

DISCUSSION PAPER SERIES

IZA DP No. 15085

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Evidence from the UKHLS**

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Apostolos Davillas

University of East Anglia and IZA

Victor Hugo de Oliveira

University of East Anglia and IPECE

Andrew M. Jones

University of York

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ABSTRACT

Is Inconsistent Reporting of Self-Assessed Health Persistent and Systematic? Evidence from the UKHLS*

We capitalise on an opportunity in the UK Household Longitudinal Study, which asks respondents the same SAH question with identical wording two times. This is done once with a self-completion and once with an open interview mode within the same household interview over four waves. We estimate multivariate models to explore which individual and household-level characteristics are systematically relevant for the likelihood and frequency of inconsistent reporting across the two modes. We find evidence of some inconsistency in reporting; 11%-24% of those who reported a particular SAH category in the self-completion mode reported inconsistently in the open interview. The probability of inconsistency is systematic and influenced by an individual's demographics, education, income, employment status, cognitive and non-cognitive skills. The same characteristics are also systematically associated with the frequency of inconsistent reporting across four UKHLS waves. Analysis of the implications of reporting inconsistencies shows no impact of SAH measurement on the magnitude of the association between income and health, estimated separately using the two SAH measures. A set of dimensions of people's physiological and biological health, captured using biomarkers, is associated equally with both SAH measures, suggesting that reporting inconsistencies in SAH may be driven by mechanisms other than people's underlying health.

JEL Classification: C10, C33, C83, I10

Keywords: measurement error, reporting bias, self-assessed health, UKHLS

Corresponding author:

Apostolos Davillas
University of East Anglia
Norwich, NR4 7TJ
UK

E-mail: a.davillas@uea.ac.uk

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1. Introduction

The interplay between socioeconomic circumstances and health is of major importance for well-being and for human capital investment. To investigate these complex links, studies have often used survey data that combine information on social and economic circumstances with self-reported health measures. This is mostly due to the limited availability of datasets that combine more objective health measures with a wide range of socioeconomic data, along with the simplicity that self-reported health measures may offer. Among self-reported health measures, self-assessed health (SAH) is widely used in economics (e.g., Aoki and Santiago, 2018; Contoyannis and Jones, 2004; Contoyannis, Jones and Rice, 2004; Currie, Duque and Garfinkel, 2015; García-Gómez, Jones and Rice, 2010; Johnson, 2010; van Doorslaer et al., 2000), and in social research (e.g., Monden, 2010; Monk, 2015). Moreover, SAH measures are widely used in epidemiological and medical research where an association with mortality has been demonstrated (e.g., Jylhä, 2009; Kaplan and Camacho, 1983; Kunst et al., 2004; Mossey and Shapiro, 1982; Hu et al., 2016).¹

Studies have sought a better understanding of the extent to which SAH can be interpreted as a good proxy of underlying health between respondents of different socioeconomic backgrounds and in general (e.g., Au and Johnston, 2014; Bago d’Uva et al., 2008; Dowd and Zajacova, 2010; Etilé and Milcent, 2006; Lindeboom and van Doorslaer, 2004). A few studies have tested the consistency of responses to SAH questions, by comparing repeated SAH questions for the same individuals collected over a short time, to assess whether individuals are willing or capable of responding consistently (e.g., Black et al., 2017; Chen et al., 2021; Clarke and Ryan, 2006; Crossley and Kennedy, 2002). Differences in capacity to respond to survey questions or in reporting behaviour may depend on respondents’ cognitive and non-cognitive skills, which may explain why some individuals tend to provide inconsistent response about their self-assessed health and others do not (Black et al., 2017). Moreover, individuals may respond inconsistently because they assess their health with some uncertainty or they have “learned” more about their health status because of the other questions that are asked between the first and the second SAH questions

¹ Although the exact wording and response options of SAH vary across surveys, it is mainly based on individual ratings of current overall health, typically on a five-point ordinal scale (for example, from “excellent” to “poor”).

— for example, specific health or disability questions can influence subsequent responses about people’s health status (Black et al., 2017; Clarke and Ryan, 2006; Crossley and Kennedy, 2002). Strategic reporting may be another reason of reporting inconsistency — for example, the broader literature on measurement error in well-being indicators argues that individuals may exhibit a "justification bias" when they overstate their poor health condition in order to rationalize their economic inactivity (e.g., Black, Johnston and Suziedelyte, 2017; Bound, 1991; Kapteyn et al., 2007; Kerkhofs and Lindeboom, 1995). Mode of data collection may be relevant here; some of the existing literature has argued that self-completion, as opposed to open interview, mode may be more reliable in eliciting accurate responses to sensitive questions especially in the presence of other household members (e.g., Conti and Pudney, 2011).

The few studies that test the consistency of responses to SAH questions, and estimate misclassification by assessing repeated SAH questions for the same individuals over a short time frame, mainly use Australian data (Black et al., 2017; Chen et al., 2021; Clarke and Ryan, 2006; Crossley and Kennedy, 2002). These studies often compare responses from SAH questions with different wording and/or SAH measures that are asked within a wider time window (up to 30 days) rather than within the time window allowed at the same household interview (Black et al., 2017; Clarke and Ryan, 2006). Often these studies are based on cross-sectional data and even when longitudinal data on duplicate responses to different SAH questions within each wave is available, they are often based on unequally spaced panels, which may limit analysis of persistent patterns in inconsistency SAH reporting behavior (Black et al., 2017; Chen et al., 2021; Clarke and Ryan, 2006; Crossley and Kennedy, 2002). Moreover, none of these studies have used more objectively measured health indicators, such as nurse-administered and blood-based biomarker data, and do not analyse whether individuals’ biological health status is reflected differently across the two SAH measured administered using different survey modes (open interview and self-completion).

Our paper contributes to this literature in a number of ways. We capitalise on the rare opportunity provided by UK Household Longitudinal Study (UKHLS) which asks respondents the same SAH question with identical wording twice (one with a self-completion mode and one with an open interview mode), mainly within

the same household interview at UKHLS Waves 2, 3, 4 and 5.² Descriptive analysis of the data show considerable inconsistency in reporting of the SAH questions within each wave. We estimate multivariate models to explore the profile of those individuals who reported inconsistently to SAH questions between the open interview and the self-completion mode within each UKHLS wave.

Second, we implement analysis to explore the frequency of reporting inconsistencies. Specifically, we study inconsistent reporting within a time frame that does not justify changes in their actual health status. Although these results do not provide guidance on whether the self-completed or the open interview mode provides more reliable SAH measures, they do provide evidence on whether the observed patterns are systematic and persistent.³ The results suggest that reporting inconsistencies are a systematic behaviour that repeats over time for certain population groups. Non-random measurement error in SAH, that is associated with socioeconomic variables, may contaminate existing research using SAH measures as outcome or explanatory covariate.

Third, the richness of our data allows us to use a detailed set of demographic and socioeconomic characteristics, cognitive and noncognitive skills as well as proxies of the micro-social environment during the household interview, such as the presence of other adults or children. The nature of the questionnaire content within the two SAH questions does not allow us to explore whether any potential “learning” effects, or “justification biases” may explain the observed inconsistencies in SAH within each wave. Instead, our analysis allows us to identify the profile of those who are more likely to report SAH inconsistently as well as those who repeat this

² The self-completion questionnaire, which also contains the relevant SAH question, was available as a paper questionnaire for Wave 2 (while administered using the computer assisted self-interviewing (CASI) survey technique at Waves 3, 4 and 5, in which the respondent uses interviewer’s digital device to complete the SAH questionnaire without an interviewer administering it to the respondent). This may indicate that although both the self-completed and open-interview SAH questions are answered within an hour or so in Waves 3-5 (the duration of the household interview), there may be some delay in the completion of the self-reported paper questionnaire as opposed to open interview SAH at Wave 2; however, the instructions to the interviewers indicate that it is expected for the respondents to complete the self-completed Wave 2 interviews whilst the interviewer are in the household (and to give them back to the interviewer) rather than send it over later in time.

³ Unlike Chen et al. (2021), our paper does not aim to assess which of the two SAH measures (the self-completion versus the open interview) is more accurate or the type and incidence of response errors associated with each of the two measures.

inconsistent reporting SAH behaviour most frequently. The potential implications of this measurement error are relevant when SAH is used as an outcome of interest.

Many datasets collect SAH measures, and researchers may pay limited attention to the collection mode (self-completion as opposed to open interview). SAH data have been routinely collected in many datasets, including the National Health and Nutrition Examination Survey (NHANES) in the US, the Survey of Health, Ageing and Retirement in Europe and the British Household Panel Survey (BHPS) in the UK. For example, SAH measures are collected using an open interview mode in the case of both the NHANES and the BHPS; however, most existing studies do not explicitly consider the potential implications of the SAH collection mode and the survey design for the SAH collection on their analysis (e.g., Contoyannis, Jones and Rice, 2004, Fichera and Gathergood, 2016; Donni, Peragine and Pignataro, 2014). Often, even when multiple measures of SAH questions with the same or similar wording are available in a dataset (at least for some waves, such as in the case of HILDA in Australia, NHANES in the USA, and UKHLS in the UK), researchers do not use all available information and often consider responses to a particular SAH question despite concerns about the consistency of responses within repeated SAH questions (e.g., Au and Johnston, 2014, Davillas et al., 2019, Nesson and Robinson, 2019). If socioeconomic status (SES) plays an important role for reporting of SAH collected with different interview modes (self-completion versus the open interview), this may be a concern for the robustness of the existing studies that use SAH as an outcome and where measurement error contributes to the error term of the SAH regression models.

We provide evidence on whether the SAH interview mode affects results for the income-health gradient – a popular topic in the socioeconomic determinants of health literature, where SAH measures are often used as health outcomes (e.g., Davillas et al., 2019; Foverskov and Holm, 2016; Fuchs, 2004; Frijters et al., 2005; Larrimore, 2011; Ziebarth, 2010). Separate linear regression models on household income are estimated using the self-completion and the open-interview SAH measures as outcome. Our results show very limited differences in the magnitude of the positive associations between income and health when health is measured using the self-completion or the open interview mode.

Finally, we use a detailed set of nurse-collected blood-based biomarker data. Unlike the self-reported health measures, biomarkers are more objective health

measures and, beyond pathogenic cases, they also provide information on pre-disease stages that may be below clinical diagnosis thresholds. This allows us to explore whether certain dimensions of physiological and biological health are reflected more strongly in the self-completion or the open interview SAH measures. This contributes to the literature on better understanding SAH as a health outcome (e.g., Au and Johnston, 2014; Jylhä, 2009). A finding that different dimensions of health have differing patterns of association with the two SAH measures may explain why econometric results may differ between the open interview and self-completion SAH measures they are used as outcomes or explanatory variables. On the other hand, if there are no differences, other mechanisms on how individuals translate and report their actual health using SAH measures may be relevant (Jylhä, 2009).

The rest of the paper is organized as follows. Section 2 presents and describes the UKHLS dataset. Section 3 presents our econometric methods. Analysis of the observed inconsistent responses to SAH questions over time and the relevant longitudinal patterns are presented in Section 4. Multivariate analysis of the association between inconsistent reporting and socioeconomic factors as well as an analysis of the potential implications for measurement error in SAH for research on the income-health gradient are presented and discussed in Section 5. Section 5 also contains our analysis on whether physiological and biological health are reflected more strongly in the self-completion or the open interview SAH measures. Section 6 concludes and provides a summary of our findings.

2. The UKHLS dataset

The data come from Understanding Society, the UK Household Longitudinal Study (UKHLS). The UKHLS is a large, nationally representative panel survey, with a design that involves overlapping 2-year waves. Individuals have been interviewed annually since the initial wave in 2009–2010 (Wave 1). The BHPS sub-sample is absorbed into the UKHLS at Wave 2. UKHLS contains a detailed set of demographics, socioeconomic, health and well-being information for all household members on an annual basis.

A feature of this dataset is that information on SAH is collected twice for each respondent at each of the UKHLS Waves 2, 3, 4 and 5, with two modes of collection: open interview and self-completion. Responses on SAH are asked during the open, face-to-face interviews for each household member and, within the same wave, using a self-completion questionnaire. This was available as a paper questionnaire for Wave 2 and using the computer assisted self-interviewing (CASI) survey technique, in which the respondent uses a computer to complete the SAH questionnaire without an interviewer administering it to the respondent⁴. Specifically, the following SAH question is asked twice, within each wave and in the time frame of the UKHLS household interview: “In general, would you say your health is: Excellent, Very Good, Good, Fair or Poor?”. Wording of the question and ordering of the health categories are identical between both measures within and between the UKHLS Waves 2-5. We have coded SAH so that higher values indicate a better health state.

To explore those factors that are associated with probability of reporting inconsistently between the open interview versus self-completion questions, within each wave, a set of longitudinally collected (unless otherwise stated) explanatory variables are used. These follow the related literature (Black et al., 2017; Chen et al., 2021; Crossley and Kennedy, 2002; Clarke and Ryan, 2006). We account for demographic and socioeconomic characteristics, measures of cognitive ability, personality traits, and indicators for the presence of other household members during the interview are included in our model specifications.

Specifically, gender and age group dummies for five-year intervals between 16 and 85 and a dummy for those over 85 years old are included in our analysis; this allows us to capture the role of age on reporting inconsistency. Two measures are used to capture the socioeconomic status of the respondents: highest educational attainment (degree, other higher qualification, A-level, GCSE, other lower qualification, no qualification) and household income (equivalized using the modified OECD scale and deflated). Employment status is captured by a four-category categorical variable (employed, unemployed, retired, and other job status). A four-category variable is used to account for marital status (married, single, separated/divorced, and widowed).

⁴ To account for this difference in the survey design across waves, wave fixed effects are used in our regression models.

Cognitive ability is considered as an important determinant of reporting behaviour (e.g., Black et al., 2017). Questionnaires place cognitive demands on respondents and, thus, it is likely that respondent's cognitive ability will affect the consistency of responses. Moreover, as cognitive ability is associated with a number of labour market outcomes (Lin et al., 2018), establishing the presence of systematic error in SAH that is relevant to cognitive ability may be of particular relevance to research exploring the effect of self-reported health measures on labour market outcomes. A large set of cognitive ability measures are collected at UKHLS wave 3; as no repeated data are available for waves 2, 4 and 5 we have to assume that cognitive ability remains fixed within the relatively short time interval between waves 2 and 5. The literature suggests that cognitive ability may be fairly stable with age (Lyons et al., 2017) and, thus, our results on the role of cognitive ability on reporting behaviour may not be contaminated by the absence of longitudinal data on cognitive ability.

We control for the following cognitive ability measures: episodic memory, i.e., the number of words the respondent can recall from a carefully recorded list of ten words (two variables for immediate, and delayed word recall); working memory, measured by counting the correct answer to a series of five (simple) numerical subtraction questions; semantic or category fluency, measured by counting the number of correct and incorrect responses to naming as many animals as the respondent can in 60 minutes; practical numerical knowledge, measured by counting the number of correct answers to five questions.

Personality traits are also collected at UKHLS Wave 3 using a 15-item questionnaire version of the Big-Five Inventory (John et al., 1991). Responses to a set of three questions (from the total of 15 questions) pertaining to each trait are then used to calculate each of the five-personality trait scores: agreeableness, conscientiousness, extraversion, neuroticism, and openness to experience. Higher scores indicate that the particular trait is more relevant to the respondent. The "Big-Five" personality traits have been used extensively in the economics literature and are viewed as a stable input in regression models; they are characterized by a limited variability over time, with any potential intra-individual personality change being mostly unrelated to adverse life events (Cobb-Clark and Schurer, 2012).

Finally, to account for the role of the micro-social environment during the open interview (which may affect reporting behaviour at the open interview but to

lesser extent for self-completion), we have included two dummy variables for the presence of other adults and children (aged 10-15) during the household interviews. Existing research has shown that social desirability bias, which is especially relevant to the presence of other household members during the open interview, may affect reporting behaviour in well-being outcomes (Conti and Pudney, 2011). Regional dummies are included to account for regional variations in health.

Longitudinal information from these explanatory variables (where available) are used for our models exploring the factors associated with the likelihood of inconsistent responses at each wave. However, in our subsequent analysis of the frequency of inconsistent reporting (i.e., the total number of inconsistent responses across the four waves), a snapshot of the explanatory variables is employed (mainly from Wave 2; and Wave 3 for the personality and cognitive ability measures).

Nurse administered and blood-based biomarker data

Nurse-collected and blood-based biomarkers are collected by trained nurses as part of their visits following the UKHLS Wave 2 and Wave 3 main waves. Wave 2 nurse visits collect data from the original UKHLS sample, while Wave 3 collects data from the BHPS sample that was absorbed into the UKHLS. We use a pooled sample of Waves 2 and 3 in our analysis to explore whether these objectively measured biomarkers have different patterns of association with our two SAH measures. Following the literature, we use a range of biomarkers (e.g., Davillas and Jones, 2020; Davillas and Pudney, 2020). We use the waist-to-height ratio (WHR) to measure adiposity. Resting heart rate and blood pressure are measured followed standard measurement protocols. Systolic blood pressure, the maximum pressure in an artery when the heart is pumping blood, diastolic blood pressure, the lowest pressure when the heart is resting, and the pulse rate are used as continuous variables; higher values indicate higher cardiovascular risks. We use a set of blood-based biomarkers relevant to inflammation, steroid hormones, fat in the blood, blood sugar and liver functioning. C-reactive protein (CRP) is our biomarker for systemic inflammation, which rises as part of the immune response to infection.⁵ The dihydroepiandrosterone sulphate (DHEAS) is the most common steroid hormone in

⁵ We follow the conventional practice and exclude those with CRP over 10 mg/L, as those values may reflect current transient infections and not chronic processes (Davillas and Pudney, 2020; Pearson et al., 2003).

the body — a primary mechanism through which psychosocial stressors may affect people’s health. Low levels of DHEAS are associated with cardiovascular and all-cause mortality risks (Ohlsson et al., 2010). The “good” cholesterol, high-density lipoprotein cholesterol (HDL), is used as our fat in the blood biomarker; lower HDL levels are associated with increased cardiovascular risks. HbA1c is a biomarker that measures blood sugar, regarded as a diagnostic test for diabetes. As a liver function test, we use albumin, the main liver protein; lower albumin levels suggest impaired liver function (Davillas and Pudney, 2020). In addition to specific markers, an index of multi-system risk that measures the wear and tear on the body, approximating the allostatic load, is also employed. Following exiting literature (Davillas and Pudney, 2020), HDL, Albumin and DHEAS are transformed to negative values to reflect ill health, and then each of the measures described above is converted into z scores and summed. To facilitate comparisons all our biomarkers and allostatic load are transformed to reflect derivations from their standard deviation.

3. Methods

Panel probit models for the likelihood of reporting inconsistency

We investigate the determinants of within-wave inconsistent SAH responses by modelling whether the responses to SAH question differ between the self-completion (H_{sc}) and the open interview (H_{OI}), administered within the same wave for all participants. Our dependent variable, y_{it} , is defined as a dichotomous variable that, for each respondent i in UKHLS wave t (2, 3, 4 and 5), takes the value of 1 if they reported differently in the H_{sc} versus the H_{OI} , and 0 otherwise.

We estimate pooled probit models. The likelihood for this model corresponds to assuming independence in the error terms across time, however the maximum likelihood estimator of the model has the quasi-maximum likelihood property and is robust to arbitrary serial correlation (e.g., Wooldridge, 2002). The probability of reporting inconsistently is given by:

$$\Pr(y_{it} = 1) = \Phi(x_{it}\beta) \tag{1}$$

where, x_{it} is the set of covariates used in our analysis, β are the relevant coefficients to be estimated, and $\Phi(\cdot)$ is the cumulative normal distribution function.

Our second specification is the random effects probit model which assumes an error components specification. This allows the error term to be decomposed into permanent and transitory components, but it is not robust to misspecification of the serial correlation. A random effect term (c_i) is included as part of the error structure, i.e., $u_{it} = c_i + e_{it}$. A random effects (RE) probit model can be estimated as:

$$\Pr(y_{it} = 1|x_{it}, c_i) = \Phi(x_{it}\gamma + c_i). \quad (2)$$

where, c_i and e_{it} are assumed to be normally distributed and independent of x_{it} . Conventional maximum likelihood estimation (MLE) methods, alongside the Gaussian quadrature procedure, can be then used for the consistent estimation of γ and σ_c^2 (Butler and Moffitt, 1982; Greene, 2003; Wooldridge, 2002). Marginal effects are estimated for the pooled and random effects models, with standard errors estimated using the delta method (Wooldridge, 2005).

Ordered probits for the frequency of the inconsistent reporting

We analyse the profile of those who reporting inconsistently more frequently than others over the four waves available. The frequency of inconsistent SAH responses is defined by the number of waves in which the (H_{sc}) differs from (H_{ol}). Our dependent variable is defined as a five-category variable; inconsistent for zero waves (always consistent), one wave (mostly consistent), two waves (moderately inconsistent), three waves (mostly inconsistent), and four waves (always inconsistent). This categorical outcome is modelled using a cross sectional ordered probit model using explanatory variables from baseline (Wave 2 or Wave 3 for the cognitive and non-cognitive measures). Marginal effects are presented to facilitate quantitative interpretation of our results (Greene, 2003).

Measurement of SAH and the income-health gradient

Among the covariates used to explore inconsistent reporting, we find that household income has a strong association. Given the large literature on the health-income gradient, this implies that differences in the interview mode may matter for studies of the income-health gradient that rely on SAH measures. Using all the available

UKHLS waves (Waves 2-5) we estimate pooled OLS regression models for each mode of SAH on household income, adjusted for individual's age, gender and wave fixed effects. SAH is coded so that higher values indicate a better health state. These models, although parsimonious, allow us to explore potential differences in the association between income and health that may be attributed to SAH measurement.

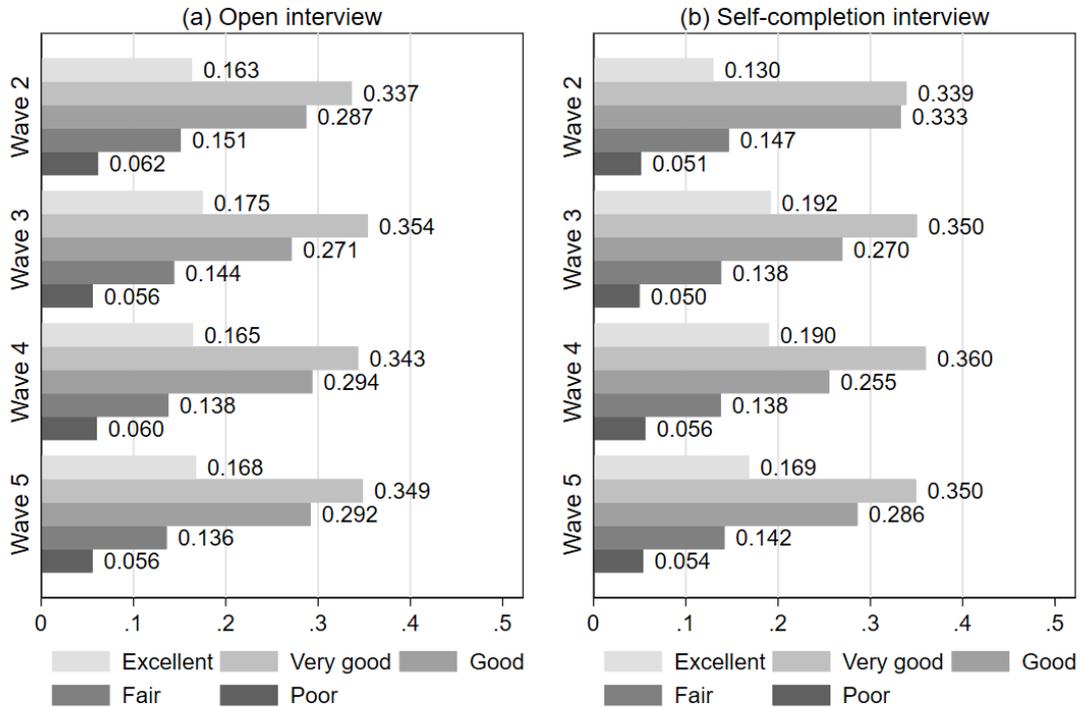
The association between biomarkers and SAH

Given the cross-sectional format of our biomarker data, linear regression models of SAH on each of our biomarkers (and for allostatic load) are estimated for the pooled Waves 2 and 3 sample; each of these models also accounts for age, gender, regional dummies and wave fixed effects. As the biomarkers are measured health indicators, comparisons of the magnitude of their associations with our two SAH measures (open interview versus the self-completion mode) may give information on whether particular dimensions of physiological and biological health are reflected more strongly in one or the other SAH measure.

4. Descriptive analysis of inconsistent responses

Figure 1 presents the distribution of responses to SAH questions for the open and the self-completion questions separately for all waves (Waves 2-5) where both of these measures are collected for each individual. These show that the *overall* marginal distributions of SAH are very similar for the two modes of data collection, especially at Wave 5. However, the two modes do not give identical distributions, and, in the earlier waves, more respondents report better health in the open interview mode. Overall, these preliminary results give us limited information about the inter-individual differences in SAH reporting between the open interview and the self-completion and only indicate the presence of moderate differences in the *overall* distribution of SAH categories.

Figure 1. Histogram of SAH responses (self-completion and open interview) by waves: unbalanced sample (obs. 161,242)



The preliminary analysis in Figure 1 is based on an unbalanced sample. However, for our analysis we need to follow the same individuals across the four waves and ensure the presence of valid responses for both SAH questions for each individual within and across waves as well as non-missing information on all explanatory variables used in our analysis — thus, a balanced sample is used for the remaining analysis. Figure 2 shows that the frequencies of the different SAH categories (for both the self-completion and the open interview question) are almost identical between the unbalanced and balanced samples; this suggests that the implications of these exclusion restrictions should be very limited for our analysis.

Figure 2. Histogram for SAH responses (self-completion and open interview): unbalanced sample (obs. 161,242), balanced sample (obs. 97,456) and balanced sample with no missing data on all variables used in the analysis (obs. 90,600).

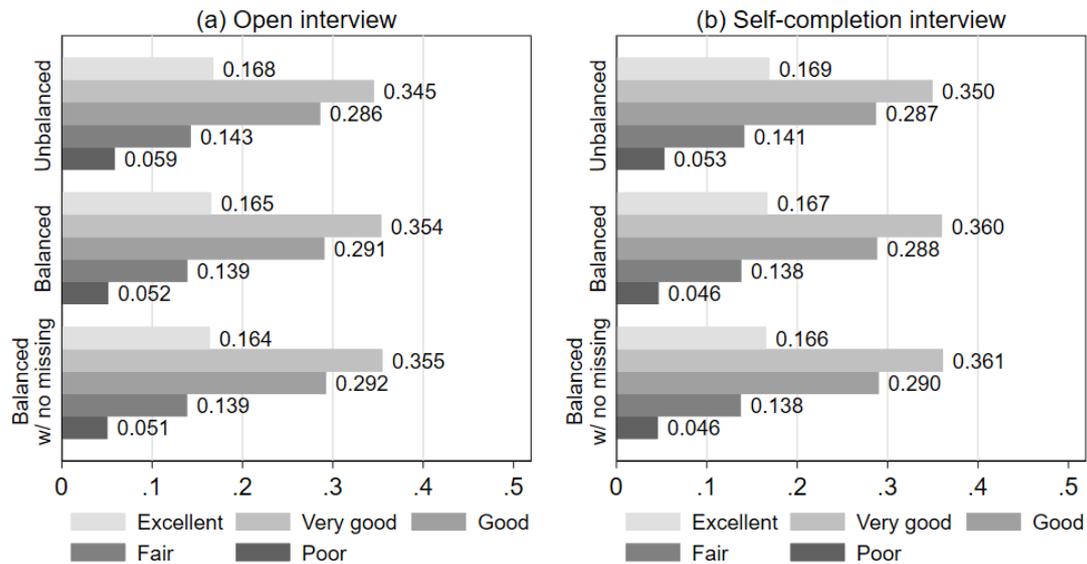
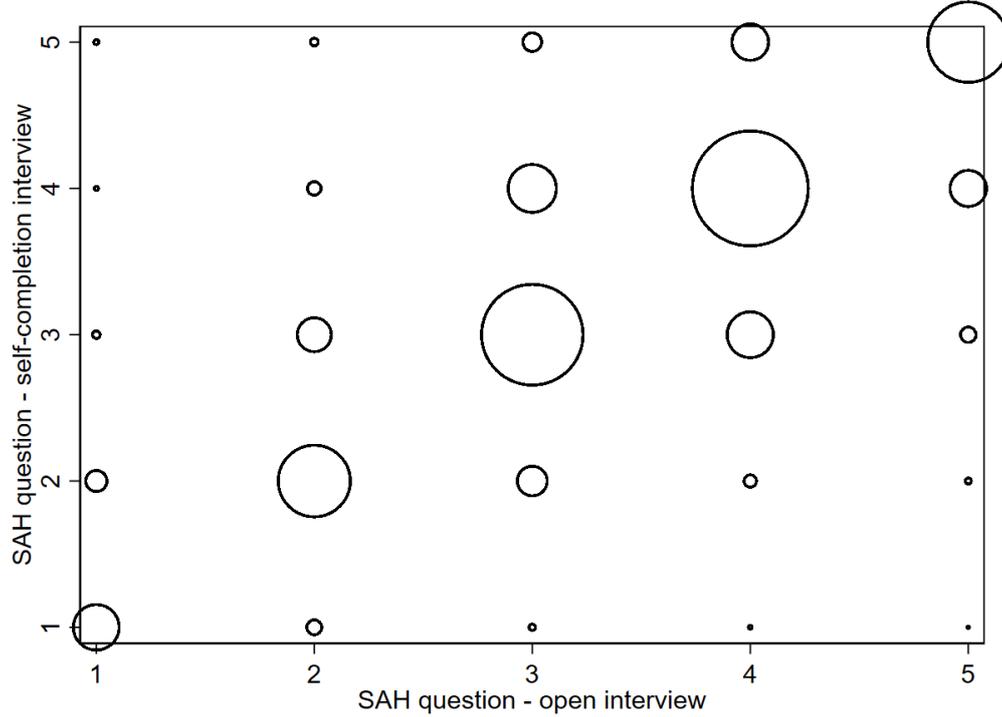


Figure 3 shows a bubble plot of responses to self-completion as opposed to open interview, using the complete cases balanced sample. This illustrates the extent and pattern of *inter-individual differences* in reporting between the two SAH measures. Although we observe that there is a concordance in responses to both SAH responses for most of the respondents (along the main diagonal), there is a sizeable proportion of respondents (as show by the size of the bubbles above and below the main diagonal) that reported their SAH inconsistently within the same interview. Table 1 presents the corresponding proportions of reporting a particular SAH status in the open interview mode conditional on responses to the self-completion SAH questions. For example, for those who reported excellent health in the self-completion interview, about 80% reported excellent health in the open interview SAH question, while the remaining respondents are distributed across all other categories (with 15% of those reporting the nearest possible category – very good health). Overall, our results show that 11%-24% of those who reported a given SAH category in self-completion mode, reported inconsistently in the open interview, with the majority of the inconsistent responses concentrated in the SAH categories that are adjacent to their self-completion responses.

Figure 3. Bubble plot – SAH self-completion versus open interview: balanced sample with non-missing information on all covariates (obs. 90,600).



Note: Each bubble is weighted by the number of respondents. Higher self-assessed health (SAH) values indicate a better health state: “1” stands for Poor, “2” Fair, “3” Good, “4” Very good and “5” Excellent.

Table 1. Distribution of SAH responses in self-completion versus the open interview questionnaire.

Self-completion interview	Open interview					Total
	Excellent	Very good	Good	Fair	Poor	
Excellent	12,015 (80.12%)	2,283 (15.22%)	578 (3.85%)	85 (0.57%)	35 (0.23%)	14,996 (100%)
Very good	2,365 (7.22%)	25,738 (78.63%)	4,321 (13.20%)	293 (0.90%)	17 (0.05%)	32,734 (100%)
Good	396 (1.51%)	3,849 (14.65%)	19,926 (75.83%)	2,026 (7.71%)	80 (0.30%)	26,277 (100%)
Fair	46 (0.37%)	261 (2.09%)	1,610 (12.92%)	9,802 (78.64%)	745 (5.98%)	12,464 (100%)
Poor	7 (0.17%)	14 (0.34%)	51 (1.24%)	354 (8.57%)	3,703 (89.68%)	4,129 (100%)
Total	14,829	32,145	26,486	12,560	4,580	90,600

Capitalising on the longitudinal nature of our data, we explore the unconditional dynamics of the observed within-wave inconsistencies. Table 2 presents summary statistics for all the observed sequences of reporting inconsistency/consistency. These sequences cover four waves, resulting in 16 ($= 2^4$) distinct sequences. We assign a value of 1 to respondents with inconsistent SAH

responses between the self-completion and open interview measures at each specific wave, and 0 otherwise.

Table 2: Distribution of inconsistent/consistent responses to SAH: balanced sample

Sequences	Frequency	Percent	Cumulative
0000	38,568	42.57	42.57
0001	6,472	7.14	49.71
0010	7,276	8.03	57.74
0100	8,712	9.62	67.36
1000	9,660	10.66	78.02
1001	2,340	2.58	80.6
1010	2,488	2.75	83.35
1100	2,964	3.27	86.62
0011	2,460	2.72	89.34
0101	2,104	2.32	91.66
0110	2,512	2.77	94.43
0111	1,124	1.24	95.67
1011	1,012	1.12	96.79
1101	1,036	1.14	97.93
1110	1,196	1.32	99.25
1111	676	0.75	100
Total	90,600	100	-

Notes: “0” stands for consistent SAH responses between the self-completion and open interview SAH measures for each particular wave; “1” for inconsistent SAH responses.

Table 2 shows that only 42.6% of our sample are classified as “always consistent” (0000). Turning to the remaining sequences, the results show that more than half of our sample (57.4%) is formed by respondents who have provided inconsistent responses about their SAH at least once. Specifically, grouping the remaining sequences with respect to frequency or consistent/inconsistent responses, those who are “mostly consistent” (0001, 0010, 0100 and 1000), i.e., within-wave inconsistent SAH reporting only once among the four waves, represent 35.5% of our total sample. Sequences which could be grouped as “moderately inconsistent” (1001, 1010, 1100, 0011, 0101, 0110), accounting for less than 1/3 of the total sample (16.4%). The proportion of the “mostly inconsistent” sequences, i.e., those who are reporting SAH within-wave inconsistently in three out of four waves (“0111”, “1011”,

“1101”, “1110”) accounts for the 4.8% of our sample. Only 0.75% are “always inconsistent” (1111)⁶.

Table 3 summarizes the transition patterns. Those grouped in the “always consistent” and “always inconsistent” groups (zero and four waves with inconsistent SAH responses) do not experience transitions. Focusing on those groups with transitions (1-3 waves with inconsistent SAH responses), multiple transitions (column c) are in overall more prevalent than single transitions (column b). Regarding the single transitions (column b), single transitions to consistent SAH responses are more likely than single transitions to inconsistent within-wave SAH responses.

Table 3. Sample distribution by number of waves with inconsistent SAH responses and transition patterns: balanced sample

#Waves with inconsistent SAH responses	[a]		[b]		[c]	[d]
	Always		Single transition to		Multiples transitions	Total
	Consistent	Inconsistent	Consistency	Inconsistency		
0	38,568	0	0	0	0	38,568
1	0	0	9,660	6,472	15,988	32,120
2	0	0	2,964	2,460	9,444	14,868
3	0	0	1,196	1,124	2,048	4,368
4	0	676	0	0	0	676
Total	38,568	676	13,820	10,056	27,480	90,600

Table 4 provides some preliminary evidence on whether the inconsistent reporting patterns over time are systematically associated with individual characteristics. For example, Table 4 shows that males are more prevalent in the “mostly inconsistent” and “always inconsistent” groups. Mean values for the age groups show heterogeneous patterns across the different sub-groups. Turning to education, lower educational categories are more prevalent for the “moderately

⁶ One may argue that the fact that only 0.75% of our sample members belongs to the always inconsistent (“1111”) category indicates that persistence is low for inconsistency responses. However, this is not true. Given that the mean probability of reporting inconsistently is 0.214, under independence, this means that we would expect that the proportion of our sample “always inconsistent” (“1111”) should be $0.214^4 = 0.002$ (or 0.21%). By contrast, in our sample, we observe 676 individuals (i.e., 0.75% of our sample) classified in the “always inconsistent” category.

inconsistent”, “mostly inconsistent” and “always inconsistent” groups as opposed to the “always consistent” or “mostly consistent” groups (as well as for the total sample). The average log of income for the total sample is about 7.2 and decreases as the number of waves with inconsistent SAH responses increases; the difference in household income between the “always consistent” and “always inconsistent” categories is approximately 25%. These results suggest that socioeconomic status (proxied by education and household income) is relevant for reporting behaviour in SAH. Regarding job status, our unconditional summary statistics show that the mean unemployment prevalence increases from 3.1% in the case of the "always consistent" sub-sample to 8.1% for the "always inconsistent" sub-sample. Turning to marital status, the unconditional summary statistics show that while the proportion of married respondents is decreasing with the increasing number of waves that individuals reported SAH inconsistently within each wave, the proportion of single respondents is increasing.

Table 4 also shows that the more consistent sub-samples have higher cognitive ability scores for the set of cognitive ability measures used in our analysis. Turning to the Big 5 personality traits, the mean values for agreeableness, conscientiousness and extraversion are higher for the always inconsistent sub-group as opposed to the whole sample and the always consistent sub-group. Concerning the micro-social environment, the unconditional mean for the presence of children (ages 10-15) during the household interview progressively increased as moving from the “always consistent” to “always inconsistent” sub-samples.

Table 4. Sample means of explanatory variables: balanced samples

Variables	Total	# of waves: inconsistent SAH measures				
		0 waves (always consistent)	1 wave (mostly consistent)	2 waves (moderately inconsistent)	3 waves (mostly inconsistent)	4 waves (always inconsistent)
Male†	0.427	0.402	0.434	0.458	0.488	0.497
Aged 16-25†	0.081	0.074	0.084	0.091	0.089	0.084
Aged 26-35†	0.144	0.154	0.143	0.125	0.130	0.127
Aged 36-45†	0.202	0.208	0.199	0.196	0.192	0.212
Aged 46-55†	0.199	0.197	0.191	0.208	0.228	0.260
Aged 56-65†	0.177	0.184	0.178	0.172	0.145	0.112
Aged 66-75†	0.135	0.131	0.137	0.141	0.142	0.130
Aged 76-85†	0.054	0.046	0.061	0.056	0.066	0.058
Aged 86 and older†	0.008	0.007	0.008	0.012	0.010	0.016
Degree†	0.254	0.300	0.239	0.192	0.167	0.216
Other higher qualification†	0.129	0.134	0.131	0.120	0.114	0.099
A-level†	0.203	0.202	0.203	0.208	0.201	0.186
GCSE†	0.209	0.189	0.213	0.238	0.240	0.275
Other low qualification†	0.097	0.085	0.101	0.115	0.119	0.101
No qualification†	0.108	0.091	0.112	0.126	0.159	0.123
Log of HH income	7.157	7.200	7.139	7.114	7.070	6.980
Employed†	0.589	0.594	0.589	0.581	0.582	0.559
Unemployed†	0.038	0.031	0.039	0.049	0.056	0.081
Retired†	0.248	0.244	0.252	0.251	0.245	0.241
Other job status†	0.124	0.130	0.121	0.118	0.118	0.118
Married†	0.687	0.702	0.679	0.672	0.671	0.629
Single†	0.162	0.153	0.166	0.174	0.168	0.209
Separated/divorced†	0.091	0.091	0.092	0.092	0.095	0.092
Widowed†	0.060	0.054	0.064	0.062	0.066	0.071
Immediate word recall	6.447	6.632	6.397	6.228	6.020	5.870
Delayed word recall	5.425	5.626	5.380	5.160	4.974	4.828
Number of correct subtractions	4.507	4.592	4.482	4.413	4.282	4.325
Verbal fluency: correct words	22.567	23.230	22.299	21.737	21.601	22.000
Verbal fluency: incorrect words	0.329	0.300	0.334	0.371	0.414	0.325
Numeric ability: correct answers	3.727	3.851	3.695	3.561	3.478	3.515
Agreeableness	5.638	5.637	5.649	5.633	5.571	5.781
Conscientiousness	5.505	5.520	5.498	5.489	5.474	5.568
Extraversion	4.583	4.562	4.604	4.588	4.594	4.604
Neuroticism	3.546	3.591	3.540	3.489	3.401	3.462
Openness to experience	4.545	4.558	4.546	4.534	4.466	4.533
Multiple adult interviews/HH†	0.720	0.728	0.712	0.715	0.720	0.753
Children (aged 10-15) interviewed/HH†	0.149	0.145	0.147	0.158	0.178	0.183
Sample size	90,600	38,568	32,120	14,868	4,368	676

Notes: † Dichotomous variables.

5. Multivariate Models

5.1 The likelihood of an inconsistent response

Table 5 presents the estimated coefficients from the pooled and random effect (RE) probit models for the probability of reporting SAH inconsistently in the self-completion and open interview within each wave. Overall, the coefficients from both models are very similar in terms of the direction of the associations and statistical significance⁷. The RE probit model imposes an error component structure on the data, decomposing the error term and modelling the time-invariant unobserved heterogeneity. Under these assumptions, the intra-class correlation coefficient (ρ) shows that about 12% of the unexplained variation in inconsistent SAH reporting behaviour is attributable to the individual effect — this is relatively low in magnitude, albeit highly statistically significant.

Table 6 presents the marginal effects, providing an indication of the magnitude of the association between our explanatory variables and the probability of reporting inconsistency. In general, the marginal effects are similar for the pooled and RE probit models; this may reflect the fairly small role of individual effects in explaining the variability of inconsistent SAH responses, which is used to scale the corresponding marginal effects for the RE model. On average men are 0.026 more likely to report inconsistent SAH than females. Those belonging to the 26-35, 36-45 and 56-65 age groups have a lower probability on average (between 0.017 and 0.021) of reporting SAH inconsistently compared to our youngest age group (16-25, reference category). We also find systematic education and income gradients in the probability of reporting SAH inconsistently. For example, the probability of inconsistent responses for those with no qualification is 0.035 higher compared to those with a university degree (reference group); the corresponding probability for those with O-level or GCSE is 0.041 higher compared to the reference group. This indicates the presence of a non-monotonic but positive association between the probability of reporting inconsistent SAH and the lower level of educational attainment as opposed the reference category (degree). Moreover, there is systematic and positive association with income, indicating that higher income is associated with a lower probability of reporting SAH inconsistently. These results are broadly consistent with existing evidence that measures of socioeconomic status are

⁷ It should be noted here that the scaling of coefficients in the pooled and RE specifications are different and they should not be compared directly in Table 5; this highlights the need to calculate the corresponding marginal effects which are on the same scale and can be compared.

important determinants of reporting behaviour in SAH and other health outcomes (e.g., Bago d’Uva, O’Donnell and van Doorslaer, 2008; Black et al., 2017; Crossley and Kennedy, 2002; Clarke and Ryan, 2006; Etilé and Milcent, 2006; Johnston, Propper and Shields, 2009). Regarding respondents’ job status, those who are retired and with other job statuses experience on average a higher probability of reporting inconsistently, compared to those employed, of about 0.027.

Table 5. Pooled probit model and random effects (RE) probit model for inconsistent responses to SAH questions.

Covariates	Pooled probit		Random Effects probit	
	Coeff.	SE	Coeff.	SE
Male	0.088***	0.012	0.095***	0.012
Aged 26-35	-0.074***	0.024	-0.078***	0.026
Aged 36-45	-0.061**	0.025	-0.065**	0.026
Aged 46-55	-0.007	0.025	-0.008	0.026
Aged 56-65	-0.063**	0.027	-0.065**	0.028
Aged 66-75	-0.019	0.032	-0.023	0.035
Aged 76-85	-0.019	0.039	-0.022	0.041
Aged 86 and older	0.002	0.065	-0.008	0.069
Other higher qualification	0.066***	0.018	0.072***	0.020
A-level	0.083***	0.016	0.090***	0.017
GCSE	0.136***	0.017	0.148***	0.018
Other low qualification	0.123***	0.021	0.135***	0.022
No qualification	0.116***	0.023	0.125***	0.024
Log of the HH income	-0.047***	0.012	-0.045***	0.013
Unemployed	0.009	0.027	-0.000	0.028
Retired	-0.097***	0.021	-0.103***	0.022
Other job status	-0.097***	0.017	-0.096***	0.018
Single	-0.003	0.018	-0.004	0.019
Separated/divorced	-0.016	0.020	-0.017	0.022
Widowed	-0.000	0.026	0.003	0.028
Immediate word recall	-0.046***	0.009	-0.049***	0.009
Delayed word recall	-0.019**	0.008	-0.020**	0.009
Number of correct subtractions	-0.030***	0.006	-0.033***	0.006
Verbal fluency: correct words	-0.023***	0.007	-0.026***	0.007
Verbal fluency: incorrect words	0.014***	0.005	0.015***	0.005
Numeric ability: correct answers	-0.065***	0.007	-0.070***	0.008
Agreeableness	-0.010*	0.006	-0.010*	0.006
Conscientiousness	-0.013**	0.006	-0.014**	0.006
Extraversion	0.006	0.006	0.007	0.006
Neuroticism	-0.026***	0.006	-0.028***	0.006
Openness to experience	0.020***	0.006	0.022***	0.006
Multiple adult interviews/HH [†]	-0.012	0.014	-0.013	0.015
Children (aged 10-15) interviewed/HH	0.032**	0.015	0.029*	0.016
Wave 3	-0.037***	0.013	-0.040***	0.014
Wave 4	-0.097***	0.013	-0.105***	0.014
Wave 5	-0.158***	0.013	-0.170***	0.014
Constant	0.294***	0.111	0.282**	0.117
Rho			0.121***	0.006
Sigma(u)			0.371***	0.010
Log-likelihood	-46,301		-46,063	
Sample size	90,600		90,600	

Notes: The pooled probit and RE probit models account for region fixed effects. Standard errors (SE) are clustered at individual level. Balanced sample is used for these estimations.

[†] Expressed in terms of deviations from their standard deviation.

* p<0.10, ** p<0.05, *** p<0.01

Table 6. Pooled probit model and random effects (RE) probit model for inconsistent responses to SAH questions: marginal effects

Covariates	Pooled probit		RE probit model	
	Marginal Effects	SE	Marginal effects	SE
Male	0.0255***	0.0034	0.0259***	0.0034
Aged 26-35	-0.0210***	0.0067	-0.0208***	0.0067
Aged 36-45	-0.0173**	0.0069	-0.0173**	0.0069
Aged 46-55	-0.0019	0.0071	-0.0022	0.0071
Aged 56-65	-0.0178**	0.0074	-0.0173**	0.0074
Aged 66-75	-0.0056	0.0093	-0.0061	0.0092
Aged 76-85	-0.0055	0.0110	-0.0059	0.0110
Aged 86 and older	0.0006	0.0189	-0.0021	0.0187
Other higher qualification	0.0195***	0.0055	0.0198***	0.0055
A-level	0.0244***	0.0049	0.0248***	0.0049
GCSE	0.0405***	0.0051	0.0412***	0.0051
Other low qualification	0.0369***	0.0065	0.0379***	0.0065
No qualification	0.0346***	0.0070	0.0351***	0.0069
Log of the HH income	-0.0135***	0.0035	-0.0122***	0.0035
Unemployed	0.0026	0.0077	-0.0001	0.0076
Retired	-0.0275***	0.0057	-0.0274***	0.0057
Other job status	-0.0271***	0.0047	-0.0252***	0.0047
Single	-0.0009	0.0052	-0.0010	0.0052
Separated/divorced	-0.0045	0.0058	-0.0045	0.0058
Widowed	-0.0001	0.0075	0.0009	0.0075
Immediate word recall†	-0.0134***	0.0025	-0.0134***	0.0025
Delayed word recall†	-0.0055**	0.0024	-0.0054**	0.0024
Number of correct subtractions†	-0.0088***	0.0018	-0.0088***	0.0018
Verbal fluency: correct words†	-0.0066***	0.0019	-0.0069***	0.0019
Verbal fluency: incorrect words†	0.0041***	0.0014	0.0041***	0.0015
Numeric ability: correct answers†	-0.0186***	0.0020	-0.0188***	0.0020
Agreeableness†	-0.0028*	0.0017	-0.0028*	0.0017
Conscientiousness†	-0.0039**	0.0017	-0.0039**	0.0017
Extraversion†	0.0018	0.0016	0.0019	0.0016
Neuroticism†	-0.0075***	0.0016	-0.0075***	0.0016
Openness to experience†	0.0059***	0.0017	0.0060***	0.0017
Multiple adult interviews/HH	-0.0035	0.0041	-0.0037	0.0041
Children (aged 10-15) interviewed/HH	0.0093**	0.0045	0.0079*	0.0045
Wave 3	-0.0107***	0.0036	-0.0108***	0.0036
Wave 4	-0.0275***	0.0036	-0.0278***	0.0036
Wave 5	-0.0441***	0.0035	-0.0444***	0.0035

Note: Marginal effects are estimated at sample means.

† Expressed in terms of deviations from their standard deviation.

* p<0.10, ** p<0.05, *** p<0.01

Our measures of cognitive ability are systematically associated with the probability of reporting inconsistently; this is broadly in line with relevant research using data from Australia (Black et al., 2017). Our detailed set of cognitive ability measures gives us the opportunity to further explore which aspects of cognitive ability are more strongly related to consistent reporting behaviours in SAH. To facilitate comparisons across the different cognitive ability variables, the estimates of the relevant marginal effects are scaled in terms of standard deviations of the variables. Overall, word recall (particularly immediate word recall), number of correct subtractions and the number of correct answers in some simple numeric ability tests are more strongly associated with the probability of reporting inconsistently. Given that word recall is related to episodic memory, i.e., memory associated with a specific event or episode, and numeracy is a measure of practical numerical knowledge, we argue that the role of these cognitive skills is much more pronounced on explaining inconsistent behaviours in reporting SAH than the associations for verbal fluency. For example, our marginal effects show that one standard deviation increase in numeric ability is associated with a lower probability of reporting inconsistently of about 0.019; the corresponding marginal effects for verbal fluency (correct words) indicates that one standard deviation increase in the measure is associated with 0.007 reduction in the probability of reporting inconsistently.

We find that the probability of reporting inconsistently is associated with conscientiousness, neuroticism and openness to experience. Higher conscientiousness scores, usually characterizing those individuals with a higher level of self-discipline, are associated with a systematically lower probability of reporting SAH inconsistently. Openness to experience is positively associated with reporting inconsistency. There are arguments that individuals more open to experiences may experience an increased probability of conflicting appraisals (Barford and Smillie, 2016); the latter may explain our findings that openness to experience is associated with individuals' tendency to report SAH inconsistently in a short time period. Higher neuroticism scores are associated with a lower probability of reporting inconsistently. Some studies have argued that neuroticism is associated with medical conditions, negatively perceived health status and frequency of visits to the GP (Jerram and Coleman, 1999; Nouri et al., 2019); those with higher scores are then more likely to have a more concrete perception of their SAH and, thus, more likely to report their SAH status more consistently.

Presence of other adults or children during the open interview seems to have a limited association with reporting inconsistencies, this suggests a limited role for the so-called micro-social environment during the open interview (Conti and Pudney, 2011) on

affecting reporting behavior in the context of SAH. Finally, our results show that the probability of reporting inconsistent SAH is monotonically decreasing across waves compared to Wave 2 (reference). This may reflect utilization of the computer-based self-completion SAH questionnaires (to replace the paper questionnaire at Wave 2, as discussed earlier) and the potential role of a “learning-by-doing” process among respondents in answering SAH questions twice within each wave.

5.2 The frequency of inconsistent responses

Our analysis so far has explored those factors that are associated with the probability of reporting inconsistently in the two SAH questions (open interview versus self-completion) within each wave. In this sub-section we characterize the profile, based on individuals’ characteristics at baseline (mainly Wave 2 or Wave 3), of those reporting inconsistently more frequently than others across our four UKHLS waves. Our dependent variable is, thus, defined as a five-category variable; inconsistent for: zero waves (always consistent), one wave (mostly consistent), two waves (moderately inconsistent), three waves (mostly inconsistent), and four waves (always inconsistent). Table 7 displays the estimated coefficients from an ordered probit model, modelling the frequency of inconsistent within-wave SAH across our four waves; the corresponding marginal effects are presented in Table 8.

Overall, the results from the ordered probit model show that those baseline characteristics that predict the probability of reporting inconsistently to SAH questions are also systematically associated with a higher frequency of reporting SAH inconsistently, i.e., the presence of “persistent” behaviour in reporting inconsistency to SAH questions across the four waves. Demographics (age and gender), education, income, employment status, cognitive and non-cognitive skills are the baseline characteristics that are most associated with a higher frequency of reporting inconsistently across the four UKHLS waves.

Table 7. Ordered probit model for the distribution of inconsistent responses across waves [0 (always consistent) to 4 (always inconsistent)]: coefficient estimates

Covariates	Coef.	SE
Male	0.126***	0.017
Aged 26-35	-0.094***	0.034
Aged 36-45	-0.049	0.034
Aged 46-55	-0.027	0.035
Aged 56-65	-0.084**	0.038
Aged 66-75	-0.045	0.048
Aged 76-85	-0.013	0.059
Aged 86-104	-0.025	0.114
Other higher qualification	0.092***	0.026
A-level	0.104***	0.024
GCSE	0.182***	0.024
Other low qualification	0.174***	0.030
No qualification	0.167***	0.032
Log of the HH income	-0.086***	0.018
Unemployed	0.035	0.038
Retired	-0.114***	0.031
Other job status	-0.150***	0.024
Single	-0.009	0.026
Separated/divorced	-0.017	0.030
Widowed	-0.022	0.040
Immediate word recall [†]	-0.067***	0.013
Delayed word recall [†]	-0.026**	0.012
Number of correct subtractions [†]	-0.044***	0.009
Verbal fluency: correct words [†]	-0.035***	0.009
Verbal fluency: incorrect words [†]	0.020***	0.007
Numeric ability: correct answers [†]	-0.092***	0.010
Agreeableness [†]	-0.014*	0.008
Conscientiousness [†]	-0.020**	0.008
Extraversion [†]	0.011	0.008
Neuroticism [†]	-0.037***	0.008
Openness to experience [†]	0.030***	0.008
Multiple adult interviews/HH	-0.013	0.022
Children (aged 10-15) interviewed/HH	0.063***	0.022
Cut-points:		
Cut 1	-1.786	
[95% CI]	[-2.100, -1.471]	
Cut 2	-0.796	
[95% CI]	[-1.110, -0.481]	
Cut 3	0.051	
[95% CI]	[-0.263, 0.366]	
Cut 4	0.925	
[95% CI]	[0.608, 1.243]	
Loglikelihood	-26,842	
Observations	22,650	

Notes: Estimation results come from a cross-section analysis in which the socioeconomic characteristics are measured in wave 2, while cognitive abilities and the Big-5 personality traits that are measured in wave 3. Robust standard errors (SE) are used and confidence intervals at the 95% significance level (95%CI) for cut-points appear in square brackets.

[†] Expressed in terms of deviations from their standard deviation.

* p<0.10 ** p<0.05 *** p<0.01

Table 8. Ordered probit model for the distribution of inconsistent responses across waves: marginal effects.

Covariates	0 waves (always consistent)		1 wave (mostly consistent)		2 waves (moderately inconsistent)		3 waves (mostly inconsistent)		4 waves (always inconsistent)	
	Marginal Effect	SE	Marginal Effect	SE	Marginal Effect	SE	Marginal Effect	SE	Marginal Effect	SE
Male	-0.0491***	0.0065	0.0123***	0.0016	0.0236***	0.0031	0.0110***	0.0015	0.0022***	0.0003
Aged 26-35	0.0372***	0.0135	-0.0105**	0.0041	-0.0175***	0.0062	-0.0078***	0.0027	-0.0015***	0.0005
Aged 36-45	0.0194	0.0136	-0.0052	0.0038	-0.0092	0.0064	-0.0042	0.0029	-0.0008	0.0005
Aged 46-55	0.0105	0.0137	-0.0028	0.0037	-0.0050	0.0065	-0.0023	0.0029	-0.0004	0.0006
Aged 56-65	0.0332**	0.0149	-0.0092**	0.0044	-0.0156**	0.0069	-0.0070**	0.0030	-0.0013**	0.0006
Aged 66-75	0.0177	0.0188	-0.0048	0.0053	-0.0084	0.0088	-0.0038	0.0039	-0.0007	0.0007
Aged 76-85	0.0051	0.0230	-0.0013	0.0061	-0.0024	0.0109	-0.0011	0.0050	-0.0002	0.0010
Aged 86-104	0.0100	0.0448	-0.0027	0.0124	-0.0047	0.0212	-0.0022	0.0095	-0.0004	0.0018
Other higher qualification	-0.0358***	0.0102	0.0083***	0.0021	0.0174***	0.0050	0.0084***	0.0025	0.0017***	0.0005
A-level	-0.0405***	0.0091	0.0095***	0.0019	0.0197***	0.0045	0.0094***	0.0022	0.0019***	0.0005
GCSE	-0.0702***	0.0090	0.0153***	0.0017	0.0344***	0.0046	0.0170***	0.0024	0.0035***	0.0006
Other low qualification	-0.0669***	0.0114	0.0137***	0.0017	0.0331***	0.0058	0.0167***	0.0032	0.0035***	0.0007
No qualification	-0.0643***	0.0121	0.0134***	0.0019	0.0317***	0.0062	0.0159***	0.0033	0.0033***	0.0008
Log of the HH income	0.0336***	0.0069	-0.0087***	0.0018	-0.0161***	0.0033	-0.0074***	0.0015	-0.0014***	0.0003
Unemployed	-0.0137	0.0148	0.0034	0.0035	0.0066	0.0072	0.0031	0.0035	0.0006	0.0007
Retired	0.0450***	0.0124	-0.0126***	0.0038	-0.0212***	0.0057	-0.0095***	0.0025	-0.0018***	0.0005
Other job status	0.0593***	0.0097	-0.0175***	0.0033	-0.0275***	0.0044	-0.0120***	0.0018	-0.0022***	0.0003
Single	0.0034	0.0103	-0.0009	0.0027	-0.0016	0.0049	-0.0007	0.0023	-0.0001	0.0004
Separated/divorced	0.0066	0.0119	-0.0017	0.0032	-0.0032	0.0056	-0.0015	0.0026	-0.0003	0.0005
Widowed	0.0085	0.0155	-0.0023	0.0042	-0.0041	0.0074	-0.0019	0.0033	-0.0004	0.0006
Immediate word recall†	0.0261***	0.0049	-0.0067***	0.0013	-0.0125***	0.0024	-0.0058***	0.0011	-0.0011***	0.0002
Delayed word recall†	0.0101**	0.0047	-0.0026**	0.0012	-0.0048**	0.0023	-0.0022**	0.0010	-0.0004**	0.0002
Number of correct subtractions†	0.0173***	0.0035	-0.0045***	0.0009	-0.0083***	0.0017	-0.0038***	0.0008	-0.0007***	0.0002
Verbal fluency: correct words†	0.0137***	0.0037	-0.0035***	0.0009	-0.0066***	0.0018	-0.0030***	0.0008	-0.0006***	0.0002
Verbal fluency: incorrect words†	-0.0078***	0.0029	0.0020***	0.0008	0.0037***	0.0014	0.0017***	0.0006	0.0003***	0.0001
Numeric ability: correct answers†	0.0361***	0.0040	-0.0093***	0.0011	-0.0172***	0.0019	-0.0080***	0.0009	-0.0015***	0.0002
Agreeableness†	0.0054*	0.0032	-0.0014*	0.0008	-0.0026*	0.0015	-0.0012*	0.0007	-0.0002*	0.0001
Conscientiousness†	0.0079**	0.0033	-0.0020**	0.0009	-0.0038**	0.0016	-0.0017**	0.0007	-0.0003**	0.0001
Extraversion†	-0.0042	0.0031	0.0011	0.0008	0.0020	0.0015	0.0009	0.0007	0.0002	0.0001
Neuroticism†	0.0145***	0.0031	-0.0037***	0.0008	-0.0069***	0.0015	-0.0032***	0.0007	-0.0006***	0.0001
Openness to experience†	-0.0118***	0.0033	0.0030***	0.0008	0.0056***	0.0016	0.0026***	0.0007	0.0005***	0.0001
Multiple adult interviews/HH	0.0050	0.0085	-0.0013	0.0022	-0.0024	0.0041	-0.0011	0.0019	-0.0002	0.0004
Children (aged 10-15) interviewed/HH	-0.0246***	0.0086	0.0059***	0.0019	0.0119***	0.0042	0.0056***	0.0021	0.0011***	0.0004

Note: Marginal effects are estimated at sample means.

† Expressed in terms of deviations from their standard deviation.

* p<0.10 ** p<0.05 *** p<0.01.

The marginal effects from the ordered probit model provide an indication of the magnitude of the association between the baseline characteristics used in our analysis and the frequency of reporting SAH inconsistently across the available four waves (Table 8). Men have an increased probability of within-wave inconsistent SAH reporting in one, two, three and all waves, while being male decreases the likelihood of consistent reporting across all four UKHLS waves. Age has a negative but non-monotonic association with inconsistently reporting SAH more frequently. For example, respondents belonging to the 26-35 or 56-65 age group at baseline, as opposed to our reference category (16-25 age group), are more likely to always report consistently.

Turning to education, we observed a strong gradient, with lower education at baseline being positively associated with a higher likelihood of being inconsistent more frequently. For example, no educational qualifications, as compared to having a university degree (reference group), are associated with being 0.013, 0.032 and 0.016 more likely to report SAH inconsistently in one, two and three waves, respectively: on the other hand, those without qualifications at baseline experience a 0.064 lower probability of consistent SAH reporting within each of the four UKHLS waves explored here. Concerning household income, there is a negative gradient, with richer respondents at baseline are less likely to within-wave inconsistently report SAH with higher frequency (inconsistent responses in one, two, three and four waves). Compared to those employed, retired respondents and those of other job statuses are also more likely to inconsistently report SAH with higher frequency. The presence of children during the open interview is associated with increased probabilities of frequent inconsistency.

The cognitive ability measures have a systematic gradient with the frequency of inconsistent reporting to SAH; higher levels of cognitive ability are associated with a larger probability of always being consistent and a decreased probability of reporting inconsistently more frequently. The magnitude of the marginal effects, which are expressed in terms of deviations for their standard deviations, show that episodic memory (captured by the word recall measures) and numerical knowledge are those cognitive skills that have a higher association with the frequency of reporting inconsistency. The role of verbal fluency is lower in magnitude, but highly statistically significant.

Regarding the Big-5 personality traits, conscientiousness and neuroticism are most strongly associated with reporting patterns in SAH. Openness to experience is associated with a lower probability of always being consistent and with increased probabilities of being inconsistent with respect to within-wave SAH responses frequently across all four UKHLS waves. Overall, these results highlight that the personality traits

that are relevant to a higher level of self-discipline, exploring perceptual information in inflexible and divergent ways and neuroticism are relevant for persistent patterns in these behaviours across the four UKHLS waves.

5.3 Implications for the income-health gradient

Our results so far show that the observed inconsistencies in reporting in SAH within each wave and the frequency of inconsistency across waves are systematic and associated with individual characteristics. Among these individual characteristics, household income may be of particular interest given the existing research on the income-health gradient based on SAH measures. We find that household income is negatively associated with the probability of reporting SAH inconsistently at each wave as well as with the probability of this being persistent across waves.

To explore whether difference in interview mode (self-completion versus open interview) affects the association between income and SAH, we estimate linear regression models for SAH regressed on household income after adjusting for age, gender and wave fixed effects (Table 9, Panel A). Recall, that we have coded SAH so that higher values indicate a better health state. Our estimates for the full sample suggest evidence of a positive and highly significant association between income and health with remarkably similar income coefficients in the case of self-completion and open interview SAH measures.

We then implement further analysis, excluding from our estimation sample certain sub-samples with specific patterns in reporting SAH. As expected, identical income coefficients are evident for the case of the two models when we restrict our analysis to those who consistently report SAH within each of the four waves used here (Table 9, Panel B: Always consistent) and there is evidence of positive and systematic associations between income and health. Analysis across all the remaining sub-samples show practically identical results, with very limited differences in the estimated associations between income and health when using our two SAH measures.

Table 9. Income gradients in SAH measured using self-completion and open interview mode: pooled OLS.

	SAH – Open Interview (H_{OI})	SAH – Self-completion (H_{SC})	Difference in coefficients
	Coef. (SE)	Coef. (SE)	p-value
Panel A: Full sample			
Log of the HH income	0.419*** (0.011)	0.419*** (0.011)	0.948
Sample size	90,600		
Panel B: Always consistent (0 inconsistencies across four waves)			
Log of the HH income	0.518*** (0.018)	0.518*** (0.018)	—
Sample size	38,568		
Panel C: Full sample excluding those always consistent (1-4 inconsistencies across four waves)			
Log of the HH income	0.335*** (0.013)	0.338*** (0.013)	0.575
Sample size	52,032		
Panel D: Inconsistent responses in 1 or 2 out of four waves in total (mostly consistent and moderately inconsistent)			
Log of the HH income	0.347*** (0.014)	0.347*** (0.014)	0.926
Sample size	46,988		
Panel E: Inconsistent responses in 3 or 4 out of four waves in total (mostly inconsistent / always inconsistent)			
Log of the HH income	0.214*** (0.040)	0.269*** (0.036)	0.123
Sample size	5,044		

Notes: Pooled OLS estimation accounts for wave fixed effects, gender and age dummies. Standard errors (SE) are clustered at individual level. The balanced sample is used for estimation. Higher SAH values indicate a better health state.

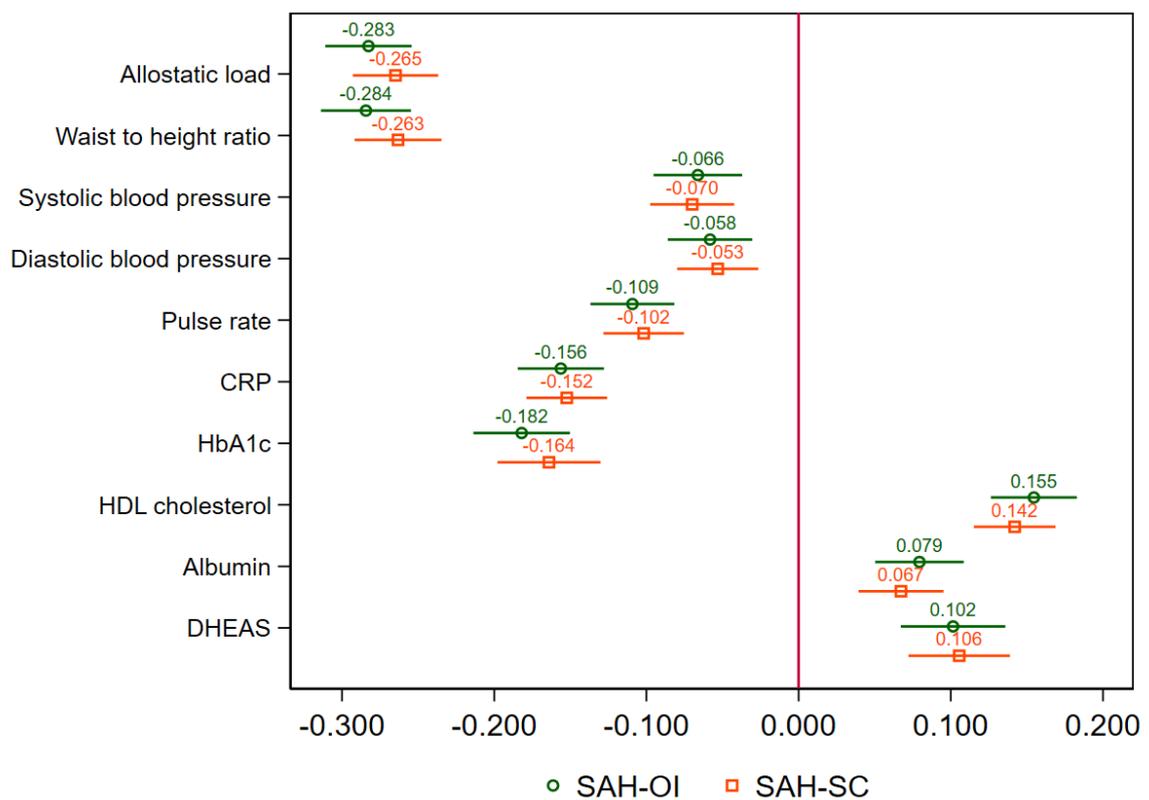
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.4 The association between biomarkers and SAH

Figure 4 presents the coefficient estimates for each of the biomarkers and for allostatic load, measured in units of standard deviations, where each of those is included separately in a linear regression model for both SAH measures. All coefficients have the expected sign: those that reflect higher health risks are negatively associated with SAH. Positive associations are observed for HDL cholesterol, Albumin and DHEAS as higher values of these biomarkers as associated with lower health risks.

Overall, the biomarker coefficient estimates do not vary systematically between the two SAH measures, indicating that there are limited differences in how these objectively collected health dimensions are associated with the two SAH measures; this is also the case for the coefficient estimates of our composite health measure – allostatic load. Allostatic load (standardized by its standard deviation), our composite biological measure, is strongly associated with SAH. Turning to the underlying biomarkers (standardized by their standard deviation), adiposity, followed by the diabetes biomarker (HbA1c), inflammation (CRP), “fat in the blood” biomarker (HDL cholesterol), resting pulse rate and stress related steroids (DHEAS) are most strongly associated with both SAH measures.

Figure 4. Coefficient estimates from biomarkers in self-completion and open interview SAH regression models.



Notes: Each of the biomarkers (and allostatic load) are included separately in linear regression models of SAH outcomes measured using the self-completion and the open interview mode. Higher SAH values indicate a better health state. All regressions account for age dummies, gender, regional dummies and wave fixed effects. Sample size: 5,907 observations.

6. Conclusion

Beyond concerns to better understand the extent to which SAH can be interpreted as a good proxy of individual's underlying health, there is a small literature on whether individuals are willing or capable to respond to SAH questions consistently. We add to this and capitalise on the rare opportunity provided by the UKHLS asking respondents the same SAH question with identical wording twice (one with a self-completion and one with an open interview mode), within the same household interview, at UKHLS Waves 2, 3, 4 and 5. Descriptive analysis shows substantial inconsistency in reporting behaviour. Within each wave, about 11%-24% of those who reported a given SAH category in self-completion mode reported inconsistently in the open interview, with the majority of the inconsistent responses concentrated in the SAH categories adjacent to their self-completion responses. Descriptive analysis of the sequences of reporting reveals that only 43% of sample members are "always consistent".

We use multivariate models to explore the profile of those who are more likely to report SAH inconsistently. Sex, age, educational attainment, household income, employment status, cognitive and non-cognitive skills are associated with the probability of reporting SAH inconsistency within a wave. Despite existing evidence that the micro-social environment during the household interviews (proxied by the presence of other adults or children during the interview) potentially affects responses to the self-completed wellbeing measures (e.g., Black et al., 2017; Conti and Pudney, 2011), we find less pronounced evidence that they play a systematic role in reporting inconsistencies in SAH.

We capitalise on the longitudinal data available to explore the profile of those who report inconsistently more frequently over the four waves of data. We find that those baseline characteristics that predict the probability of reporting inconsistently are also systematically associated with a higher frequency of reporting inconsistently.

Our evidence suggests that the observed reporting inconsistency in SAH is not a random measurement error; individuals with certain characteristics are unable (or unwilling) to report SAH consistently across the two measures using different modes of administration (self-completed versus open interview). Socioeconomic status, among other individual characteristics, plays an important role in reporting inconsistency. This may suggest that existing studies that use SAH as an outcome, modelled as a function of socioeconomic status, may be contaminated with the corresponding results potentially encompass significant biases. Analysis of the association between income and health we shows no evidence that measurement in SAH affects the results. Finally, of particular

interest, we do not find systematic differences in the association between our SAH measures, administered using the open interview and the self-completion mode, and a large set of objectively measured nurse-collected and blood-based biomarkers. This may suggest that reporting inconsistencies are driven by mechanisms other than people's physiological and biological health (or at least the dimensions of physical health captured by our set of biomarkers). Overall, our results raise some concerns for the way in which SAH is measured, as the consistency of responses is associated with socioeconomic and demographic characteristics, cognitive skills, and personality traits.

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