Social capital, deprivation and self-rated health: does reporting heterogeneity play a role? Results from the English Longitudinal Study of Ageing

Abstract

Self-rated health (SRH) is commonly assessed in large surveys, though responses can be influenced by different individuals' perceptions of and beliefs about health. Therefore, instead of providing evidence of 'true' health disparities across groups, findings may actually reflect reporting heterogeneity.

Using data from participants aged 50 years and older from the English Longitudinal Study of Ageing (ELSA) Wave 3 (2006/07; participation rate =73%), associations between three dimensions of social capital (local area & trust, social support and social networks), deprivation and SRH were examined using the vignette methodology in 2341 individuals who completed both the self-report and at least one of the 18 vignettes. Analysis employed a hierarchical probit model (HOPIT).

Individuals expressing low local area & trust social capital (beta= -0.276, $p<0.001$) and those with poor social networks (beta= -0.280, $p<0.001$) were more likely to report poor SRH in HOPIT models accounting for reporting heterogeneity, but unadjusted ordered probit analyses still correctly show a negative relationship between low local area & trust social capital (beta= -0.243, $p<0.001$) and those with poor social networks (beta= -0.210, $p<0.01$), though they somewhat tend to underestimate its strength. Neither social support nor deprivation appeared to have any effect on SRH regardless of reporting heterogeneity.

Anchoring vignettes offer a relatively uncomplicated and cost-effective way of identifying and correcting for reporting heterogeneity to improve comparative validity of self-report measures of health. This analysis underlines the need for caution when using unadjusted self-reported measures to study the effects of social capital on health.

Keywords

Social capital; self-rated health; ageing; vignettes; health disparities; deprivation

Word count: 7988

Introduction

Empirical evidence has consistently demonstrated a relationship between social capital and self-rated health (SRH) (Chen and Meng, 2015; Giordano et al., 2012; Kawachi et al., 1999; Kawachi and Berkman, 2014; Koutsogeorgou et al., 2015; Nieminen et al., 2013, 2010), but because there is no 'gold standard' of how to measure social capital, the strength of the association is uncertain. A simple definition of social capital is: the “resources that are accessed by individuals as a result of their membership of a network or a group” (Kawachi and Berkman, 2014). While there is a debate around the conceptualisation of social capital (Kawachi et al., 2004; Poortinga, 2006; Szreter and Woolcock, 2004) most agree that it is multidimensional and that it carries different interpretations depending on who defines it and on their disciplinary traditions.

Social capital has been suggested to improve health through norms and attitudes that influence healthy behaviours, and psychosocial networks that increase access to health care and mechanisms that enhance self-esteem (Kawachi et al., 1999; Kawachi and Berkman, 2014; Lindström, 2008). Conversely, social capital can also have a negative impact on health, including the promotion (but also cessation) of risky behaviours (e.g. smoking), exchanging wrong information, the exclusion of ‘outsiders’, and downward-levelling norms (Burt, 1992; Campos-Matos et al., 2016; Christakis and Fowler, 2008; Kawachi and Berkman, 2014; Rosenquist et al., 2011). Interventions have been conducted to evaluate social capital’s impact on health with varying success(Coll-Planas et al., 2016).

While the literature is vast on the health effects of individual level disadvantage, area level deprivation can affect health by increasing an individual’s sense of being deprived of status, resulting in frustration, shame and stress, which in turn may lead to adverse health consequences. On the other hand areas which are least deprived may be wealthier

and thus have more local facilities and resources which can have a positive impact on health (Glymour et al., 2014; Zhang et al., 2013). However, rather than using instruments designed for a specific purpose (Sánchez-Santos et al., 2013), different methods to measure deprivation at area-level have been employed, making the strength of associations uncertain. The Index of Multiple Deprivation (IMD) is a measure of deprivation at the lower super output area (LSOA) which has been used in the UK since 2000 and is an instrument specifically designed for such a purpose (Noble et al., 2004). It is based on the idea of distinct dimensions of deprivation which can be recognised and measured separately, but combined into an overall score.

To measure health in large cohort surveys, it is common that a subjective measure based on self-report is employed, preferably in combination with the use of objective measures. However, the latter may be too expensive to implement in large population surveys. Nevertheless SRH has been shown to have robust associations with "hard" outcomes such as mortality (Barger et al., 2016). Many international cohort studies have employed measures of SRH collected sequentially over time, including the English Longitudinal Study of Ageing (ELSA) (Steptoe et al., 2013). However, the primary issue with using such self-reports alone is that different individuals may have different beliefs and perceptions about the concept of health. The comparability of self-reported information can vary across social groups (within countries) or across countries because of: unequal access to medical providers or health information; diagnosis avoidance (inadvertent or intentional avoidance of medical screening/testing); or interpersonal incomparability across groups if they use different reference groups or interpret questions or concepts differently (Burgard and Chen, 2014). Researchers also usually have little insight as to what individuals are actually thinking of when they assess their health (Au and Johnston, 2014). Therefore,

instead of providing evidence of 'true' health disparities, findings may actually reflect *reporting heterogeneity*.

To help overcome the problems of interpersonal incomparability of subjective measures, such as self-reports, King et al. 2004 proposed a technique using anchoring vignettes(King et al., 2004). The vignettes were presented as a way to alleviate problems which occur when different groups of participants understand and use the Likert scales for self-reports in different ways (e.g. 1=very bad health to 5=very good health). This heterogeneity in reporting styles is also known as differential item functioning (DIF). Graphically, this problem is illustrated in Figure 1. Previous research has been conducted into the use of anchoring vignettes to access group differences in SRH (Au and Lorgelly, 2014; Grol-Prokopczyk et al., 2015, 2011; Peracchi and Rossetti, 2012; Xu and Xie, 2015), but to our knowledge, only one so far has specifically used the anchoring vignettes technique to improve comparability of SRH and social capital (Chen and Meng, 2015).

As outlined above, studies have demonstrated associations between social capital and SRH. However, these studies did not take into account the possibility of reporting heterogeneity distorting SRH disparities associated with social capital. Therefore, using nationally representative data, we aim to better estimate the relationship between social capital and SRH among English adults aged 50 years and older. By improving the interpersonal comparability of SRH, we can conduct simulations to illustrate the potential magnitude of the effect of reporting heterogeneity in estimating the distribution of SRH from self-reported survey data.

Methods

Population

ELSA is a panel study of a representative cohort of men and women living in England aged 50 years and older, and their partners of any age. It was designed as a sister study to the Health and Retirement Study in the US and follows many of the same principles. The study commenced in 2002, and the sample has been followed up every two years using computer-assisted personal interviews and self-completion questionnaires, with an additional nurse visit for the assessment of biomarkers every four years (main interview). More detailed information on the design of ELSA can be found elsewhere(Steptoe et al., 2013). Data for this current study is from ELSA Wave 3 (2006/07). The participation rate in Wave 3 was 73% (total individual respondents to wave 3 divided by total individuals eligible for wave 3). After excluding partners aged <50 years (n=428), 9343 main interviews were completed. 2341 individuals also completed a module on self-completion health vignettes (at least one of the 18 vignettes answered; covering the health domains pain, sleeping, mobility, memory, breathing and depression) and a self-rated health question using a similar five-point Likert scale.

Self-rated health assessment

SRH was collected during the main interview. Individuals were asked to rate their own general health on a five-point Likert scale ('Would you say your health is...') which was reverse coded to be increasing in good health (1= very poor to 5=very good).

Social capital assessment

The framework adopted by the Office for National Statistics (ONS) (Siegler, 2014) and introduced by the Organisation for Economic Co-operation and Development (OECD) (Scrivens and Smith, 2013) was used as a basis to select 21 different variables within ELSA

143 that could be used to represent social capital. In this framework, there are four different
144 aspects of social capital: [1] personal relationships; [2] social network support; [3] civic
145 engagement; and [4] trust and cooperative norms. Of the 21 variables selected, only two
146 mapped onto 'civic engagement' (member of at least one organisation, club or society and
147 voluntary work). Therefore, the 21 variables were reduced to three social capital dimensions
148 using factor analysis. The three dimensions were [1] local area & trust, [2] social support and
149 [3] social networks. Factor loadings ≥0.3 were retained. The factor loadings and dimensions
150 are outlined in Table S1 in the Online Supplementary Material.
151 The three dimensions created align well with the ONS framework. [1] "Local area &
152 trust" matches the concepts of trust and cooperative norms or shared values that shape the
153 way people behave towards each other and as members of society (nine factors; all found in
154 the same section of ELSA questionnaire - local area), [2] "social support" is closely related to
155 the level of resources or support that a person can draw from in their personal relationships
156 (six factors; all in reference to spouse/partner, children, family and friends), and [3] "social
157 networks" incorporates aspects of both "personal relationships" and "civic engagement" (six
158 factors). It includes variables which refer to both the structure and nature of people's
159 personal relationships (number of close relationships, meet ups/communication) and the
160 actions and behaviours that can be seen as contributing positively to the collective life of a
161 community or society (member of an organisation and volunteering). The composite
162 reliability {a test of internal consistency - measures the overall reliability of a collection of
163 heterogeneous but similar items} (Colwell, 2016) of the dimensions of social capital were
164 0.84 (local area & trust), 0.81 (social support) and 0.66 (social networks).
165 The three factor scores were divided into quintiles. The top quintile included persons
166 with high levels of social capital with regard to the dimension in question. Respectively, the

bottom quintile included those with the least social capital in that dimension. For the purposes of this analysis, we created two separate dichotomised variables for each dimension. High social capital coded as 1=top quintile and 0=bottom four quintiles. Low social capital coded as 1=bottom quintile and 0=top four quintiles.

Deprivation assessment

ELSA deprivation data was obtained separately via an application process which was approved by the NatCen Data Release Panel. IMD2004 is a measure of multiple deprivation at the lower super output area (LSOA) (Noble et al., 2004). IMD2004 is based on the idea of distinct dimensions of deprivation which can be recognised and measured separately. People may be counted as deprived in one or more of the domains depending on the number of types of deprivation that they experience. IMD2004 is conceptualised as a weighted area level aggregation of these specific dimensions of deprivation: [1] income deprivation; [2] employment deprivation; [3] health deprivation and disability; [4] education, skills and training deprivation; [5] barriers to housing and services; [6] living environment deprivation; [7] crime. Each dimension index consists of a score which is then ranked. The higher the score, the more deprived is the LSOA. The IMD2004 scores were provided from NatCen as quintiles. The top quintile included persons who were most deprived. Respectively, the bottom quintile included those who were least deprived. For the purposes of this analysis, we created two separate dichotomised variables. Most deprived coded as 1=top quintile and 0=bottom four quintiles. Least deprived coded as 1=bottom quintile and 0=top four quintiles.

Vignette assessment

191 The 18 vignettes within the health self-completion questionnaire are outlined in the
192 Online Supplementary Material. They cover several different health domains, including pain,
193 sleeping, mobility, memory, breathing and depression (three vignettes each). Briefly,
194 individuals were asked to rate the health limitations of various hypothetical persons who
195 experience different circumstances related to health on a five-point Likert scale. Possible
196 responses, once reverse coded to be increasing in good health, ranged from 1= extreme
197 health problem to 5=no health problem. Individuals were asked to assume that each of the
198 hypothetical persons had the same age and background as their own. Anchoring vignettes
199 are designed to take into account the fact that people of different countries, sex, age bands
200 and socio-economic groups may rate similar circumstances differently. Further detailed
201 information on anchoring vignettes can be found elsewhere (Jones et al., 2013).
202
203 *Covariates assessment*
204 Health behaviours and other covariates were recorded during the main interviews.
205 Four health behaviours included smoking, alcohol, physical activity and sleeping. Smoking
206 status was coded as current vs. not current smoker. Alcohol frequency, but not consumption
207 volume was available and was coded as low/moderate (once or twice per week to once or
208 twice per year), high (almost every day to three or four times per week) and abstainer (not
209 at all in last 12 months). Physical activity was coded as active (moderate to high physical
210 activity) vs. low/sedentary. Sleeping was coded as restless during past week vs. not restless.
211 Other covariates included age, sex, living arrangements, education and household
212 income. Age was classified into four categories: 50-59, 60-69, 70-79 and 80+ years old.
213 Living arrangements were classified into two categories: living alone and
214 cohabiting/married. Education was classified into three categories: basic (no/basic

qualifications), secondary (higher education but below a degree), and higher (degree or above). Income was included as a continuous variable which was based on the sum of employment, state benefit, state and private pension, asset, and other income; each member of the benefit unit was assigned the total benefit unit level income. The OECD equivalence scale was used (assigned a weight of 1 to the household head, 0.5 to second adults and dependent children aged 14 and over and a weight of 0.3 to children under 14 years of age) (39) and total income was scaled by a factor of £1000.

Statistical methods

All statistical analysis was performed using STATA IC V.13.1 (StataCorp, Texas, USA).

A standard ordered probit model was used as a baseline model with which we could compare our more flexible specification which does not impose the assumption of reporting homogeneity, to assess the extent to which this assumption biases the estimated health effects.

Individuals rated the vignettes describing the hypothetical cases similar to how they rated their own SRH. As they represent fixed levels of health, individual variation in vignette ratings characterise reporting heterogeneity (DIF). This 'external' vignette information can therefore be used to model the cut-points on the Likert scale (which are assumed fixed in the ordered probit model) as functions of the individual's characteristics. These cut-points can then be used to purge reporting heterogeneity from the SRH, making it possible to identify 'true' health effects. This is achieved through the use of a hierarchical probit model (HOPIT).

The HOPIT model has two components. The vignette component models the cut-points as functions of the covariates allowing for reporting heterogeneity. To relax the

restriction of parallel cut-point shift (covariates affect all cut-points by the same magnitude) in this component, a generalised ordered probit model is used. The health component represents the relationship between SRH and covariates, with the cut-points determined by the vignette component, linking individual's SRH to the observed severity categories. Further detailed information on these models can be found elsewhere (Jones et al., 2013). The reference scale used in the HOPIT approach is arbitrary as it is the group represented by the omitted categories in the generalised ordered probit. By applying any reference scale of interest, it is possible to conduct simulations to illustrate the potential magnitude of the effect of reporting heterogeneity in estimating the distribution of SRH. This is achieved by reclassifying all responses and making them consistent with that scale (Heiland and Yin, 2015). For example, the predicted distribution of health categories can be visualised by applying a HOPIT correction for self-reporting heterogeneity *and* reclassifying all responses in accordance with the inferred response scales of people with either high or low social capital, for each dimension of interest.

Results

Table 1 represents descriptive statistics for sociodemographic variables, health behaviours and vignette ratings for the whole sample, and for the sub-groups of high and low social capital within each of the three dimensions and deprivation. The main results are for all individuals who answered at least one of the 18 health vignettes and the SRH question (whole sample; n_{max}=2,341 individuals contributing a maximum of 42,138 observations [person-vignettes]). Those individuals with high social capital in any of the dimensions were generally older (not statistically significant for social networks), married females. Those with good social networks tended to be highly educated (P<0.01) whereas the opposite was seen

in those with good social support (P<0.001). As for health behaviours, those with low local area & trust social capital and good social networks tended to be non-smokers (P=0.01 and P<0.001, respectively). Those with good social networks were more likely to be drinkers (P=0.02). Those with high local area & trust social capital and good social networks reported higher physical activity (P=0.05 and P<0.001, respectively). Individuals with high social capital in any of the dimensions reported better sleep (borderline statistically significant for social networks, P=0.06). Those with high social capital in any of the dimensions also rated their SRH higher. Individuals who were least deprived tended to be married and more highly educated (both P<0.001). They tended not to be current smokers but drank alcohol more frequently (both P<0.001). However, they were more physically active (P<0.001) and reported better sleep (P<0.01). They rate their own SRH higher than the most deprived.

Table 2 compares the estimated coefficients in the latent health index implied by the different specifications of the ordered probit model and HOPIT. Two different models are shown: Model 1 includes all our dimensions of social capital (local area and trust, social support and social networks) and deprivation simultaneously with age and sex, and Model 2 is similar to Model 1 except it also includes the sociodemographic and health behaviours. A model including only one dimension of social capital (e.g. social support only) or deprivation at a time, along with age and sex and the vignette dummies was also derived, though the results were similar to those seen in model 1 (data not shown). For direct comparisons to be made between the two specifications, the scale of the estimated sigma in the HOPIT needs to be close to 1 because the scale in the ordered probit is normalised to 1, while it is estimated (up to the normalisation of scale in the vignette component) in the HOPIT. The estimated sigma in this analysis for model 1 was 1.16, but was 1.02 in model 2. Therefore, making direct comparisons between the two specifications in the fully adjusted model

(model 2) is not problematic, but caution needs to be taken when making direct comparisons between the two specifications in model 1. Thus, the following results are in reference to model 2. The ordered probit is the most restricted specification that disregards any reporting heterogeneity. Individuals expressing low local area & trust social capital (beta = -0.243, p <0.001) and those with poor social networks (beta = -0.210, p <0.01) were more likely to report poorer SRH. These findings remained evident when allowing for non-parallel cut-point shift (HOPIT), though ignoring reporting heterogeneity tended to marginally underestimate the detrimental effect on SRH of having low local area & trust social capital (Beta = -0.276, p <0.001) and poor social networks (Beta = -0.280, p <0.001). Post-estimation tests (using "suest" command in STATA which tests for intra-model and cross-model hypotheses) between the betas in the ordered probit versus the HOPIT model were not statistically significant for low local area & trust (p=0.61) or poor social networks (p=0.28).

Neither social support nor deprivation appeared to have any effect on SRH regardless of DIF. However, in model 1, a significant negative coefficient for low social support (beta = -0.209, p <0.01) and for the most deprived group (beta = -0.186, p <0.05), and a significant positive coefficient for the least deprived (beta = 0.308, p <0.001) lost statistical significance once adjusted for sociodemographic variables and health behaviours (model 2). Males reported poorer SRH in both the ordered probit (beta = -0.200, p <0.001) and HOPIT models (beta = -0.261, p <0.001). The age categories were negatively associated with SRH (model 2) and these effects remained non-significant, except for age 70-79 which became statistically significant when reporting heterogeneity was accounted for (beta = -0.185, p <0.05).

Table S2 in the Online Supplementary Material compares the estimated coefficients of the ordered probit model and HOPIT for each of the six domains of health that were also

311 asked in the self-completion questionnaire. The same covariates used in Model 2, Table 2
312 were used. Overall, these individual results align well with our main analysis using SRH to
313 represent an overall indicator of general health; the negative effect of low social capital is
314 greater for the majority of the six health domains and all three measures of social capital
315 when reporting heterogeneity is accounted for. Post-estimation tests between the betas for
316 social capital in the ordered probit versus the HOPIT models were statistically significant at
317 the 5% level across three domains of health and statistically significant at the 10% level
318 across four domains (emboldened in Table S2).

319 The response scales inferred from vignette classifications made by respondents of
320 high and low social capital within each of our three dimensions, and deprivation, can be
321 useful to researchers who rely on self-reported measures. Table S3 in the Online
322 Supplementary Material shows the results of the generalised ordered probit model of
323 individuals' rating of the vignettes' health (vignette component of the HOPIT model). This
324 model accommodates the potential for a non-parallel cut-point shift, allowing the covariates
325 to affect each of the cut-points differently. The coefficients vary considerably across cut-
326 points, and in many cases, the effects are not monotonic. Two model specifications were
327 performed similar to Table 2. A positive coefficient implies a rightwards shift in the cut-
328 point, suggesting that, on average, individuals from the corresponding group characterize
329 the health problems presented in the vignette as more severe. Likewise, a negative
330 coefficient implies a leftwards shift in the cut-point.

331 Figure 2 displays simulations to illustrate the potential magnitude of the effect of
332 reporting heterogeneity in estimating the distribution of SRH. The top graph shows the
333 empirical (unadjusted) distribution of SRH among ELSA participants aged 50 years and older
334 who answered at least one of the 18 health vignettes. The second graph represents a

predicted distribution of SRH using HOPIT procedures without any correction for reporting heterogeneity (similar to an ordered probit model). In the latent (own) health index, the same set of covariates as in Model 2 were included (age, sex, sociodemographic variables and health behaviours).

By applying any reference scale of interest in the HOPIT specification, we can reclassify all responses and make them consistent with that response scale. The bottom graphs in Figure 2 display the predicted distribution of SRH after applying a HOPIT correction for reporting heterogeneity and reclassifying all responses in accordance with the reference scale of interest: response scales of high and low social capital within each of our three dimensions or in accordance with the response scales of least/most deprived. The predicted distributions are consistent with the findings reported in Table S2 and differ mainly from the second graph at the threshold good vs. very good health. For example, when the scales inferred for the groups with poor social networks were used, the predicted distributions were more concentrated at the category "very good health", consistent with Model 2, Table S2. They have a lower threshold to what constitutes very good health compared to those with good social networks.

Discussion

SRH is a subjective measure often used as an indicator of general health in large cohort studies, and is regarded as a robust predictive measure of mortality, morbidity & physical functioning (Grol-Prokopczyk et al., 2011). The conceptual framework for health supports the view that it is best represented as a multidimensional set of domains (Salomon et al., 2003). The World Health Organisation (WHO) developed a set of core health domains that best describe different aspects of health status directly (Sadana et al., 2002; Salomon et

al., 2003). The 18 vignettes used in ELSA covered six health domains: pain, sleeping, mobility, memory, breathing and depression, which are included as part of the WHOs core domains of health. There were three vignettes per domain listing the health condition (e.g. pain) in increasing severity. Furthermore, studies have consistently shown associations between poor SRH and physical health (pain, sleeping, breathing and mobility), whether or not it relates to limitations (e.g. our vignettes ask about health problems/limitations), and mental health (Borim et al., 2014; Chang-Quan et al., 2010; Latham and Peek, 2013). Therefore, it was felt that this set of six health domains covered by the vignettes would be sufficiently exhaustive to capture the most common dimensions of SRH in our main analysis.

What our results show is that low local area & trust and poor social networks are associated with poorer SRH in HOPIT models accounting for reporting heterogeneity, but while ordered probit analyses still correctly show a negative relationship between these social capital dimensions and SRH, they somewhat underestimate its strength. Moreover, our simulations illustrate the potential magnitude of reporting heterogeneity in estimating the distribution of SRH by demonstrating the impact of different response scales. In particular, the distribution at the cut-point good vs. very good health tended to differ (across social capital and deprivation categories) after applying a HOPIT correction for self-reporting heterogeneity and reclassifying all responses in accordance with the chosen scale. Also, the bad and very bad self-reported health distribution was greatly diminished after applying the HOPIT correction and reclassification. Our analysis highlights the caution that needs exercised when using unadjusted self-reported measures to study the effects of social capital and deprivation on health.

Social capital, as highlighted in the introduction, is a multidimensional concept which can have both positive and negative effects on health. When we applied the most flexible

383 model incorporating the hypothetical health vignettes and accommodating for non-parallel
384 cut-point shift (HOPIT) arising from reporting heterogeneity, we demonstrated that those
385 individuals with low local area & trust social capital and poor social networks were less likely
386 to report good health. These results are consistent with the literature.
387 Having a higher opinion of your local area and a greater sense of trust, and belonging
388 to broader social networks can bring certain benefits and resources that would not
389 otherwise be available. These resources are not all necessarily at an individual level but can
390 be garnered via the group-level dynamics within such environments (Kawachi and Berkman,
391 2014). Individual health benefits secured by virtue of membership include social support
392 (exchange of affective support), social influence (promotion of healthy behaviours), social
393 control (status and rewards) and social participation (opportunities to learn new skills, self-
394 esteem and promotion of belongingness). Additional benefits to health include access to
395 material resources such as health services, job opportunities and finance (Eriksson, 2011;
396 Kawachi et al., 1999; Kawachi and Berkman, 2014; Lindström, 2008). Collective health
397 benefits secured through norms and collective efficacy include trust, solidarity and
398 reciprocity, which promotes a health-enabling environment through attitudes that influence
399 healthy behaviours, diffusion of knowledge and information (social contagion) and the
400 potential to influence political and community decisions/resources (Eriksson, 2011; Kawachi
401 and Berkman, 2014). The availability and distribution of such resources will have an impact
402 on how individual's not only rate their own SRH, but may modify their judgement of what
403 constitutes good and bad health in the hypothetical vignettes.
404 Contrary to previous research which has found detrimental health effects of
405 deprivation (Diez Roux and Mair, 2010; Roux et al., 2001; Stafford and Marmot, 2003), the
406 current study found no evidence of an effect on SRH of living in a deprived neighbourhood

in both the ordered probit and HOPIT model specifications when adjusted for sociodemographic variables and health behaviours. This could be due, at least in part, to how deprivation is measured. The conceptual framework behind IMD2004 uses LSOA data to construct an aggregate area based score and is agnostic with respect to the causes of deprivation. Therefore, a LSOA scored as relatively deprived by the index may contain large numbers of people who are not deprived, and conversely, LSOA which are relatively less deprived might contain people experiencing significant disadvantage. Nevertheless we acknowledge that both area level and individual level attributes contribute to deprivation and we may not have been able to fully separate their effects. Therefore, caution is warranted when interpreting our findings for deprivation, especially as the data is cross-sectional in nature.

We originally hypothesised that relying on SRH alone without accounting for reporting heterogeneity would underestimate the detrimental effect of low social capital on SRH. Unadjusted ordered probit analyses still correctly demonstrated a negative relationship between some of the social capital dimensions and SRH, though they somewhat underestimated its strength (Table 2). It was also hypothesised that those with low social capital might use lower response thresholds for what constitutes a health problem when responding to the hypothetical vignettes (Table S3). Our simulations illustrate the impact of these response thresholds on standard measures of SRH when reclassifying all responses in accordance with high and low social capital (for each dimension) and deprivation.

Overall, this study demonstrates the importance of accounting for reporting heterogeneity when conducting comparative studies, either between sub-groups or across whole countries. Anchoring vignettes offer a relatively uncomplicated and cost-effective way of identifying and correcting for DIF to improve comparative validity of self-reported

431 measures such as SRH. Future research is needed to improve vignette methodology while
432 retaining its simplicity with respect to survey operation and anchoring performance,
433 especially with large scale population surveys in which resources are limited.
434
435 **Strengths and Limitations**
436 Anchoring vignettes have a number of advantages over earlier methods of
437 identifying and correcting for DIF. They are less error-prone and can both identify DIF and
438 statistically correct for it (HOPIT); they are relatively cheap to implement in that they only
439 require a small number of additional survey items and be given to a proportion of the whole
440 sample; and they may allow a means of improving comparative validity of self-reported
441 measures. Health vignettes thus have the potential to serve a valuable role in health
442 research, enabling more accurate empirical work and more rigorous honing of theory (Grol-
443 Prokopczyk et al., 2011). However, the use of anchoring vignettes comes with potential
444 limitations. The assumptions of vignette equivalence and response consistency may not
445 always hold true in the HOPIT models. For example, given the complex multidimensional
446 nature of health, vignette descriptions are likely to be incomplete, and individuals may call
447 upon their own experience to impute the missing information (lack of vignette equivalence)
448 (van Soest et al., 2011). Similarly, individuals may report their own situation with a certain
449 strategic consideration that is absent from vignette assessment (failure of response
450 consistency) (d'Uva et al., 2011). The precise wording of the cut-points used in the current
451 study between the SRH and the health vignettes varied somewhat though it was generally
452 thought to impart the same understanding (e.g. 'no health problem' in vignette equivalent
453 to 'very good health' in the SRH). A few researchers have attempted to test these
454 assumptions separately (d'Uva et al., 2011; Grol-Prokopczyk et al., 2015), but rigorous tests

of these assumptions require extra data such as valid and reliable objective health measures, which were not collected at Wave 3 of ELSA. Additionally, as with SRH, there may be reporting heterogeneity in the social capital variables, but to our knowledge no nationally representative study, including ELSA, has developed social capital vignettes. Therefore, we could not take into account reporting heterogeneity in these measures. However, the present study is a first step towards a better understanding of the effects of reporting heterogeneity and the utility of anchoring vignettes in survey data on the social capital and deprivation disparities in health. Other limitations of the current study are the potential for unmeasured covariates and residual confounding and the fact that the health vignettes module was only completed once at Wave 3 (2006/07). Therefore, we could not analyse vignettes longitudinally, incorporating changes in perceptions and reporting of health into the models. However, with 18 vignettes in total, covering six different health domains, we have a very comprehensive data set in a large, representative sample of individuals aged 50 years and older throughout England.

Avenues for Future Research

These results may be more indicative of 'true' health disparities or may be the result of diverging 'attitudes' between social capital groupings. Overall, policy solutions require an overarching approach by addressing the social determinants of health that are inclusive of all sectors of the community. High quality research is required to identify how best to tackle health inequalities and policy solutions for each group might be quite different.

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Figure 1. Reporting of health across two groups illustrating reporting heterogeneity

A hypothetical vignette person with the same objective degree of health (represented by the dotted vertical line) is classified as having an extreme health problem by individuals with high social capital, while individuals with low social capital may characterise the same person as having a severe health problem.

Figure 2. Simulations illustrating the potential magnitude of the effect of reporting heterogeneity in estimating the distribution of health problem severity from self-reported survey data using the ELSA Wave 3 (2006/07) cohort, men and women aged 50 years and older

"Empirical distribution" refers to the distribution of self-rated health among the whole sample who have answered at least one of the 18 health vignettes and the self-report. "Estimated distribution without adjusting for reporting heterogeneity" refers to the distribution of self-rated health estimated using the HOPIT procedure but without adjusting reporting heterogeneity, which is similar to an ordered probit model. "Reclassification using high social capital/least deprived" and "Reclassification using low social capital/most deprived" refers to the distribution of self-rated health adjusted for reporting heterogeneity in accordance with the estimated scales (based on Model 2, Table S2) for high and low social capital with regard to the dimension in question/least and most deprived.

Table 1 Descriptive statistics for analytic sample in the ELSA Wave 3 (2006/07) cohort, men and women aged 50 years and older[a]

			Local area & trust				Social support				Social networks				Index of Multiple Deprivation 2004			
	Whole sample (n_{max} = 2341) (obs_{max} =42,138)		High[b] (n_{max} = 418) (obs_{max} =7524)		Low[b] (n_{max} = 403) (obs_{max} =7254)		High (n_{max} = 417) (obs_{max} =7506)		Low (n_{max} = 431) (obs_{max} =7758)		High (n_{max} = 408) (obs_{max} =7344)		Low (n_{max} = 410) (obs_{max} =7380)		Least deprived[c] (n_{max} = 616) (obs_{max} = 11,088)		Most deprived[c] (n_{max} = 285) (obs_{max} = 5130)	
	Percent / Mean	SD	Percent / Mean	SD	Percent / Mean	SD	Percent / Mean	SD	Percent / Mean	SD	Percent / Mean	SD	Percent / Mean	SD	Percent / Mean	SD	Percent / Mean	SD
Age	65.40	10.10	66.74	10.22	62.96	9.80	66.92	10.12	63.21	9.78	65.50	9.30	64.81	10.30	65.18	10.12	65.66	10.04
50-59	0.35	0.48	0.32	0.47	0.45	0.50	0.30	0.46	0.44	0.50	0.33	0.47	0.39	0.49	0.36	0.48	0.32	0.47
60-69	0.30	0.46	0.27	0.44	0.28	0.45	0.28	0.45	0.30	0.46	0.31	0.46	0.29	0.45	0.30	0.46	0.31	0.46
70-79	0.24	0.43	0.29	0.46	0.20	0.40	0.29	0.46	0.17	0.38	0.27	0.45	0.22	0.42	0.23	0.42	0.27	0.45
80+	0.11	0.31	0.12	0.32	0.07	0.25	0.12	0.33	0.09	0.28	0.08	0.28	0.10	0.31	0.11	0.31	0.09	0.29
Male	0.44	0.50	0.40	0.49	0.48	0.50	0.40	0.49	0.49	0.50	0.38	0.49	0.54	0.50	0.45	0.50	0.41	0.49
Living arrangements																		
Living alone	0.28	0.45	0.27	0.44	0.33	0.47	0.25	0.43	0.37	0.48	0.25	0.43	0.33	0.47	0.22	0.41	0.44	0.50
Cohabit/married	0.72	0.45	0.73	0.44	0.67	0.47	0.75	0.43	0.63	0.48	0.75	0.43	0.67	0.47	0.78	0.41	0.56	0.50
Education[d]																		
Basic	0.43	0.49	0.40	0.49	0.42	0.49	0.53	0.50	0.32	0.47	0.27	0.44	0.45	0.50	0.30	0.46	0.64	0.48
Secondary	0.40	0.49	0.45	0.50	0.38	0.49	0.39	0.49	0.42	0.49	0.49	0.50	0.39	0.49	0.47	0.50	0.27	0.45
Higher	0.17	0.38	0.15	0.36	0.19	0.39	0.08	0.27	0.26	0.44	0.24	0.43	0.16	0.37	0.23	0.42	0.08	0.28
Current smoker	0.14	0.35	0.12	0.33	0.18	0.39	0.18	0.38	0.14	0.34	0.06	0.24	0.20	0.40	0.09	0.28	0.28	0.45
Drinking frequency[e]																		
Low / moderate	0.53	0.50	0.53	0.50	0.55	0.50	0.54	0.50	0.51	0.50	0.54	0.50	0.51	0.50	0.51	0.50	0.61	0.49
High	0.35	0.48	0.35	0.48	0.32	0.47	0.33	0.47	0.38	0.49	0.38	0.48	0.35	0.48	0.42	0.49	0.21	0.41
Abstainer	0.12	0.32	0.12	0.33	0.13	0.34	0.13	0.33	0.11	0.31	0.08	0.27	0.13	0.34	0.07	0.26	0.19	0.39
Physical activity; active	0.72	0.45	0.73	0.44	0.67	0.47	0.69	0.46	0.73	0.44	0.81	0.39	0.65	0.48	0.80	0.40	0.54	0.50
No complaint sleeping	0.59	0.49	0.66	0.47	0.50	0.50	0.62	0.49	0.53	0.50	0.65	0.48	0.59	0.49	0.64	0.48	0.55	0.50
Self-rated health[f]	3.89	0.88	4.00	0.83	3.66	0.88	3.92	0.91	3.84	0.85	4.04	0.80	3.68	0.96	4.05	0.79	3.52	0.97
Vignette: Pain	3.04	1.06	3.02	1.06	3.03	1.04	3.01	1.08	3.10	1.01	2.99	1.05	3.05	1.06	3.05	1.04	2.98	1.07
Vignette: Sleep	2.59	0.85	2.54	0.82	2.59	0.85	2.60	0.83	2.65	0.82	2.50	0.81	2.62	0.87	2.57	0.81	2.58	0.85
Vignette: Mobility	2.68	1.00	2.66	0.99	2.66	0.98	2.62	1.00	2.72	0.98	2.63	0.99	2.66	0.97	2.66	0.98	2.66	0.97
Vignette: Memory	3.11	1.00	3.10	1.02	3.12	0.98	3.07	1.02	3.18	0.98	3.14	1.00	3.09	0.98	3.15	0.99	3.05	0.97
Vignette: Breathing	2.17	0.95	2.17	0.94	2.18	0.93	2.17	0.98	2.17	0.92	2.13	0.90	2.19	0.96	2.16	0.92	2.15	0.89
Vignette: Depression	2.60	1.04	2.58	1.05	2.59	1.02	2.59	1.07	2.62	1.02	2.55	1.03	2.65	1.05	2.55	1.01	2.55	1.01

[a] Excludes those aged <50 years, did not participate in health self-completion questionnaire (no vignette responses)) or no self-rated health reported

[b] High = top quintile of factor-analysis score for social capital dimension; Low = bottom quintile of factor-analysis score for social capital dimension

[c] Least = bottom quintile of IMD2004; Most = top quintile of IMD2004

[d] Basic = no/basic qualifications; Secondary = higher education but below a degree; Higher = degree or above

[e] Low/moderate = 2 times per week or less; High = 3+ times per week; Abstainer = no times in previous 12 months

[f] Five-point Likert scale (1 = very bad/extreme problems to 5 = very good/no problems)

Table 2 Ordered probit and HOPIT regressions of self-rated health in the ELSA Wave 3 (2006/07) cohort, men and women aged 50 years and older[a]

	Ordered probit		HOPIT		Ordered probit		HOPIT	
	β	**SE**	**β**	**SE**	**β**	**SE**	**β**	**SE**
	Model 1				**Model 2**			
Local area & trust								
High[b]	-0.012	(0.064)	-0.005	(0.078)	0.028	(0.067)	0.055	(0.073)
Low[b]	-0.363***	(0.065)	-0.433***	(0.078)	-0.243***	(0.068)	-0.276***	(0.073)
Social support								
High	-0.040	(0.066)	-0.147	(0.080)	0.024	(0.070)	-0.063	(0.076)
Low	-0.099	(0.063)	-0.209**	(0.076)	-0.027	(0.066)	-0.119	(0.071)
Social networks								
High	0.034	(0.065)	0.088	(0.080)	-0.044	(0.069)	0.003	(0.076)
Low	-0.272***	(0.064)	-0.407***	(0.076)	-0.210**	(0.067)	-0.280***	(0.071)
Least deprived[c]	0.154**	(0.056)	0.308***	(0.068)	0.003	(0.059)	0.110	(0.064)
Most deprived[c]	-0.275***	(0.080)	-0.186*	(0.096)	-0.047	(0.086)	0.155	(0.092)
Age 60-69	-0.156**	(0.060)	-0.265***	(0.072)	-0.066	(0.063)	-0.133	(0.069)
Age 70-79	-0.371***	(0.064)	-0.520***	(0.077)	-0.130	(0.072)	-0.185*	(0.078)
Age 80+	-0.542***	(0.089)	-0.674***	(0.108)	-0.099	(0.106)	-0.131	(0.114)
Male	-0.040	(0.049)	-0.083	(0.059)	-0.200***	(0.053)	-0.261***	(0.057)
Vignette dummies	No		Yes		No		Yes	
Socio-demographic dummies	No		No		Yes		Yes	
Health dummies	No		No		Yes		Yes	
N	2046		2046		1926		1926	

[a] Excludes those aged <50 years, did not participate in health self-completion questionnaire (no vignette responses) or no self-rated health reported

[b] High = top quintile of factor-analysis score for social capital dimension; Low = bottom quintile of factor-analysis score for social capital dimension

[c] Least = bottom quintile of IMD2004; Most = top quintile of IMD2004

Model 1: All dimensions of social capital (local area & trust, social support and social networks) & IMD2014 simultaneously

Model 2: All dimensions of social capital (local area & trust, social support and social networks), IMD2014, the socio-demographic covariates (education, living arrangements and income), and health behaviours (smoking, alcohol, physical activity and sleep) simultaneously

* p<0.05, ** p<0.01, *** p<0.001

Figure 1: 1.5 columns

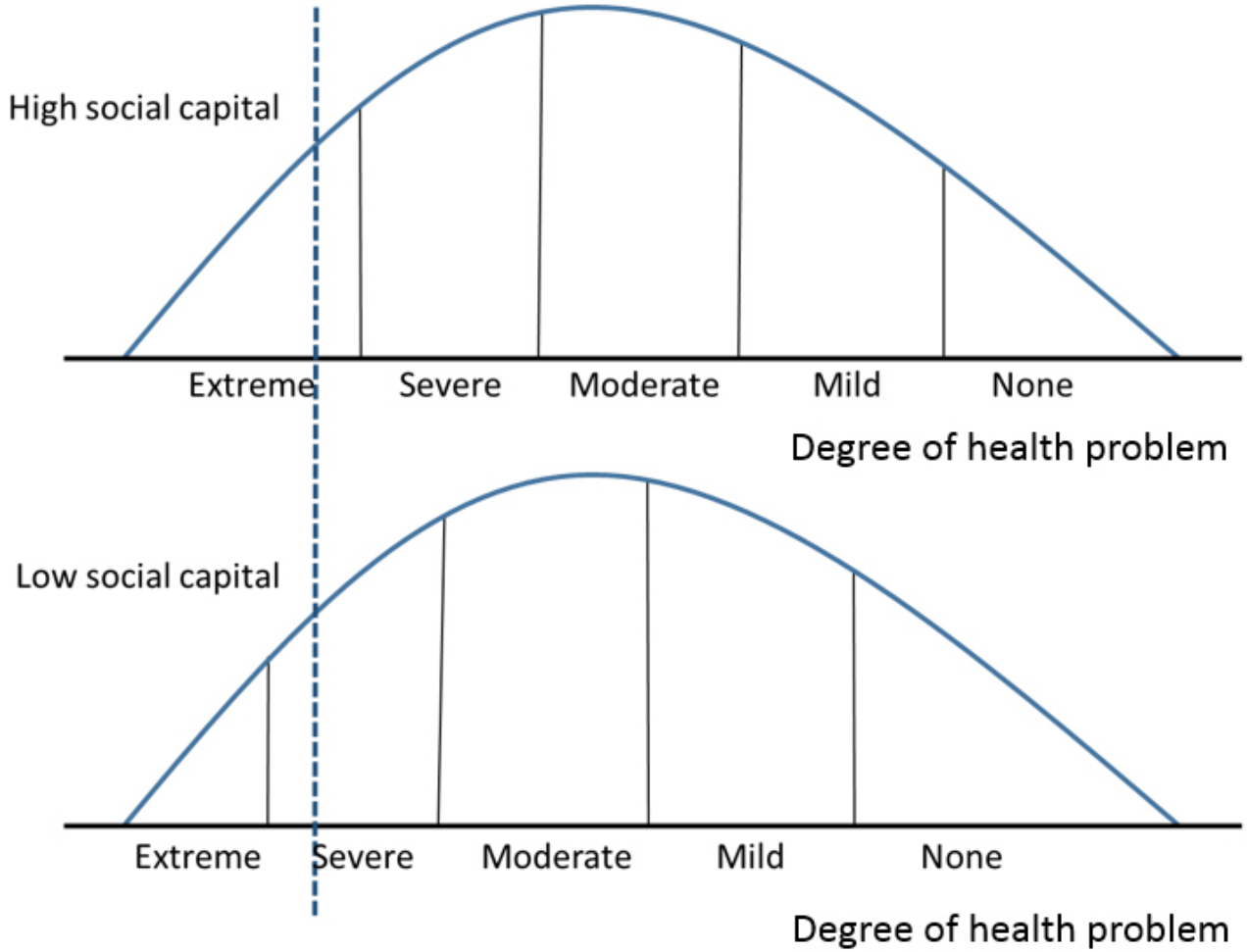

Figure 2: 2 columns