) | q(95) |
|---|---|---|---|---|---|---|---|
| BMI | $\Omega_A$ | 0.22 | 0.09 | 0.45 | 1.24 | 2.80 | 2.22 |
| | $\Omega_B$ | -0.05 | 0.35 | 0.33 | -0.48 | 0.00 | 0.60 |
| | $\Omega_C$ | -4.92 | -2.10 | -3.34 | -5.18 | -2.87 | -3.48 |
| | $\Omega^{dimension}$ | 0.17 | 0.43 | 0.78 | 0.75 | 2.80 | 2.82 |
| | $\Omega^{duration}$ | -4.70 | -2.01 | -2.89 | -3.95 | -0.06 | -1.27 |
| Waist Circumference | $\Omega_A$ | 1.23 | 0.08 | 0.68 | 0.34 | 2.02 | 2.96 |
| | $\Omega_B$ | -0.86 | 0.09 | 0.16 | 0.78 | -0.05 | -0.07 |
| | $\Omega_C$ | -3.97 | -1.18 | -4.00 | -3.36 | -3.56 | -2.81 |
| | $\Omega^{dimension}$ | 0.37 | 0.17 | 0.84 | 1.12 | 1.96 | 2.89 |
| | $\Omega^{duration}$ | -2.74 | -1.10 | -3.32 | -3.01 | -1.55 | 0.15 |
| Diastolic BP | $\Omega_A$ | 0.15 | 0.29 | 0.36 | -0.27 | 0.29 | 0.99 |
| | $\Omega_B$ | -0.57 | 0.32 | -0.15 | 0.24 | 0.13 | -0.16 |
| | $\Omega_C$ | 0.89 | -1.48 | -0.61 | 0.25 | -0.96 | -2.16 |
| | $\Omega^{dimension}$ | -0.41 | 0.61 | 0.21 | -0.02 | 0.42 | 0.83 |
| | $\Omega^{duration}$ | 1.05 | -1.19 | -0.24 | -0.02 | -0.67 | -1.16 |
| Systolic BP | $\Omega_A$ | 0.12 | 1.75 | -0.19 | 0.98 | 2.14 | 3.28 |
| | $\Omega_B$ | -0.27 | -0.14 | -0.28 | -0.23 | -0.12 | 0.06 |
| | $\Omega_C$ | 1.59 | -0.08 | 0.76 | -0.20 | -5.10 | 0.45 |
| | $\Omega^{dimension}$ | -0.15 | 1.61 | -0.47 | 0.75 | 2.02 | 3.35 |
| | $\Omega^{duration}$ | -0.02 | 3.35 | -0.66 | 1.73 | 4.16 | 6.63 |
| Resting heart rate | $\Omega_A$ | 0.12 | 1.75 | -0.19 | 0.98 | 2.14 | 3.28 |
| | $\Omega_B$ | 0.84 | 0.29 | 0.75 | 0.47 | 0.20 | -0.42 |
| | $\Omega_C$ | 3.06 | -1.96 | 1.41 | -0.32 | -1.84 | -2.64 |
| | $\Omega^{dimension}$ | 0.96 | 2.04 | 0.56 | 1.45 | 2.34 | 2.86 |
| | $\Omega^{duration}$ | 3.19 | -0.21 | 1.23 | 0.66 | 0.30 | 0.64 |
| C-Reactive Protein | $\Omega_A$ | 27.71 | 13.19 | 0.83 | 6.92 | 13.77 | 37.93 |
| | $\Omega_B$ | 3.28 | -10.06 | 0.55 | 0.76 | 2.03 | 1.30 |
| | $\Omega_C$ | -21.29 | -12.23 | -0.21 | 4.95 | -19.17 | -76.55 |
| | $\Omega^{dimension}$ | 30.99 | 3.13 | 1.38 | 7.68 | 15.80 | 39.23 |
| | $\Omega^{duration}$ | 6.42 | 0.96 | 0.62 | 11.88 | -5.40 | -38.62 |
| Fibrinogen | $\Omega_A$ | 2.74 | 1.36 | 0.65 | -1.02 | 0.54 | 1.60 |
| | $\Omega_B$ | -0.81 | -0.12 | 0.24 | 1.10 | 1.03 | -0.69 |
| | $\Omega_C$ | -4.54 | -0.69 | -1.15 | -0.25 | -4.92 | -2.05 |
| | $\Omega^{dimension}$ | 1.93 | 1.24 | 0.89 | 0.08 | 1.58 | 0.91 |
| | $\Omega^{duration}$ | -1.80 | 0.67 | -0.50 | -1.28 | -4.37 | -0.45 |
| HbA1c | $\Omega_A$ | 0.99 | 0.78 | 0.44 | 2.29 | 6.17 | 20.11 |
| | $\Omega_B$ | 0.15 | 0.39 | 0.71 | -0.43 | -0.34 | -2.74 |
| | $\Omega_C$ | 0.98 | 2.48 | -0.10 | -3.63 | -15.96 | -46.83 |
| | $\Omega^{dimension}$ | 1.15 | 1.17 | 1.15 | 1.86 | 5.83 | 17.37 |
| | $\Omega^{duration}$ | 1.98 | 3.26 | 0.34 | -1.35 | -9.79 | -26.72 |
| Cholesterol Ratio | $\Omega_A$ | -1.40 | -0.22 | 1.45 | 0.25 | 0.86 | -0.31 |
| | $\Omega_B$ | -0.40 | -0.19 | 0.41 | 1.26 | 0.96 | 2.60 |
| | $\Omega_C$ | -1.04 | -3.81 | -1.57 | -0.38 | 1.83 | -1.58 |
| | $\Omega^{dimension}$ | -1.81 | -0.41 | 1.85 | 1.51 | 1.82 | 2.28 |
| | $\Omega^{duration}$ | -2.45 | -4.04 | -0.13 | -0.13 | 2.70 | -1.89 |

Calculations based on Equation 6.
*All numbers are in percentage points

## References


Acabchuk, R. L., J. Kamath, J. D. Salamone, and B. T. Johnson (2017). Stress and chronic illness: The inflammatory pathway. Social Science & Medicine 185, 166.

Adjaye-Gbewonyo, K. and I. Kawachi (2012). Use of the yitzhaki index as a test of relative deprivation for health outcomes: a review of recent literature. Social Science & Medicine 75(1), 129–137.

Alkire, S. (2002). Dimensions of human development. World Development 30(2), 181–205.

Alkire, S. and J. Foster (2011). Counting and multidimensional poverty measurement. Journal of Public Economics 95(7), 476–487.

Bago d'Uva, T., O. O'Donnell, and E. Van Doorslaer (2008). Differential health reporting by education level and its impact on the measurement of health inequalities among older europeans. International Journal of Epidemiology 37(6), 1375–1383.

Blázquez, M., E. Cottini, and A. Herrarte (2014). The socioeconomic gradient in health: how important is material deprivation? The Journal of Economic Inequality 12(2), 239–264.

Bossert, W., L. Ceriani, S. R. Chakravarty, and C. D'Ambrosio (2013). Intertemporal material deprivation. In G. Betti and A. Lemmi (Eds.), Poverty and Social Exclusion: New Methods of Analysis, pp. 128–48. Routledge.

Bossert, W., C. D'Ambrosio, and V. Peragine (2007). Deprivation and social exclusion. Economica 74(296), 777–803.

Braveman, P. A., C. Cubbin, S. Egerter, S. Chideya, K. S. Marchi, M. Metzler, and S. Posner (2005). Socioeconomic status in health research: one size does not fit all. JAMA 294(22), 2879–2888.

Buchinsky, M. (1998). Recent advances in quantile regression models: a practical guideline for empirical research. Journal of Human Resources 33(1), 88–126.

Carrieri, V. and A. M. Jones (2017). The income-health relationship 'beyond the mean': New evidence from biomarkers. Health Economics 26(7), 937–956.

Contoyannis, P. and A. M. Jones (2004). Socio-economic status, health and lifestyle. Journal of Health Economics 23(5), 965–995.

Contoyannis, P., A. M. Jones, and N. Rice (2004). The dynamics of health in the British Household Panel Survey. Journal of Applied Econometrics 19(4), 473–503.

Cuesta, M. B. and S. Budría (2014). Deprivation and subjective well-being: Evidence from panel data. Review of Income and Wealth 60(4), 655–682.

Davillas, A. and S. Pudney (2017). Concordance of health states in couples: Analysis of self-reported, nurse administered and blood-based biomarker data in the uk understanding society panel. Journal of Health Economics 56, 87–102.

Deaton, A. (2001). Relative deprivation, inequality, and mortality. Technical report, National Bureau of Economic Research.

Deaton, A. S. and C. H. Paxson (1998). Aging and inequality in income and health. The American Economic Review 88(2), 248–253.

Decancq, K. and M. A. Lugo (2012). Inequality of wellbeing: a multidimensional approach. Economica 79(316), 721–746.

Dowd, J. B. and A. Zajacova (2010). Does self-rated health mean the same thing across socioeconomic groups? evidence from biomarker data. Annals of Epidemiology 20(10), 743–749.

Eibner, C. and W. N. Evans (2005). Relative deprivation, poor health habits, and mortality. Journal of Human Resources 40(3), 591–620.

Ferrer-i Carbonell, A. (2005). Income and well-being: an empirical analysis of the comparison income effect. Journal of Public Economics 89(5-6), 997–1019.

Firpo, S., N. M. Fortin, and T. Lemieux (2009). Unconditional quantile regressions. Econometrica 77(3), 953–973.

Glei, D. A., N. Goldman, V. M. Shkolnikov, D. Jdanov, S. Shalnova, M. Shkolnikova, and M. Weinstein (2013). To what extent do biomarkers account for the large social disparities in health in Moscow? Social Science & Medicine 77, 164–172.

Gruenewald, T. L., S. Cohen, K. A. Matthews, R. Tracy, and T. E. Seeman (2009). Association of socioeconomic status with inflammation markers in black and white men and women in the coronary artery risk development in young adults (CARDIA) study. Social Science & Medicine 69(3), 451–459.

Ishii, S., A. S. Karlamangla, M. Bote, M. R. Irwin, D. R. Jacobs Jr, H. J. Cho, and T. E. Seeman (2012). Gender, obesity and repeated elevation of c-reactive protein: data from the CARDIA cohort. PloS One 7(4), e36062.

Johnston, D. W., C. Propper, and M. A. Shields (2009). Comparing subjective and objective measures of health: Evidence from hypertension for the income/health gradient. Journal of Health Economics 28(3), 540–552.

Jones, A. M. and J. Wildman (2008). Health, income and relative deprivation: Evidence from the BHPS. Journal of Health Economics 27(2), 308–324.

Jürges, H. (2007). True health vs response styles: exploring cross-country differences in self-reported health. Health Economics 16(2), 163–178.

Jürges, H., E. Kruk, and S. Reinhold (2013). The effect of compulsory schooling on health—evidence from biomarkers. Journal of Population Economics 26(2), 645–672.

Kim, J. and E. Durden (2007). Socioeconomic status and age trajectories of health. Social Science & Medicine 65(12), 2489–2502.

Lorgelly, P. K. and J. Lindley (2008). What is the relationship between income inequality and health? evidence from the BHPS. Health Economics 17(2), 249–265.

Loucks, E. B., J. W. Lynch, L. Pilote, R. Fuhrer, N. D. Almeida, H. Richard, G. Agha, J. M. Murabito, and E. J. Benjamin (2009). Life-course socioeconomic position and incidence of coronary heart disease: the framingham offspring study. American Journal of Epidemiology 169(7), 829–836.

Mangyo, E. and A. Park (2011). Relative deprivation and health which reference groups matter? Journal of Human Resources 46(3), 459–481.

Millán, J., X. Pintó, A. Muñoz, M. Zúñiga, J. Rubiés-Prat, L. F. Pallardo, L. Masana, A. Mangas, A. Hernández-Mijares, P. González-Santos, et al. (2009). Lipoprotein ratios: physiological significance and clinical usefulness in cardiovascular prevention. Vascular Health and Risk Management 5, 757.

Nicholas, A., R. Ray, and K. Sinha (2018). Differentiating between dimensionality and duration in multidimensional measures of poverty: Methodology with an application to China. Review of Income and Wealth doi:10.1111/roiw.12313.

Sen, A. (1985). Commodities and capabilities. North-Holland, Amsterdam.

Shorrocks, A. F. (2013). Decomposition procedures for distributional analysis: a unified framework based on the shapley value. The Journal of Economic Inequality 11(1), 99–126.

Stiglitz, J. E., A. Sen, J.-P. Fitoussi, et al. (2010). Report by the commission on the measurement of economic performance and social progress. Technical report, Paris: Commission on the Measurement of Economic Performance and Social Progress.

Subramanyam, M., I. Kawachi, L. Berkman, and S. Subramanian (2009). Relative deprivation in income and self-rated health in the United States. Social Science & Medicine 69(3), 327–334.

Van Doorslaer, E. and A. M. Jones (2003). Inequalities in self-reported health: validation of a new approach to measurement. Journal of Health Economics 22(1), 61–87.

WHO (2011). Use of glycated haemoglobin (HbA1c) in diagnosis of diabetes mellitus: abbreviated report of a who consultation. Technical report, World Health Organisation.

Wilkinson, R. and K. Pickett (2011). The spirit level: Why greater equality makes societies stronger. Bloomsbury Publishing USA.

Yitzhaki, S. (1979). Relative deprivation and the gini coefficient. The Quarterly Journal of Economics 1(May), 321–324.

# 6 Appendix

Table A1: Descriptive statistics for health measures

| Health variables | Mean | q(10) | q(25) | q(50) | q(75) | q(95) |
|---|---|---|---|---|---|---|
| BMI ($Kg/m^2$) | 28.75 | 22.50 | 25.00 | 27.95 | 31.68 | 39.07 |
| Waist Circumference (cm) | 96.50 | 78.25 | 86.30 | 95.75 | 105.70 | 121.95 |
| Systolic blood pressure (mmhg) | 128.54 | 107.50 | 116.75 | 127.00 | 139.00 | 159.00 |
| Diastolic blood pressure (mmhg) | 73.54 | 60.00 | 66.00 | 73.00 | 81.00 | 92.50 |
| Resting heart rate (bpm) | 68.80 | 55.50 | 61.00 | 68.00 | 75.50 | 89.00 |
| C-Reactive Protein (mg/l) | 3.31 | 0.40 | 0.70 | 1.50 | 3.20 | 11.50 |
| Fibrinogen (g/l) | 2.88 | 2.20 | 2.50 | 2.80 | 3.20 | 4.00 |
| HbA1C (mmol/mol) | 38.30 | 32.00 | 34.00 | 37.00 | 40.00 | 52.00 |
| Cholesterol Ratio (TC:HDL) | 3.84 | 2.38 | 2.87 | 3.57 | 4.53 | 6.45 |

Table A2: Description of dimensions of multidimensional deprivation

| Domain | Indicator | Description |
|---|---|---|
| Education | Low level of formal education of respondent or household head | 1 if respondent is uneducated; or highest level is less than high school; 0 higher than high school (A-level). |
| Economic Activity | Employment status of individual | 1 if individual is unemployed / retired/ carer/student/longtime sick and no other household member working. 0 if individual is employed/self employed, or atleast one member working. |
| Housing Conditions | Shortage of space | 1 if yes, 0 otherwise |
| | Not enough light | 1 if yes, 0 otherwise |
| | Lack of adequate heating | 1 if yes, 0 otherwise |
| | Damp walls, floors | 1 if yes, 0 otherwise |
| | Does not have separate bathroom | 1 if yes, 0 otherwise |
| | No central heating | 1 if yes, 0 otherwise |
| Consumer Goods | Lack: video recorder/dvd player | 1 if yes, 0 otherwise |
| | Lack: deep freeze or fridge freezer | 1 if yes, 0 otherwise |
| | Lack: washing machine | 1 if yes, 0 otherwise |
| | Lack: tumble drier | 1 if yes, 0 otherwise |
| | Lack: dishwasher | 1 if yes, 0 otherwise |
| | Lack: home computer/pc | 1 if yes, 0 otherwise |
| | Lack: satellite dish/ sky television | 1 if yes, 0 otherwise |
| | Lack: cable television | 1 if yes, 0 otherwise |
| Car ownership | No car available in the household | 1 if yes, 0 otherwise |
| Affordable Lifestyle | Can not afford replace furniture | 1 if yes, 0 otherwise |
| | Can not afford feed visitors once a month | 1 if yes, 0 otherwise |
| | Can not afford keep house well decorated | 1 if yes, 0 otherwise |
| Financial hardship | Been over two months late with rent | 1 if yes, 0 otherwise |
| | Housing payment required cutback | 1 if yes, 0 otherwise |
| | Cannot afford to pay for annual holiday | 1 if yes, 0 otherwise |
| Social engagement | Frequency of talking to neighbours | 1 if twice a month or less. 0 if once a week or most days. |
| | Frequency of meeting people | 1 if twice a month or less. 0 if once a week or most days. |
| Environment | Pollution/environmental problems | 1 if yes, 0 otherwise |
| | noise from neighbours | 1 if yes, 0 otherwise |
| Security | Vandalism or crime in neighbourhood | 1 if yes, 0 otherwise |

Table A3: Description and summary statistics for the covariates used in the health regression models

| Variable | Description | Mean | Standard Deviation |
|---|---|---|---|
| Age (years) | Age (15-19) | 0.01 | 0.08 |
| | Age (20-24) | 0.03 | 0.16 |
| | Age (25-29) | 0.05 | 0.22 |
| | Age (30-34) | 0.08 | 0.26 |
| | Age (35-39) | 0.10 | 0.30 |
| | Age (40-44) | 0.12 | 0.32 |
| | Age (45-49) | 0.11 | 0.31 |
| | Age (50-54) | 0.10 | 0.30 |
| | Age (55-59) | 0.10 | 0.30 |
| | Age (60-64) | 0.09 | 0.28 |
| | Age (65-69) | 0.08 | 0.26 |
| | Age (70-74) | 0.06 | 0.24 |
| | Age (75-79) | 0.05 | 0.21 |
| | Age (80-84) | 0.03 | 0.16 |
| | Age (85+) | 0.01 | 0.11 |
| Gender | Male | 0.46 | 0.50 |
| Race | White | 0.98 | 0.15 |
| Marital Status | Single | 0.10 | 0.30 |
| | Married | 0.75 | 0.43 |
| | Separated/Divorced | 0.08 | 0.26 |
| | Widowed | 0.07 | 0.26 |
| Region | North East | 0.03 | 0.18 |
| | North West | 0.09 | 0.29 |
| | Yorkshire and Humber | 0.07 | 0.26 |
| | East Midlands | 0.07 | 0.25 |
| | West Midlands | 0.06 | 0.24 |
| | East of England | 0.07 | 0.26 |
| | London | 0.05 | 0.21 |
| | South East | 0.10 | 0.30 |
| | South West | 0.07 | 0.25 |
| | Wales | 0.19 | 0.39 |
| | Scotland | 0.20 | 0.40 |
| Household characteristics | Household size | 2.71 | 1.28 |
| | Number of kids | 0.54 | 0.92 |
| Household type | Lone Parent | 0.03 | 0.18 |
| | Couple: with children | 0.28 | 0.45 |
| | Couple: without children | 0.48 | 0.50 |
| | Single: non elderly | 0.09 | 0.28 |
| | Single: elderly | 0.09 | 0.29 |
| | Other: group households | 0.02 | 0.12 |
| | Multiple family households | 0.01 | 0.11 |

Table A4: Income and deprivation gradient

| Dependent Variable | (1) Variables | (2) OLS | (3) q(10) | (4) q(25) | (5) q(50) | (6) q(75) | (7) q(95) |
|---|---|---|---|---|---|---|---|
| BMI | $\ln(\text{income})_{LT}$ | -0.478* | -0.113 | -0.381 | -0.501 | -0.979** | -2.408*** |
| | | (0.278) | (0.327) | (0.293) | (0.335) | (0.452) | (0.744) |
| | Absolute | -0.211 | -5.827* | -1.954 | -2.466 | -4.075 | 10.08 |
| | Deprivation ($\Omega_{LT}$) | (2.779) | (3.266) | (2.889) | (3.349) | (4.437) | (8.918) |
| | | | N=2626 | | | | |
| Waist | $\ln(\text{income})_{LT}$ | -1.704** | -1.657 | -1.187 | -1.661* | -2.452** | -1.580 |
| | | (0.678) | (1.046) | (0.887) | (0.897) | (0.963) | (1.758) |
| | Absolute | 2.564 | -6.869 | -3.956 | -8.934 | -6.087 | 45.61** |
| | Deprivation ($\Omega_{LT}$) | (6.702) | (10.27) | (8.721) | (8.915) | (9.502) | (20.89) |
| | | | N=2548 | | | | |
| Systolic BP | $\ln(\text{income})_{LT}$ | 0.310 | 0.761 | 0.361 | 1.464 | 0.847 | -4.506* |
| | | (0.913) | (1.240) | (1.075) | (1.129) | (1.399) | (2.475) |
| | Absolute | -2.358 | 6.595 | -6.357 | 2.798 | -0.783 | -4.046 |
| | Deprivation ($\Omega_{LT}$) | (9.257) | (12.95) | (11.09) | (11.69) | (14.48) | (28.94) |
| | | | N=2141 | | | | |
| Diasotic BP | $\ln(\text{income})_{LT}$ | 0.581 | 1.360 | 0.565 | 0.821 | 0.173 | 0.517 |
| | | (0.598) | (1.025) | (0.833) | (0.765) | (0.869) | (1.432) |
| | Absolute | 2.070 | 1.758 | -0.543 | 1.082 | -0.892 | 3.128 |
| | Deprivation ($\Omega_{LT}$) | (6.065) | (11.45) | (8.359) | (7.832) | (8.750) | (17.66) |
| | | | N=2141 | | | | |
| Resting heart rate | $\ln(\text{income})_{LT}$ | -1.114* | 1.211 | 0.133 | -1.836** | -1.690* | -2.901 |
| | | (0.628) | (0.839) | (0.685) | (0.785) | (0.973) | (1.845) |
| | Absolute | 16.35** | 16.20** | 14.13** | 8.299 | 15.59 | 36.33* |
| | Deprivation ($\Omega_{LT}$) | (6.366) | (7.897) | (6.339) | (7.953) | (10.29) | (19.91) |
| | | | N=2145 | | | | |
| C-Reactive Protein | $\ln(\text{income})_{LT}$ | -1.043** | -0.0785 | -0.103 | -0.246* | -0.804*** | -4.433* |
| | | (0.446) | (0.0719) | (0.0726) | (0.127) | (0.304) | (2.277) |
| | Absolute | 4.851 | 1.061* | 0.488 | 0.280 | 5.481* | 33.82 |
| | Deprivation ($\Omega_{LT}$) | (4.526) | (0.614) | (0.719) | (1.270) | (3.280) | (24.89) |
| | | | N=1777 | | | | |
| Fibrinogen | $\ln(\text{income})_{LT}$ | -0.142*** | -0.127** | -0.115*** | -0.121*** | -0.168*** | -0.185* |
| | | (0.0354) | (0.0549) | (0.0414) | (0.0419) | (0.0480) | (0.0999) |
| | Absolute | 0.0850 | 0.358 | 0.517 | 0.218 | -0.333 | 0.466 |
| | Deprivation ($\Omega_{LT}$) | (0.359) | (0.478) | (0.390) | (0.427) | (0.519) | (1.191) |
| | | | N=1767 | | | | |
| HbA1c | $\ln(\text{income})_{LT}$ | -1.280** | 0.259 | 0.0960 | -1.150*** | -0.733* | -5.520 |
| | | (0.540) | (0.345) | (0.296) | (0.297) | (0.442) | (4.337) |
| | Absolute | 8.072 | 8.418** | 11.68*** | 5.157* | 6.802 | 41.02 |
| | Deprivation ($\Omega_{LT}$) | (5.534) | (3.357) | (3.034) | (2.983) | (4.917) | (52.67) |
| | | | N=1683 | | | | |
| Cholesterol Ratio | $\ln(\text{income})_{LT}$ | -0.304*** | -0.0566 | -0.176** | -0.287*** | -0.356*** | -0.962*** |
| | | (0.0801) | (0.0707) | (0.0747) | (0.0859) | (0.122) | (0.323) |
| | Absolute | 0.296 | -0.839 | -0.796 | 0.753 | 0.633 | 0.653 |
| | Deprivation ($\Omega_{LT}$) | (0.812) | (0.787) | (0.814) | (0.923) | (1.308) | (3.396) |
| | | | N=1777 | | | | |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A5: Income and relative deprivation gradient

| | VARIABLES | OLS | q(10) | q(25) | q(50) | q(75) | q(95) |
|---|---|---|---|---|---|---|---|
| BMI | ln(Income) | -0.466* | -0.00634 | -0.354 | -0.497 | -0.934** | -2.423*** |
| | | (0.269) | (0.313) | (0.283) | (0.326) | (0.438) | (0.723) |
| | Relative | 0.0669 | -5.982 | -2.326 | -4.067 | -5.269 | 16.58 |
| | Deprivation | (3.967) | (4.692) | (4.080) | (4.764) | (6.295) | (13.38) |
| | | | N=2467 | | | | |
| Waist | ln(Income) | -1.712*** | -1.494 | -1.244 | -1.611* | -2.365** | -1.796 |
| Circumference | | (0.656) | (1.004) | (0.856) | (0.873) | (0.933) | (1.643) |
| | Relative | 4.016 | -5.698 | -8.694 | -13.25 | -7.125 | 69.03** |
| | Deprivation | (9.426) | (14.08) | (12.14) | (12.76) | (13.45) | (30.53) |
| | | | N=2548 | | | | |
| Systolic BP | ln(Income) | 0.508 | 0.721 | 0.559 | 1.449 | 1.107 | -4.587* |
| | | (0.884) | (1.199) | (1.043) | (1.094) | (1.351) | (2.397) |
| | Relative | 3.623 | 9.844 | -3.301 | 4.263 | 8.764 | -10.16 |
| | Deprivation | (13.35) | (19.04) | (15.94) | (17.23) | (21.37) | (48.94) |
| | | | N=2141 | | | | |
| Diastolic BP | ln(Income) | 0.661 | 1.365 | 0.637 | 0.921 | 0.377 | 0.645 |
| | | (0.579) | (1.003) | (0.808) | (0.741) | (0.844) | (1.392) |
| | Relative | 6.721 | 3.233 | 1.844 | 5.736 | 6.376 | 10.41 |
| | Deprivation | (8.745) | (18.85) | (12.65) | (11.38) | (12.49) | (27.61) |
| | | | N=2141 | | | | |
| Resting | ln(Income) | -1.384** | 0.839 | -0.0765 | -2.229*** | -1.899** | -3.125* |
| heart rate | | (0.608) | (0.833) | (0.667) | (0.761) | (0.936) | (1.824) |
| | Relative | 17.84* | 13.63 | 16.36* | -0.890 | 18.91 | 54.27* |
| | Deprivation | (9.188) | (10.98) | (8.647) | (11.47) | (15.16) | (32.32) |
| | | | N=2145 | | | | |
| C-Reactive | ln(Income) | -1.004** | -0.0883 | -0.116* | -0.257** | -0.867*** | -4.488** |
| protein | | (0.432) | (0.0697) | (0.0704) | (0.123) | (0.295) | (2.232) |
| | Relative | 9.661 | 1.424* | 0.343 | 0.0536 | 6.858 | 55.00 |
| | Deprivation | (6.449) | (0.736) | (1.008) | (1.798) | (4.889) | (38.55) |
| | | | N=1777 | | | | |
| Fibrinogen | ln(Income) | -0.148*** | -0.133** | -0.130*** | -0.124*** | -0.173*** | -0.196** |
| | | (0.0344) | (0.0533) | (0.0400) | (0.0405) | (0.0465) | (0.0976) |
| | Relative | -0.0765 | 0.371 | 0.323 | 0.249 | -0.775 | 0.379 |
| | Deprivation | (0.513) | (0.608) | (0.527) | (0.611) | (0.784) | (1.899) |
| | | | N=1767 | | | | |
| HbA1c | ln(Income) | -1.207** | 0.178 | -0.0501 | -1.207*** | -0.651 | -4.190 |
| | | (0.525) | (0.336) | (0.287) | (0.288) | (0.429) | (4.221) |
| | Relative | 16.71** | 11.24** | 14.30*** | 6.611 | 14.89* | 122.7 |
| | Deprivation | (8.041) | (4.362) | (4.136) | (4.302) | (7.596) | (84.91) |
| | | | N=1683 | | | | |
| Cholesterol | ln(Income) | -0.315*** | -0.0433 | -0.158** | -0.299*** | -0.360*** | -0.989*** |
| Ratio | | (0.0777) | (0.0686) | (0.0726) | (0.0834) | (0.118) | (0.314) |
| | Relative | 0.111 | -0.919 | -0.676 | 0.843 | 0.897 | 0.0666 |
| | Deprivation | (1.158) | (1.247) | (1.232) | (1.366) | (1.887) | (4.553) |
| | | | N=1777 | | | | |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1