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Economic gradients in loneliness, social isolation and social support: Evidence from the UK Biobank

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ABSTRACT

Despite the substantial literature on how loneliness is associated with poor health and premature mortality, there is little detailed research on the extent of its economic gradients. We provide this evidence using a sample of around 400,000 respondents aged 40–70 years from the UK Biobank, who were assessed between 2006 and 2010. We focus on differences in loneliness, as well as social isolation and a lack of social support, across educational attainment, household income, local area deprivation, and recent experience of financial stress. We employ two statistical approaches, the first exploiting the large sample size and detailed geographical information about where respondents live, so we compare individuals who differ in their economic status but reside within the same postcode district. The second approach exploits the fact that for around 36,000 respondents we observe their social health and economic circumstances at two points in time (second wave of assessment conducted between 2014 and 2020), so we conduct a panel analysis that accounts for intercorrelations between the social health measures, and controls for incomplete follow-up of panel members. Across both approaches, we find a substantially higher probability of reporting loneliness, social isolation and a lack of social support, for men and women with lower economic status. Together with the existing health-loneliness literature, these findings establish a 'loneliness pathway' contributing to health inequalities, and consequently a need for effective interventions that might address loneliness and social isolation as part of a broad policy initiative on health inequalities.

1. Introduction

Loneliness is highly prevalent across the life course, and is predicted to increase with demographic changes: ageing populations, more people living alone, and with chronic health conditions (Cacioppo and Cacioppo, 2018a). Some commentators even argue that there is an epidemic of loneliness in many countries (Murthy, 2020), and lockdown restrictions during the COVID-19 pandemic have further heightened this concern (Banerjee and Rai, 2020). Recent surveys, conducted prior to the outbreak of the COVID-19 pandemic, find that around half of all adults in Australia, the UK and US feel lonely at least sometimes, with the highest prevalence in the youngest and oldest age groups (e.g. Ballard, 2019; Cigna, 2018; Lim, 2018; Lim et al., 2020). Moreover, a substantive literature finds that loneliness is strongly related to worse health outcomes and lower wellbeing (e.g. Cacioppo and Cacioppo, 2018b, 2018a; Courtin and Knapp, 2017; Gerst-Emerson and Jayawardhana, 2015; Holt-Lunstad et al., 2015; Steptoe et al., 2013). In fact, loneliness has been found to be a bigger risk factor for mortality than obesity and physical inactivity, and is on par with smoking (Flegal et al., 2013; Holt-Lunstad et al., 2010, 2015). Loneliness is also strongly associated with suicidal ideation and suicidal attempts, even after accounting for common mental disorders (Stickley and Koyanagi, 2016). Consequently, there are substantive costs of loneliness to healthcare systems (Kung et al., 2021; Mihalopoulos et al., 2020). Loneliness is therefore becoming increasingly recognised as a major public health, demographic and economic issue that needs to be addressed. In this paper we provide detailed evidence on the extent of economic gradients in loneliness, but also in social isolation and lack of social support, using UK data on around 400,000 individuals aged 40–70.

What is loneliness? It can be defined as the negative emotional response to the discrepancy between the quantity, or quality, of social relationships that individuals have, versus what they want (de

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Jong-Gierveld, 1987; Peplau and Perlman, 1982). It is therefore a measure of perceived social scarcity (Mullainathan and Shafir, 2013), and has been described as “social pain” (Cacioppo et al., 2006). Pathways by which loneliness can lead to disease are highlighted in Cacioppo and Hawkley (2003), and include (1) direct effects (affecting health by influencing lifestyle, health behaviours and health care utilisation), (2) heightened or excessive response to stress (i.e. reduced stress-buffering), and (3) poor physiological repair and maintenance processes (e.g. lack of sleep).

There are good grounds to think that loneliness follows an economic gradient; in other words, that loneliness might be strongly linked to educational attainment, income, local area deprivation, and financial stress (Kung et al., 2021). For instance, a lack of investment in children can hinder the development of the emotional skills necessary to seek out and maintain high-quality social relationships (Qualter et al., 2015). The experience of unemployment can eliminate or reduce the potential for important work-related interactions and friendships. Moreover, a lack of financial resources can prevent or limit participation in a wide range of social activities, and not owning a home can reduce the incentive to invest socially in local communities. Individuals residing in more deprived areas may have limited access to public amenities that encourage social interaction, and high crime rates might deter social activities such as walking in the neighbourhood (Janke et al., 2016). Additionally, financial stress is a major cause of marital separation, leading to the loss of a fundamental intimate relationship (Kung et al., 2021). Despite the extensive literature on loneliness, with limited exceptions, the main focus in psychology, epidemiology and public health has not been on potential economic drivers. Some studies have shown that those with low education and limited income have a higher probability of being lonely, but many of these studies rely on descriptive analysis or simple multivariate regression models, and often on relatively small samples. As Niedzwiedz et al. (2016, p. 25) note, “A disadvantaged socioeconomic position is linked with loneliness, but in general, studies have rarely adopted an inequalities lens."

It is also the case that few studies have simultaneously assessed the extent of economic gradients for loneliness with salient related measures, namely social isolation and perceived social support (Holt-Lunstad, 2018; Holt-Lunstad et al., 2017). Hereafter we collectively refer to these three measures as ‘social health’, but these are distinct constructs: in contrast with loneliness - a subjective measure reflecting the perceived inadequacy of social engagements (i.e. some people report being lonely even when they have regular social interactions, while others enjoy solitude) - social isolation captures structural aspects including quantity and type, and provides a relatively objective measure of an individual’s involvement in social relationships (e.g. living alone; not regularly meeting with family or friends; not a member of a club or society) (Scharf and de Jong Gierveld, 2008; Valtorta et al., 2016). Importantly, evidence suggests that the correlation between measures of loneliness and social isolation are moderate (Kung et al., 2021; Newall and Menec, 2017). However, social isolation has also shown significant associations with mortality and poor health outcomes, even after accounting for loneliness (Ge et al., 2017; Hakulinen et al., 2018; Newall and Menec, 2017; Shankar et al., 2011; Steptoe et al., 2013). Social isolation does not tap into the function aspects, or quality, of these interactions; these are better captured by social support measures, where individuals appraise their interactions with regard to the availability of emotional support and/or access to resources (finances, goods, services or information) (Fiorillo and Sabatini, 2015; Valtorta et al., 2016; Wang et al., 2017). However, it is worth noting that chronically lonely individuals may perceive a lower level of social support than what is necessarily available to them, giving rise to a stronger correlation between loneliness and social support. That is, they may have more negative social impressions of others and interpret social encounters more negatively (Qualter et al., 2015), in line with the evolutionary theory of loneliness (Cacioppo and Cacioppo, 2018b).

After reviewing the existing literature we believe that there still remains considerable uncertainty about the nature and extent of economic gradients in these key measures of social health. The aim of this paper is to build upon existing evidence (reviewed in the next section) on loneliness, as well as social isolation and lack of social support, by providing statistical analyses using nearly 400,000 adults in the UK Biobank residing in over 1400 postcode districts. With detailed geographical identifiers at each interview, we are able to identify respondents living in the same postcode district, and to measure the level of area deprivation in which respondents reside, which we exploit in an extensive cross-sectional analysis. In addition we estimate a transition model that simultaneously models each of the three social health measures, and incorporates repeat observations on a sample of around 36,000 adults (collected as part of the Biobank Imaging study). This model also explicitly controls for incomplete follow-up of panel members. Our primary focus is on differences across educational attainment, household income, neighbourhood deprivation, as well as recent major life events including financial stress.

2. Background literature

Although not extensive, there is an existing literature that has examined the link between measures of social health and various measures of economic status including educational attainment, employment status, income and wealth, although not all studies have this as their primary focus. Most tend to find higher economic status to be a protective factor against the risk of experiencing loneliness (Aylaz et al., 2012; e.g. Bosma et al., 2015; Bu et al., 2020; Cohen-Mansfield et al., 2016; Fokkema et al., 2012; Fokkema and Naderi, 2013; Hansen and Slagsvold, 2016; Kung et al., 2021; Lasgaard et al., 2016; Luhmann and Hawkley, 2016; Menec et al., 2019; Niedzwiedz et al., 2016; Pinquart and Sorensen, 2001; Victor and Yang, 2012). Further, a greater risk of loneliness has been found for individuals in lower-status occupations (Finlay and Kobayashi, 2018), those receiving a disability pension (Lasgaard et al., 2016), those with low satisfaction with their living situation (Fokkema and Naderi, 2013; Scharf and de Jong Gierveld, 2008), and those facing a worsening of their financial situation (de Jong Gierveld et al., 2015). Loneliness is also generally higher in areas of socioeconomic deprivation (Beere et al., 2019).

However, not all studies find consistent economic gradients: some find that loneliness does not differ by levels of education, income (Zebhauser et al., 2015) or social class (Wenger et al., 1996). Lasgaard et al. (2016) further show that education predicts loneliness only in young adulthood. Luhmann and Hawkley (2016) find that after controlling for income, higher educated people are lonelier, perhaps because they have higher standards when evaluating their relationships, or have fewer high-quality relationships altogether. While among middle-aged adults, full-time employment is associated with lower loneliness, this is not significant for older adults (Hansen and Slagsvold, 2016; Luhmann and Hawkley, 2016). In contrast, among younger adults, full-time employment is associated with higher loneliness (Hansen and Slagsvold, 2016). Deeg and Thomése (2005) find that neighbourhood comparisons matter: low-income individuals in high-status neighbourhoods, and high-income individuals in low-status neighbourhoods, are lonelier than their respective neighbourhood counterparts. Some studies also find individuals in rural areas to be less lonely than urban dwellers (Beere et al., 2019).

Fewer studies have examined the extent of economic gradients in social isolation and perceived social support, and findings on the direction of associations have been mixed. With regard to isolation, studies show a gradient with regard to social class (Wenger et al., 1996), income (Bosma et al., 2015; Eckhard, 2018; Menec et al., 2019), material deprivation (Mood and Jonsson, 2016; Scharf et al., 2005) and education (Ajrouch et al., 2005; Van Groenou and Van Tilburg, 2003). For unemployment, men show an initially reduced risk of isolation, but this risk increases with the duration of unemployment; whereas women have a reduced risk of isolation throughout (Eckhard, 2018). Interestingly, Menec et al. (2019) found that lower income, but higher educational attainment, correspond to greater social isolation, perhaps due to migration and thus less contact with the family network, among the higher educated. Higher education can be predictive of larger social networks (Ajrouch et al., 2005; Van Groenou and Van Tilburg, 2003), but not necessarily a higher frequency of contact or a larger number of very close friends (Ajrouch et al., 2005). Paúl et al. (2003) find social networks to be larger among rural elderly individuals, who show lower levels of educational attainment and income, than among their urban counterparts.

The literature on socioeconomic inequalities in social support is again considerably smaller than for loneliness, and worth discussing in the context of the measures used and types of support. Overall, there appears to be two overarching types of support: instrumental, which refers to the provision of tangible help such as personal care or financial resources; and emotional, which reflects the ability to share feelings and problems, affection, feeling loved and a sense of belonging. Van Groenou and Van Tilburg (2003) find that educational attainment and occupational prestige are associated with greater availability of instrumental (e.g. help with chores and transport) and emotional support (e.g. sharing of personal experiences and feelings) from non-family relationships. Greater instrumental, but not emotional, support from kin is seen among lower educated individuals, perhaps stemming from their own cultural preferences, or that they have fewer financial resources and are thus less able to purchase instrumental support from other sources.

Shields and Wheatley Price (2005) find that individuals with higher educational attainment and household income are more likely to report having supportive family or friends who, can be relied upon no matter what, will see that they are taken care of if needed (instrumental); give them support and encouragement, make them feel loved, and accept them just as they are (emotional). The authors further discuss that higher educated individuals may be more likely to practice enhanced communication and conflict resolution skills in their relationships, and that higher income increases opportunities for social interactions and activities, via ownership of a telephone, car or other technology. Being out of the labour force due to long-term sickness is also related to lower perceived social support (cf. Lasgaard et al., 2016), but this association is not seen for unemployment or neighbourhood-level deprivation.

More recently, Mood and Jonsson (2016) show small negative effects of perceived material deprivation, but not absolute or relative income poverty, on whether individuals have a close friend who can help if they get sick (instrumental), or if they need company or someone to talk to about their troubles (emotional). Eckhard (2018) also find income poverty to be associated with having nobody to ask for help if they were to "need long-term care" (instrumental), or with whom they discuss "important matters" (emotional).

Appendix Info 1 provides the sample size, age of sample, and country of origin, for each of the above studies. It is clear that the sample available in the Biobank is large by comparison, which allows for more precise estimates of the independent associations between the various measures of economic status and social health. However, it is worth noting that the studies (including ours) are mostly based on samples from Europe, including the UK. Fewer studies are based on data from, for example, Turkey (Aylaz et al., 2012), Israel (Cohen-Mansfield et al., 2016), Northern America (Ajrouch et al., 2005; Menec et al., 2019) and Australasia (Beere et al., 2019; Kung et al., 2021). As such the economic patterns of social health reviewed here may, to an extent, be specific to these societies. Fewer studies have examined whether these patterns differ between cultures. This may be an important consideration, given that the prevalence of loneliness can differ by country (Fokkema et al., 2012; Hansen and Slagsvold, 2016) and immigrant status and identity (Fokkema and Naderi, 2013; Niedzwiedz et al., 2016), at least partially due to differences in socioeconomic status (Fokkema et al., 2012; Fokkema and Naderi, 2013).

3. Data

3.1. UK Biobank

To provide evidence on the extent of economic gradients in social health we use data from the UK Biobank, a large-scale prospective study of around 500,000 respondents across the nation. The Biobank was established with the aim of improving prevention, diagnosis and treatment of a large array of serious and life-threatening diseases of middle and old ages. Between 2006 and 2010, the Biobank invited around 9.2 million 40- to 70-year-olds registered with the National Health Service (NHS), who lived within reasonable traveling distance (up to 25 miles), to attend one of 22 assessment centres across England, Scotland and Wales. The assessment centres were opened incrementally; we provide in Appendix Info 2 a map of the locations and information on their operation dates and recruitment.

The response rate was 5.5%. The baseline assessment visit involved a verbal interview and self-completion questionnaires pertaining to demographic and socioeconomic factors, and health and lifestyle behaviours. Additionally, a wide range of physical and anthropometric measurements were taken including body composition, grip strength and bone density; as well as blood, saliva and urine samples. Respondents were asked to consent to have their health-related records (e.g. hospital admissions) linked to their Biobank data, and to be recontacted for further sub-studies (Allen et al., 2012; Sudlow et al., 2015; UK Biobank, 2007). Notably, respondents are not representative of the general UK population: they have been shown to be economically better off, healthier and have better lifestyle behaviours, implying a "healthy volunteer" selection bias (Fry et al., 2017). We are thus not able to use the Biobank to estimate the national prevalence of loneliness, social isolation or lack of social support. However, this lack of representativeness of the Biobank, which was indeed primarily designed for examining exposure-disease associations, should not limit the generalisability of our findings from analysing economic gradients (Fry et al., 2017): first, we have sufficiently large numbers at different levels of economic conditions (our 'exposures'), and second, as is required in observational studies, we are able to control for relevant sources of bias, using both individual- and residential area-level characteristics. If anything, we expect that we might under-estimate the extent of economic gradients using this volunteer sample.

Since the baseline assessment (2006–2010), subsets of respondents have been followed up for additional data collection. This includes a multi-modal imaging assessment visit (ongoing since 2014) aimed at collecting data from 100,000 respondents living within reasonable distance of dedicated, purpose-built centres in Stockport, Newcastle-upon-Tyne, Reading and Bristol. These centres have been sequentially opened, starting with Stockport. For this imaging assessment, centre locations were selected based on availability of public transport links and driving times, as travel time was found to be an important factor determining response (Littlejohns et al., 2020). Importantly, we are able to employ data on loneliness, social isolation and social support, as well as other socioeconomic circumstances and relevant covariates from these additional assessment visits.

The UK Biobank data is continually being updated and we use the February 2021 release that provides baseline data for 502,488 respondents, with imaging data available on 48,998 of these respondents. The UK Biobank received ethical approval from the North West Multi-centre Research Ethics Committee (16/NW/0274). Our estimation sample consists of 380,505 respondents (201,473 women, 179,032 men) at baseline (2006–2010, referred to as wave 1 in our panel analysis), and 36,153 respondents (18,040 women, 18,113 men) that we observe both at baseline and in the imaging data (2014–2020, wave 2 in our panel analysis). Our sample excludes respondents who were at baseline: (1) living in temporary, sheltered or care accommodations, (2) living in households of more than eight individuals, (3) aged under 40 or over 70 years (very few), or (4) those with missing information on loneliness, social isolation, social support, economic status or other relevant covariates (detailed below). The sample characteristics for the baseline respondents, and for those we observe in both waves, are provided in Appendix Table A1. At baseline the average age of women and men is 55.7 years and 56.6 years, respectively; and around 69% of women and 78% of men report to be married. The average number of people in the household is around 2.5, and the average number of children is 1.8 (with around 36% having children living in the household). About one-third report having a long-term illness, disability or infirmity (29.0% of women, 34.3% of men) and the vast majority of the sample are ethnically white (96%). However, the respondents who have attended an imaging centre (thus observed in both waves) are 1–2 years younger, more highly educated, more likely to be employed, and have higher incomes, than the full baseline sample. By wave 2 the age range of these respondents is 45–82 years, and the average number of years between the baseline interview and imaging assessment is just under 9 years (ranging between 3.8 and 13.8 years). Importantly, we control for time lapsed between waves in our panel transition model.

Appendix Table A2 shows the geographical spread of respondents with respect to the baseline (wave 1) interview centres. Due to this sampling framework the data are not geographically nationally representative, but it does provide a good coverage across Britain (England, Scotland and Wales). As noted earlier we observe individuals residing in 1430 postcode districts. However, from the 36,153 respondents observed in both the baseline survey and imaging study, 21,438 (59%) attended the Stockport imaging centre, 9339 (26%) attended the Newcastle centre and 5325 (15%) attended the Reading centre, with only 51 having attended the Bristol centre by February 2021.

3.2. Measuring social health: loneliness, social isolation and social support

Studies have measured the different aspects of social health in many ways. In Appendix Table A3 we provide some salient examples, which place the measures that we use in context. Loneliness is most commonly measured using the UCLA Loneliness Scale (Russell et al., 1980) or its shortened revised versions. Rather than asking directly about loneliness, this scale is derived from three questions about how often a person feels that they lack companionship, feels left out, or isolated from others. To a smaller extent the de Jong Gierveld scale (de Jong-Gierveld and Kamphuls, 1985) has been used to measure loneliness among older individuals (Courtin and Knapp, 2017; Pinquart and Sorensen, 2001; Routasalo and Pitkala, 2003). This scale is based on six items relating to experiencing a general sense of emptiness, often feeling rejected, missing having people around them, not having enough people that they feel close to, but also social support aspects of having plenty of people to rely on when they have a problem (instrumental), and having many people that they trust completely (emotional).

Other studies have employed a single-item measure of the frequency of loneliness (e.g. "How often have you felt lonely?"), although there is some concern that the direct inclusion of the term "lonely" can render the measure dependent on contextual effects, and on respondents' values and understanding of the concept (Routasalo and Pitkala, 2003). There may also be differences in willingness to report loneliness (Russell et al., 1980; Victor et al., 2005). However, evidence suggests that direct measures of loneliness are highly correlated with the three-item UCLA measure (around 0.88), meaning that individuals rating themselves as lonely on the UCLA items are likely to also rate themselves as lonely on direct measures (Office for National Statistics, 2018). In the Biobank, loneliness is measured using a binary indicator for the direct question "Do you often feel lonely?", to which response options are "Yes" and "No". To allow for gender differences in the reporting of loneliness, all our analyses are conducted separately for women and men. In the baseline sample, 20.8% of women and 14.5% of men report often feeling lonely; in the panel sample, the prevalence is lower by around 20% (16.5%, 11.6%; see Appendix Table A1).

The measures available in the Biobank for social isolation and social support come from the items "How often do you visit friends or family or have them visit you?" and "How often are you able to confide in someone close to you?". The responses to both these questions are provided on a six-point frequency scale, ranging from "almost daily" to "never or almost never" (with visits having an additional option for "no friends/family outside the household). We note that our measure of social isolation is narrower than some used in the literature, such as in Wenger et al. (1996), and is more similar to, for example, that used in Bosma et al. (2015). Consistent with our loneliness measure, we use binary versions, namely having visits less than once a month to indicate social isolation, and never having someone close to confide in to indicate lack of social support (emotional support). Using these definitions, just over 6% of women, and 10.2% of men report to be socially isolated, and 10% of women and 18.5% of men report lacking social support, in the baseline sample. Again, these rates are qualitatively consistent in the panel sample, but generally lower than the baseline sample. In sum, compared with men, more women report experiencing frequent loneliness, but fewer women are socially isolated or lacking social support.

Interestingly, the raw correlations between the three social health measures at baseline are: loneliness/social isolation = 0.080 for men, 0.065 for women; loneliness/lack of social support = 0.173, 0.156; and social isolation/lack of social support = 0.112, 0.097. This is consistent with previous studies finding these correlations to be modest (Kung et al., 2021; Newall and Menec, 2017). However, in our panel transition model we explicitly allow for loneliness, social isolation and lack of social support to be jointly determined (i.e. allowing for unobserved factors which may jointly determine all three aspects).

3.3. Persistence in social health

Although limited to two waves, the data allow us to distinguish between transient and persistent social health concerns. Previous research indicates a reasonably high level of stability in loneliness (Mund et al., 2019), and the empirical persistence rates in Table 1 confirm this. For loneliness and lack of social support, the empirical probabilities of having poor social health at wave 2 conditional on poor social health at wave 1 is around 0.5. But social isolation is far more persistent, with a recurrence probability of more than 0.9 for both men and women. This suggests that individuals vary considerably in their psychological responses over time to persistent social isolation – with social isolation in some cases being the outcome of personal choice, possibly reflecting underlying trait-like preferences for company.

3.4. Measuring economic status

Our primary measures of economic status are: (1) highest educational attainment (college or university degree, A or AS levels, O levels or GCSEs, professional or other qualifications, or none of these), (2) annual pre-tax household income bands (under £18,000, £18,000-£30,999, £31,000-£51,999, £52,000-£100,000, or above £100,000), and (3) neighbourhood socioeconomic environment, measured by deciles of the Townsend Deprivation Index in the Lower Layer Super Output Area (LSOA) in which respondents reside. The Townsend Index is an overall measure of area socioeconomic deprivation that comprises four components: percentage of individuals who are unemployed, percentage of

Table 1
Empirical probabilities of persistence at wave 2 conditional on loneliness/social isolation/lack of social support at wave 1.

Social health indicator	Women	Men
Loneliness	0.508 [0.492, 0.525]	0.463 [0.442, 0.483]
Social isolation	0.935 [0.930, 0.939]	0.937 [0.933, 0.940]
Lack of social support	0.448 [0.424, 0.471]	0.507 [0.489, 0.524]

Note: 95% confidence intervals in brackets.

households who do not own a car, percentage of households who do not own their home, and the extent of household overcrowding. We additionally provide estimates for employment status (in paid or self-employment; unemployed; retired; sick or disabled; or other situations including volunteering, studying and caring).

Appendix Table A1 provides descriptive statistics for these measures at baseline, for the full baseline sample and for respondents we observe in the panel setting. At baseline, just over one-third of the men and women have a college or university degree (35.1%, 36.8%), and the sample provides a wide spread of household income. Even though the Biobank is a volunteer sample, around 20% of men and women reside in households with an annual income of less than £18,000. The median household income falls within the £31,000-£51,999 band, which is reasonably consistent with the median gross household income in the UK (based on equivalised household disposable income, 2008–09 values) of £36,151 (Office for National Statistics, 2020). Some 61.5% (59.7% of women, and 63.4% of men) of the baseline sample are working in some form of paid employment or self-employment, and given the age of the sample respondents (40–70) around one-third are retired. As previously noted, the panel sample is more educated, more likely to be employed, and have higher incomes.

3.5. Recent major life events

Biobank respondents are additionally asked about major life events that they experienced within the two years prior to interview in both waves. In particular, the events cover many potential drivers of social health: any serious illness, injury or assault to themselves (8.4% of women, 10.3% of men) or to a close relative (14.3%, 9.1%); death of a spouse or partner (1.9%, 1.0%) or a close relative (22.1%, 20.2%); and marital separation or divorce (3.5%, 3.1%). Most importantly, for the focus of our analysis, respondents were asked if they experienced financial stress in the past two years (12.6%, 12.2%). For respondents observed in both waves, 9.7% of women and 9.2% of men reported such financial difficulties.

3.6. Other covariates

In our statistical models we also more comprehensively (compared with most other studies) control for demographic characteristics that might reasonably be thought to be risk factors for loneliness, social isolation or lack of social support. These are age, marital status, ethnic background, household composition (number of people, and number of own children), number of siblings (brothers, sisters), whether their parents are still alive, and whether they have any long-standing illness, disability or infirmity. Additionally, we control for area-level characteristics using assessment centre locations at baseline (i.e. 22 locations spread across Britain in both the fixed effects and transition models), and area of residence (i.e. 1430 postcode districts in the fixed effects model) at the time of assessment. To obtain postcode districts, we use the easting-northing coordinates at which respondents were resident at the time of assessment, which were constructed based on the Ordnance Survey (OSGB) reference, rounded to the nearest kilometre. We first transform these rounded coordinates into longitude and latitude values, which we then reverse geocode into postcode districts using the Stata opencagegeo module (Zeigermann, 2016).

4. Empirical strategy

We use two statistical approaches, the first taking advantage of the large baseline sample, comprising respondents who reside across all the postcode districts, while the second approach uses the panel sample that allows for a model of transitions in social health.

4.1. Regression analysis with postcode fixed effects

We start by using a linear probability regression model that includes fixed effects (intercepts) for each of the 1430 postcode districts where respondents are observed to reside. This means that on average we observe 266 respondents per postcode district. Consequently, our gradient estimates are identified by comparing individuals who differ in their economic status but reside within the same local area. The benefit of this is that it eliminates any potential for local area confounding factors between economic status and social health.

More formally, the regression model takes the form:

$$Y_{ia} = X_{ia}\beta + U_a + \varepsilon_{ia} \tag{1}$$

where Y_{ia} is any of the three (binary) indicators for loneliness, social isolation and lack of social support; i, a indexes the ith observed individual within the ath postcode district, X_{ia} is a vector of covariates (all varying between and within postcode districts), U_a is a postcode district-specific fixed effect and ε_{ia} a random term varying independently across individuals and postcode districts. No restriction is imposed on the correlation between X_{ia} and U_a. The predicted probability of an adverse outcome for Y_{ia} conditional on $X_{ia} = X$ is $\widehat{p}_{ia}(X) = X\widehat{\beta} + \widehat{U}_a$. We summarise the economic gradients captured by this model by calculating the mean estimated effect of varying (for example) household income from any category 0 to any other category 1. Define $X_{ia}^{(0)}$ and $X_{ia}^{(1)}$ to be the covariate vector X_{ia} but with the income indicators modified for all individuals to give income categories 0 and 1 respectively. The average marginal effect of varying income from category 0 to 1 is then $N^{-1}\sum_{ia}[\widehat{p}_{ia}(X_{ia}^{(0)}) - \widehat{p}_{ia}(X_{ia}^{(1)})]$, where N is the number of individuals across all postcode districts.

4.2. Non-linear transitional panel analysis

Our second approach exploits the two-wave panel aspect of the data available for 36,153 respondents, using a transition model which allows for non-ignorable partial follow-up of individuals at wave 2. Re-defining the notation, the model uses the three binary indicators $Y_1 \dots Y_3$ of loneliness, social isolation and lack of social support. We have two waves of observation, giving outcomes $Y_{1it} \dots Y_{3it}$ for sampled individuals $i = 1 \dots n$ over waves $t = 1, 2$. At the baseline wave $t = 1$, we observe a vector of explanatory covariates X_i, and at re-interview (in the imaging wave) $t = 2$ another set of covariates Z_i. There are thus eight outcome regimes for wave 1, $Y_{1i1} \dots Y_{3i1} = 0, 0, 0$ to 1,1,1. Define $R_i = [R_{i1} \dots R_{i8}]$ to be the set of binary indicators identifying which of those eight outcomes is observed for individual i.

For a large proportion (around 90%) of baseline respondents, there is no wave 2 observation available. As previously noted, this is mostly because of survey design reasons: re-interviews (as part of the ongoing imaging study) are limited in the Biobank to respondents living in the catchment areas of imaging centres. However, even for those within the catchments, there will be to some degree the usual attrition processes of non-contact, refusal and mortality. These processes may be endogenously related to social health, so we incorporate an endogenous follow-up process in the statistical modelling.

The full model is:

$$Y_{1i1}^{*} = X_i\beta_1 + U_{1i} \tag{2}$$

$$Y_{2i1}^{*} = X_i\,\beta_2 + U_{2i} \tag{3}$$

$$Y_{3i1}^{*} = X_i\,\beta_3 + U_{3i} \tag{4}$$

$$Y_{1i2}^{*} = Z_i\,\gamma_1 + R_i\delta_1 + V_{1i} \tag{5}$$

$$Y_{2i2}^{*} = Z_i\,\gamma_2 + R_i\,\delta_2 + V_{2i} \tag{6}$$

$$Y^*_{3i2} = Z_i\gamma_3 + R_i\,\delta_3 + V_{3i} \tag{7}$$

$$A^*_i = X_i\lambda + R_i\theta + W_i \tag{8}$$

where $Y^*_{1i1} \dots Y^*_{3i2}, A^*_i$ are latent continuous variables driving the three observable binary indicators of social health. The vectors $\beta_j, \gamma_j, \delta_j$ $(j = 1, 2, 3)$; λ, θ contain coefficients to be estimated. The variables $U_{1i}, U_{2i}, U_{3i}, V_{1i}, V_{2i}, V_{3i}, W_i$ are random terms assumed to be normally distributed with zero means and unit variances. The correlations within U_{1i}, U_{2i}, U_{3i} are ρ_{12} ,ρ_{13},ρ_{23} and within V_{1i}, V_{2i}, V_{3i} are φ_{12}, φ_{13}, φ_{23}, which are estimated as parameters. The two blocks of error terms U_{1i}, U_{2i}, U_{3i} and V_{1i}, V_{2i}, V_{3i} are assumed to be independent, since the wave 2 outcomes are modelled conditionally on the wave 1 outcome. The random term W_i is independent of the $U_{1i} \dots U_{3i}$, since the follow-up model is conditional on the observed wave 1 outcome. We also assume W_i to be independent of V_{1i}, V_{2i}, V_{3i}.

The observed binary indicators Y_{jit} are generated through the following mechanism. For the observed outcome at wave 1:

$$Y_{ji1} = 1 \text{ if } Y^*_{ji1} > 0 \text{ and } 0 \text{ otherwise},\ j = 1, 2, 3;\ i = 1 \dots n \tag{9}$$

giving the eight possible outcome regimes indicated by R_i. At wave 2, there are nine possible outcomes, since non-follow up ("attrition") is another possibility. Thus:

$$Y_{ji2} = 1 \text{ if } Y^*_{ji2} > 0, A^*_i < 0 \text{ and } 0 \text{ otherwise},\ j = 1, 2, 3 \tag{10}$$

$$A_i = 1,\ [Y_{1i2} \dots Y_{3i2}] \text{ missing if } A^*_i > 0 \tag{11}$$

The composite likelihood for individual i is:

$$L_i = Pr(Y_{1i1}, Y_{2i1}, Y_{3i1}|X_i) \times \{A_i Pr(A_i = 1|Z_i, R_i)$$

$$+ (1 - A_i)[1 - Pr(A_i = 1|Z_i, R_i)]Pr(Y_{1i2}, Y_{2i2}, Y_{3i2}|Z_i, R_i)\} \tag{12}$$

The components $Pr(Y_{1i1}, Y_{2i1}, Y_{3i1}|X_i)$ and $Pr(Y_{1i2}, Y_{2i2}, Y_{3i2}|Z_i, R_i)$ are computed as trivariate normal d.f.s and $Pr(A_i = 1|Z_i, R_i)$ as a univariate normal d.f.. The ML estimator is computed by maximising numerically the log likelihood $L = \sum_i L_i$.

5. Results and discussion

Both models are estimated separately for men and women. The full set of parameter estimates for the linear probability models are presented in Appendix Tables A4 and A5, and we later show the sensitivity of the main gradient estimates to a different cut-off for social isolation and lack of social support in Appendix Tables A6. The estimated parameters for the non-linear transition models are shown in Appendix Tables A7, A8 and A9. All estimates and calculations we present in this section are derived from these estimates. Our main focus is on the extent of economic gradients across four dimensions: household income, financial stress, educational attainment and local area deprivation. Overall, we find robust evidence of substantive economic gradients in social health, but their extent differs across the three outcomes and by gender. Results for employment status, and demographic and household characteristics, are also discussed. Appendix Table A7 shows that the correlation parameters from the joint modelling of the three outcomes in the transition model are highly significant, but strongest for loneliness and lack of social support (around 0.3), and weakest for loneliness and social isolation (around 0.15). The modest size of these residual correlations and the significant coefficient differences across equations (2)-(4) and (5)-(7) confirm that our three measures of social health are distinct aspects rather than alternative indicators of a single underlying concept. At the end of this section, we also discuss our estimates of loss to sample through non-follow up or attrition.

5.1. Household income

We start with household income, which is captured by five broad bands in the Biobank. Fig. 1 shows the estimated gradients graphically from the linear probability model (a,c,e) and the baseline component of the transition model (b,d,f). The plotted points are estimates of $E_{X^*}\{Pr(Y = 1|\textit{income category } j, X^*)\}$, where Y is any of the social health indicators, X^* is the baseline covariate vector with the exception of the income variables, and $E_{X^*}\{\}$ is the expectation with respect to the population distribution of the covariates X^*. For estimation purposes, $Pr(Y = 1|\textit{income category } j, X^*)$ is given by the fitted model and $E_{X^*}\{\}$ is replaced by the analogous sample average. Confidence intervals (95%) take into account sampling variation in the model parameters and the averaging over sampled X^*.

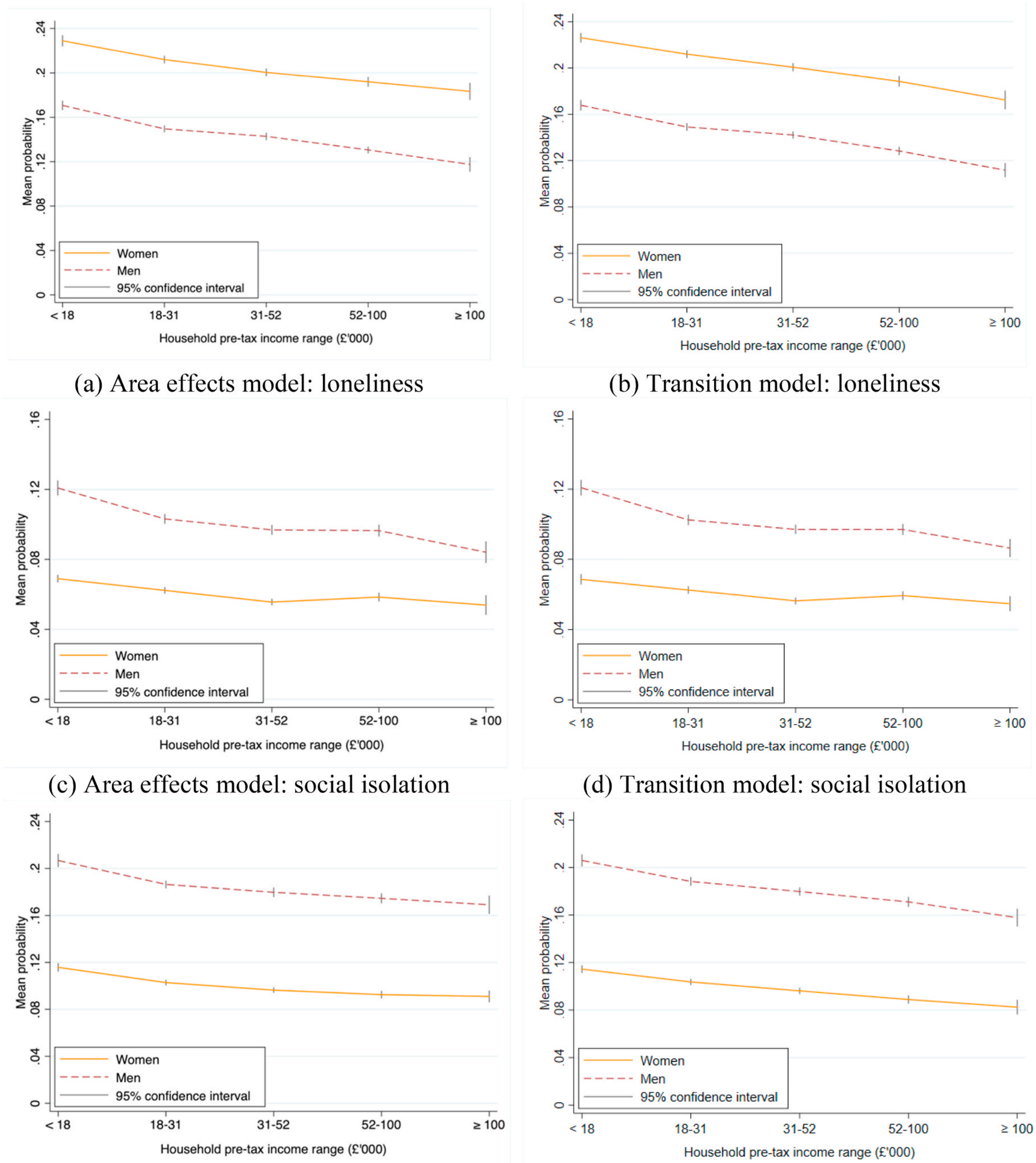
For the household income profiles at baseline (wave 1), both models provide very similar profiles. These show that more women than men report often feeling lonely across the whole income distribution, whereas more men than women consistently report more social isolation and particularly a lack of social support. In every case there is a significant (with tight confidence intervals) household income gradient, which is particularly pronounced for loneliness and a lack of social support. In contrast to men, the gradient in social isolation for women is close to flat across the income distribution. The implication of this is that the amount of income that a household has is not a strong predictor of how often women interact (visit) with friends or family.

Fig. 2 shows the income profile of the sample mean of the estimated joint probabilities for the three social health measures, as we hypothetically vary each individual's household income from the highest to lowest category. The gradient in this joint probability is apparent for all three measures of social health, but only achieves statistical significance for loneliness for this smaller sample of individuals present at both waves. Table 2 gives quantitative summaries of the income gradients between the top and bottom categories (bands). From the baseline (wave 1) component of the model, the estimated rise in the mean probability of experiencing loneliness as household income moves from the highest to lowest category is just over 5 percentage points, amounting to a proportional rise of 31.1% for women and 50.1% for men. Similarly, very strong income gradients are found for both social isolation and lack of social support. Again, we find that the smallest gradient is for social isolation for women.

The joint probabilities of loneliness, social isolation or lack of social support at both waves 1 and 2 indicate the longer-term relationship between income and social health. The mean joint probability is necessarily less than the marginal probability for wave 1, and the absolute impact is consequently smaller. However, in terms of proportional impacts, the estimates are very large for all three aspects of social health, ranging from a 44.1% rise (loneliness in women) to 81.6% (social isolation among men).

5.2. Financial difficulties

While the Biobank provides information on the level of household income, it also asks respondents about the occurrence of financial stress in the two years prior to interview, which may arise from unemployment, high expenses or debt accumulated in the past. However financial difficulties arise, they could act as a severe constraint on an individual's social activities. Table 3 shows the estimated mean impacts of financial difficulties, with 95% confidence intervals shown in squared brackets. These estimates are average effects: mean differences $Pr(Y = 1|X^{(1)}) - Pr(Y = 1|X^{(0)})$ predicted by the relevant model, where Y is any of the three indicators for loneliness, social isolation and lack of social support; and $X^{(0)}$ and $X^{(1)}$ are the observed covariate vector with the financial stress indicator set to 0 and 1 respectively. Again, we show alternative estimates from the linear probability model and the non-linear transition model for the baseline (wave 1). We also show



(a) Area effects model: loneliness

(b) Transition model: loneliness

(c) Area effects model: social isolation

(d) Transition model: social isolation

(e) Area effects model: lack of support

(f) Transition model: lack of support

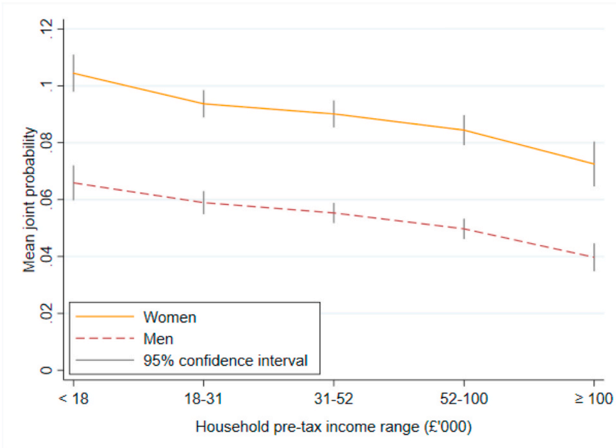
Fig. 1. Income gradients at wave 1 for the cross-section linear probability model with area effects and the baseline component of the two-wave transition model.

corresponding estimates for wave 2 respondents derived from the transition model, conditioning on the observed wave 1 outcome.

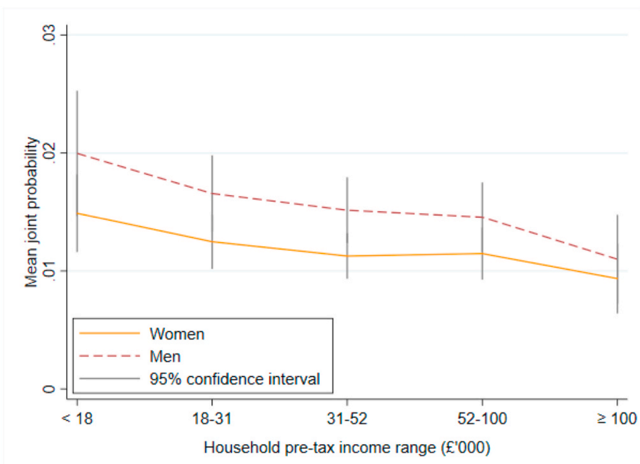
In relation to the sample prevalence of the three social health measures these are again large effects. The estimated average effect of recent financial difficulties is a proportionate increase in the number of people experiencing frequent loneliness by 27–58% (i.e. 5.7/20.8; 12.0/20.8) for women and 38–72% (i.e. 5.5/14.5; 10.4/14.5) for men, depending on the model and wave used. Similarly, social isolation rises by one or two percentage points, equivalent to a 23–25% (i.e. 1.4/6.1; 1.5/6.1) rise in the number of women classed as socially isolated, with a corresponding 16–21% (i.e. 1.6/10.2; 2.1/10.2) increase in the number of men. For lack of social support, the estimated impacts are similar: 22–32% (i.e. 2.2/10.2; 3.3/10.2) for women and 17–23% (i.e. 3.1/18.5; 4.2/18.5) for men.

5.3. Educational attainment

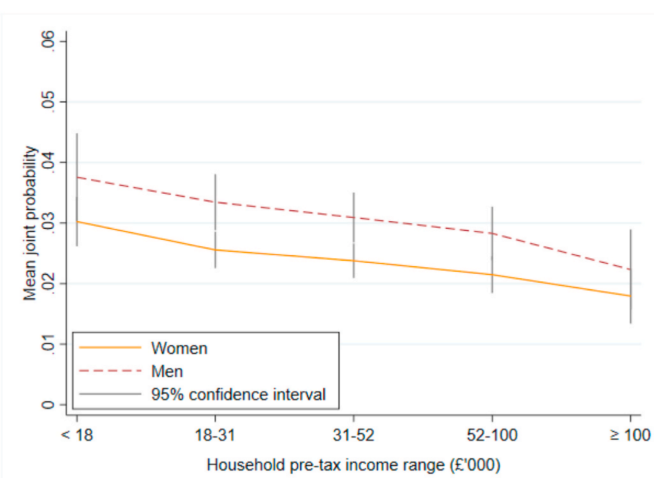
The estimates provided in Appendix Tables A4-A5 clearly show that the better educated have a substantively lower probability of reporting often feeling lonely and lacking someone to confide in at baseline, but this is not so clear cut for social isolation (visits). These are summarised in the top panel of Table 4, which provides estimates of the difference in probabilities between the highest education level (degree) and the lowest (no qualification). From the linear probability model, a college or university degree is associated with differences in the probability of loneliness by around 35% (6.5) and lack of social support by 60% (5.1) among women, with the corresponding estimates for men being smaller at around 8% (1.1) and 40% (6.5). Similar estimates are found from the baseline (wave 1) estimates from the transition model. In contrast, we



(a) Loneliness



(b) Social isolation



(c) Lack of support

Fig. 2. Income gradients in the joint probability of loneliness at both waves 1 and 2.

Table 2
Summary of income gradients in loneliness, social isolation and lack of social support.

	Linear probability model: Impact[a] on mean wave 1 probability	Transition model	
		Impact[a] on mean wave 1 probability	Impact[a] on mean wave 1 and 2 joint probability
Women			
Loneliness	4.6 p.p. (24.8%)	5.4 p.p. (31.1%)	3.2 p.p. (44.1%)
Social isolation	1.5 p.p. (28.1%)	1.4 p.p. (25.4%)	0.6 p.p. (59.2%)
Lack of support	2.5 p.p. (27.3%)	3.2 p.p. (38.9%)	1.2 p.p. (68.5%)
Men			
Loneliness	5.3 p.p. (45.3%)	5.6 p.p. (50.1%)	2.6 p.p. (65.9%)
Social isolation	3.7 p.p. (43.7%)	3.4 p.p. (39.8%)	0.9 p.p. (81.6%)
Lack of support	3.8 p.p. (22.3%)	4.8 p.p. (30.4%)	1.5 p.p. (68.3%)

Note: Impact is expressed as a difference in percentage points (p.p.) or proportionately (%).
[a] Difference between mean probability when all sample individuals have income reset to the highest category and mean probability when all individuals are assigned to the lowest income category.

Table 3
Estimated impact[a] in percentage points of financial stress.

Model	Loneliness	Social isolation	Lack of support
Women			
Linear model (wave 1)	12.0	1.5	3.2
	[11.4, 12.6]	[1.1, 1.8]	[2.7, 3.7]
Transition model (wave 1)	10.8	1.4	3.3
	[10.2,11.4]	[1.1, 1.8]	[2.8, 3.7]
Transition model (wave 2)	5.7	1.4	2.2
	[3.6, 7.8]	[0.0, 2.8]	[0.5, 4.0]
Sample proportion (wave 1)	20.8	6.1	10.2
Men			
Linear model	10.4	2.1	4.2
	[9.8, 10.9]	[1.6, 2.5]	[3.6, 4.8]
Transition model (wave 1)	8.7	1.9	4.0
	[8.2, 9.3]	[1.4, 2.3]	[3.4, 4.6]
Transition model (wave 2)	5.5	1.6	3.1
	[3.5, 7.5]	[-0.3, 3.4]	[0.6, 5.5]
Sample proportion (wave 1)	14.5	10.2	18.5

Note: Figures in square brackets are 95% confidence intervals.
[a] Difference (in percentage points) between mean probability when all sample individuals have the financial difficulty indicator set to 1 and mean probability when all individuals are assigned no recent financial shock.

find that having a degree is significantly associated with a higher probability of being socially isolated for both women (−10.0%) and men (−5.9%); that is, being less likely to often visit friends or family, or have them visit. This could be explained by those with a degree being more likely to be employed, and thus having less time for such social interactions, but these estimates are conditional on controlling for employment status in the models.

Turning to the transition (the difference in social health between waves 1 and 2), from the final column of Table 4 we see that having a degree relative to no qualifications is highly predictive of a substantively lower joint probability of loneliness and a lack of social support in both waves 1 (baseline) and wave 2 (imaging study). In fact, the proportionate change in the probabilities is even greater for loneliness (46%, 21.6%) and lack of support (91.8%, 60.9%) for women and men, than when we focus only on wave 1. One interesting change, however, is that when we consider both waves of data, we now find that education does reduce social isolation (12.9%, 10.1%). Finally, the gradients across each level of educational attainment are plotted in Fig. 3 for the linear probability model (wave 1) and the joint probabilities from the transition model. These highlight that the education gradient in loneliness is

Table 4
Summary of education and neighbourhood deprivation gradients in loneliness, social isolation and lack of social support.

	Linear probability model: Impact[a] on mean wave 1 probability	Transition model	
		Impact[a] on mean wave 1 probability	Impact[a] on mean[b] wave 1 and 2 joint probability
Education gradients			
Women			
Loneliness	6.5 p.p. (34.7%)	6.9 p.p. (37.6%)	3.8 p.p. (46.0%)
Social isolation	−0.7 p.p. (−10.0%)	−0.7 p.p. (−10.3%)	0.2 p.p. (12.9%)
Lack of support	5.1 p.p. (60.1%)	5.2 p.p. (63.5%)	1.8 p.p. (91.8%)
Men			
Loneliness	1.1 p.p. (7.8%)	1.5 p.p. (10.1%)	1.1 p.p. (21.6%)
Social isolation	−0.7 p.p. (−5.9%)	−0.7 p.p. (−6.6%)	0.2 p.p. (10.1%)
Lack of support	6.5 p.p. (40.8%)	7.0 p.p. (45.0%)	1.6 p.p. (60.9%)
Neighbourhood deprivation gradients			
Women			
Loneliness	1.4 p.p. (6.6%)	0.8 p.p. (4.1%)	0.4 p.p. (4.5%)
Social isolation	2.6 p.p. (47.4%)	2.2 p.p. (45.9%)	0.5 p.p. (45.1%)
Lack of support	2.0 p.p. (20.1%)	1.1 p.p. (11.5%)	0.3 p.p. (12.3%)
Men			
Loneliness	1.9 p.p. (13.6%)	1.5 p.p. (10.9%)	0.6 p.p. (11.2%)
Social isolation	3.2 p.p. (34.5%)	2.9 p.p. (34.4%)	0.5 p.p. (36.8%)
Lack of support	2.2 p.p. (12.3%)	0.8 p.p. (4.3%)	0.3 p.p. (8.5%)

Note: Impact is expressed as a difference in percentage points (p.p.) or proportionately (%).

[a] For education gradients, this is the difference between mean probability when all sample individuals have education reset to the highest category (degree) and mean probability when all individuals are assigned to the lowest education category (no qualifications). For neighbourhood deprivation gradients, this is the difference between mean probability when all sample individuals have their Townsend Deprivation Index decile reset to the lowest category (least deprived) and mean probability when all individuals are assigned to the highest category (most deprived).

[b] Mean over subsample of individuals observed in both waves.

steeper for women than men, about the same for lack of social support, but that the relationship between education and social isolation might not be monotonic across the education levels.

5.4. Neighbourhood deprivation

Economic disadvantage may operate at the level of the individual and at the level of the neighbourhood. We measure neighbourhood deprivation using deciles of the Townsend Deprivation Index, calculated at the small LSOA level. The estimated differences between the deciles are jointly statistically significant in both the linear probability and transition models, for all three outcome measures and both genders (p-values for joint significance of the deprivation dummies are less than 0.01, except for the loneliness equation in the transition model for women, where $p = 0.0117$). Note that these effects are identified by comparing individuals who reside in the same postcode district, but differ in the level of deprivation in their smaller area (there are multiple LSOAs in each postcode district). Fig. 4 shows the estimated average effect of varying the level of neighbourhood deprivation from the bottom to top decile, while keeping other observed characteristics at their observed values. Estimates from both the linear probability model (a,c, e) and transition model (b,d,f) are shown. Although statistically significant, the neighbourhood gradient is quantitatively small for loneliness and lack of social support, but much stronger for social isolation, driven by a particularly strong gradient in the top 30% of the deprivation range.

Our social isolation measure is an indicator of the absence of social interaction rather than its perceived quality. Deprived neighbourhoods tend to have poorer quality housing, few local amenities, poorer environmental quality and greater concerns about personal safety, all of which are potential barriers to exercising the personal demand for social activities. Low incomes and long working hours of others within the same deprived neighbourhood may also have the effect of reducing the potential supply of opportunities to socialise with others.

The bottom panel of Table 4 further provides quantitative summaries of these deprivation gradients which, for perceived loneliness and lack of social support, are considerably smaller than the gradients found for household income and education shown in Table 2 and the top panel of Table 4. However, for social isolation, the deprivation gradient is nearly twice the size of the income gradient for women, whereas for men, the deprivation gradient is slightly smaller than the income gradient. For these neighbourhood deprivation gradients (unlike those for income, education and financial stress), the linear probability model gives larger gradients than does the transition model – a difference possibly attributable to its ability to control for postcode district effects.

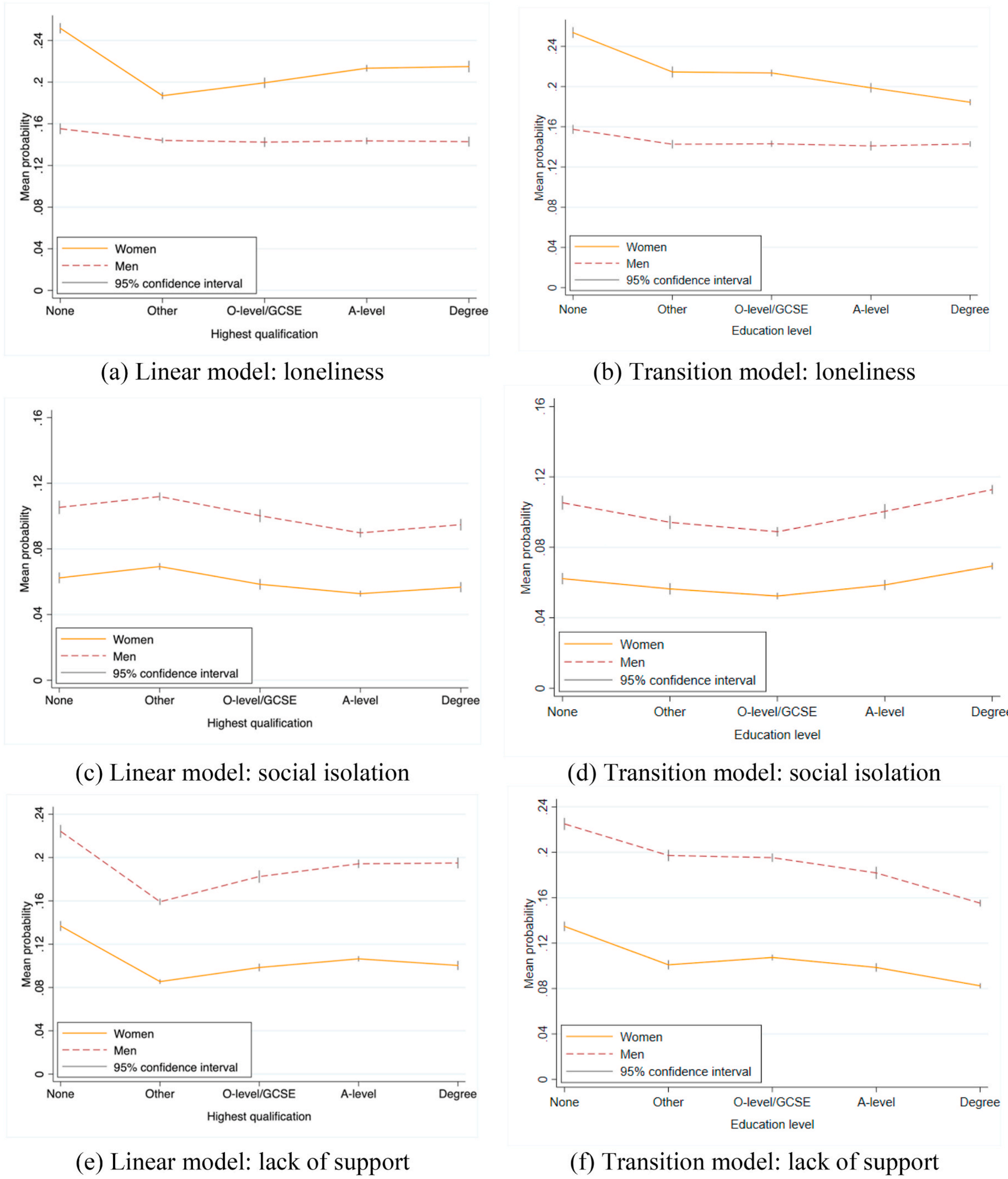
5.5. Employment status

Noting that the minimum age of respondents is 40, Appendix Tables A4-A5 (linear probability regression) show that even after controlling for educational attainment, household income and local area deprivation in the models, employment status is a significant predictor of social health. Compared with being employed (employee or self-employed), being unemployed is associated with increased probabilities of loneliness (by 5.6 percentage points), social isolation (2.0) and a lack of social support (3.2) for women, and loneliness (3.1) and a lack of social support (1.9) for men. Interestingly, unemployment is not associated with increased social isolation for men. In contrast, across all three measures, being retired is significantly associated with better social health outcomes. Moreover, being unable to work due to disability is strongly linked to an increased risk of loneliness, and to a lesser extent a lack of social support, and (for women) increased social isolation. These findings are largely confirmed by the wave 1 transition model estimates, as shown in Appendix Table A8. In terms of explaining transitions, the wave 2 estimates presented in Appendix Table A9 suggest that moving to retirement is associated with better social health, particularly reduced loneliness and social isolation. However, there is no evidence that retirement changes perceived social support. While not being able to work due to disability does not predict a change in social health for women, it does suggest greater loneliness and decreased social support for men.

5.6. Robustness to different cut-off points for social isolation and support

Our binary measures of social isolation and lack of social support are based on particular cut-offs on six-point ordinal scales, that is, having visits less than once a month to indicate social isolation, and never having someone close to confide in to indicate absence of social support. For the baseline sample, prevalences are 6.1% for women and 10.2% for men for social isolation, and 10.2% for women and 18.5% for men for lack of support (Appendix Table A1). Here we examine the robustness of the economic gradients if we 'soften' each measure by one point on the scale, such that social isolation indicates having visits less than once a week, and lack of social support reflects not being able to confide in someone close at least on a monthly basis. This increases the prevalence of social isolation to 18% for women and 26% for men, and lack of support to 16% for women and 24% for men.

Given the similarity of the economic gradients found using both the fixed effects and panel models, in Appendix Table A6 we only provide estimates for the fixed effects linear probability model. The results confirm the substantive economic gradients: for example, having a degree-level qualification reduces the probability of social isolation by



(a) Linear model: loneliness (b) Transition model: loneliness

(c) Linear model: social isolation (d) Transition model: social isolation

(e) Linear model: lack of support (f) Transition model: lack of support

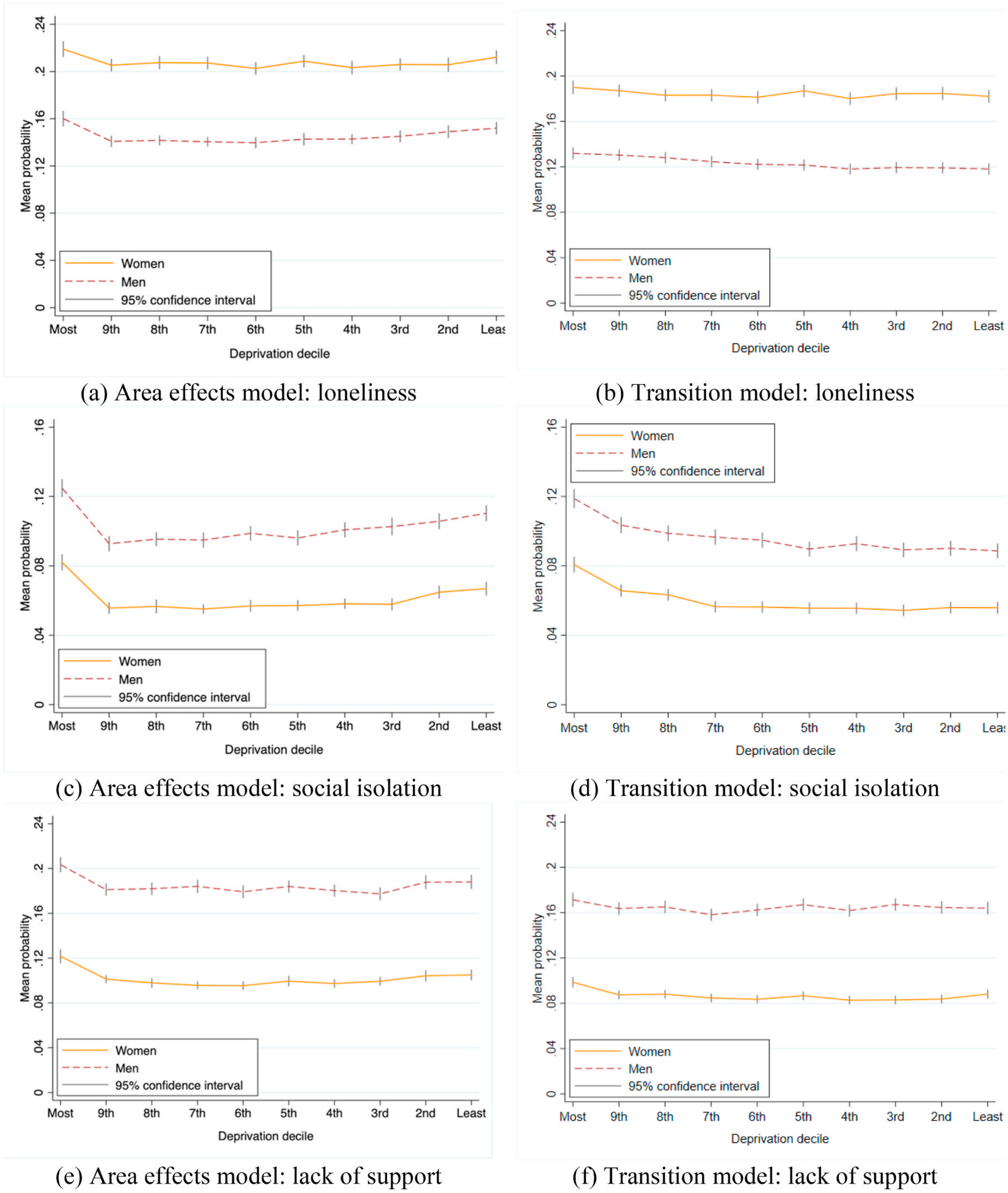
Fig. 3. Transition model: Education gradients for the probabilities of loneliness, isolation and lack of support at baseline wave 1, and for their joint probabilities at both waves 1 and 2.

around 25% for women and 20% for men relative to the mean prevalence, compared to having no qualifications. The corresponding differences for lack of support are 37% and 23%, respectively. Having an annual household income of less than £18,000 is linked to increased probabilities of both social isolation and lack of social support, as is having recently experienced financial stress, and living in the most deprived (10th decile) areas. Additionally, unemployment is significantly associated with lack of social support, but this is not the case for social isolation.

5.7. *Demographic and household characteristics*

There are a number of well-established predictors of loneliness including poor health, being single, and living alone (Hawkley et al., 2022). Studies have also found complex relationships between loneliness, age and gender (Barreto et al., 2020; Hawkley et al., 2022). However, age is consistently found across our models to have a predominantly protective effect on social health, with loneliness, social isolation and lack of support all declining with age after controlling for the wide range of other characteristics represented by the covariates in the models. The one exception to this is that for women, the predicted probability of a lack of support rises up to age 47, declining thereafter.

As expected, marriage (or cohabitation) greatly reduces the estimated probability of loneliness in particular, but also to a lesser extent the probabilities of social isolation and (for men) a lack of social support. The protective effect of marriage is substantially stronger for men than



(a) Area effects model: loneliness (b) Transition model: loneliness

(c) Area effects model: social isolation (d) Transition model: social isolation

(e) Area effects model: lack of support (f) Transition model: lack of support

Fig. 4. Neighbourhood deprivation gradients at wave 1 for the cross-section linear probability model with area effects and the baseline component of the two-wave transition model.

for women, which is consistent with the findings that men tend to have a stronger reliance on their spouses as confidants, and for the maintenance of social contacts (Stroebe et al., 2001; Wörn et al., 2020).

Household size and structure have complex effects. For both men and women, the probability of loneliness is monotonically decreasing with household size but the probability of social isolation is more strongly increasing – the existence of many contacts within households thus appears to act as a substitute for contacts outside. As might be expected, the largest step in these household size profiles is the distinction between a single person and a couple. For women, unlike men, there is only a small negative household size effect on the probability of lack of support. Family appears to meet support needs better for men than for women. Having children increases the risk of loneliness and – for women only – that effect rises with the number of children they have. In contrast, a greater number of children reduces the probability of social isolation for both parents. To a smaller extent, large families also tend to reduce both parents' probability of a lack of social support.

Having family external to the household is also important: having surviving parents appears to be protective for all three measures of social health. This relationship is stronger for women than for men and with the exception of social support, it is stronger with a surviving mother than a surviving father. It has been found that siblings are associated with less loneliness (Distel et al., 2010), and we find small reductions in the probabilities of loneliness and lack of support for women. In contrast, for men there is some evidence that (a large number of) siblings tend to increase loneliness and social isolation. These sibling effects are likely to be a mixture of short- and very long-term influences: current availability of siblings increases the pool of potential social contacts, while we might speculate that having a large number of siblings during childhood affects the social skills that are carried into adult life.

There is strong evidence of differences between ethnic groups (Victor et al., 2012). Women with South Asian heritage have a substantially higher probability of loneliness, isolation and lack of support than the reference white group, but the relationships for South Asian men are smaller for the probability of lack of support and negligible for social isolation. East Asian ethnicity is associated with elevated probabilities of social isolation and lack of support (especially for women), but not loneliness. Black African and Caribbean ethnicities are estimated to reduce rather than increase the probability of loneliness relative to whites, significantly so for men. However, black ethnicity is linked to higher probabilities of social isolation and lack of support, particularly for women.

5.8. Follow-up at wave 2

The transition model we specified contains a component representing the possibly endogenous non-follow up process, which we present in Appendix Table A8. Note that this process is a composite, covering elements of survey design (i.e. living close to an imaging centre), refusal and non-contact, and also potentially mortality given the age of the respondents. Nevertheless, the pattern is consistent with what is found in many other longitudinal surveys: the probability of loss to sample rises strongly with age, illness and disability, minority ethnic identity, low educational attainment, low income and financial distress, and high neighbourhood deprivation. Moreover, it is found to be endogenous in the sense that at least one of the possible outcome states involving loneliness at wave 1 significantly raises the probability of absence at wave 2. Thus, including the modelling of sample inclusion at wave 2 as we have done is important.

6. Conclusion

Despite having a high GDP per capita, we find that poor social health is highly prevalent in Britain. This is important because loneliness, social isolation and lack of social support have all been linked to worse health and wellbeing, including an increased risk of mortality. Moreover, these social health issues are predicted to increase with demographic changes: ageing populations, more people living alone, and with increased chronic health conditions. While there has been a great deal of research on these health links, there have been fewer studies focusing on the extent of economic inequalities in social health (Niedzwiedz et al., 2016). Such studies are important for shedding light on the focus of potential policies aimed at improving social health in the population.

The contribution of this paper is to provide a detailed study of economic gradients in loneliness, but also social isolation and lack of social support, using data on nearly 400,000 respondents observed in the UK Biobank. It is important to study each of these different dimensions of social health because while to some extent they will be jointly determined, the correlation between them is modest (e.g. a person can be lonely without being socially isolated or lacking in social support). However, we find that the correlation between loneliness and lack of social support is stronger than the correlation between loneliness and social isolation. In particular we examine the extent to which these measures of social health vary by educational attainment, household income, recent financial stress and neighbourhood deprivation. We fit two different statistical models, one that exploits the large sample size and detailed geographical information about where respondents live, and one that exploits the fact that around 36,000 respondents are tracked so that we observe their social health and economic circumstances at two points in time. This allows us to shed some light on the persistence of social health by economic status.

However, there are a number of limitations to our study. First, although we have been able to control for a rich host of covariates in our models, we cannot make any strong claims of causality. Second, we only observe respondents aged 40–70 years at baseline in the Biobank, so we are unable to examine the extent of economic gradients in social health for younger or older people. Third, we are reliant on single-item measures of loneliness, social isolation and social support.

Importantly, we find strong and robust evidence of substantial economic gradients in all three measures of social health after controlling for a wide array of demographic characteristics. Those with low education levels, low household income, and residing in the most deprived areas have a substantively higher probability of experiencing at least one aspect of poor social health. Women report more loneliness than men across the whole household income distribution, while the opposite is the case for social isolation and lack of social support. As an example of the magnitudes, moving from the highest to the lowest income category increases the mean probability of reporting often feeling lonely by around a quarter of the well-established short-term impact of the death of a spouse, or conversely, almost half of the benefit of being married rather than single. Additionally, the experience of recent financial stress substantially compounds the risk of experiencing all forms of poor social health.

The literature contains discussions on how income can influence loneliness insofar as it leads to opportunities for more (quantity) and/or better (quality) social connections (Beere et al., 2019; Klinenberg, 2016; Pinquart and Sorensen, 2001). Qualitative results have shown that higher income can provide resources that enable social leisure activities, whereas low income jobs may include shift work, irregular hours and multiple jobs resulting in less time for socialising (Finlay and Kobayashi, 2018). Several studies have found that loneliness appears more closely related to quality rather than quantity of connections (e.g. Fokkema and Naderi, 2013; Pinquart and Sorensen, 2001), although the opposite might be true in deprived communities (Paúl et al., 2003). Our findings suggest that household income is strongly related to increases in both the quantity (isolation) and quality (social support) of connections. However, we do find important differences by gender: the gradient in loneliness and social isolation is stronger for men than women, whereas the gradient in social support is stronger for women. In other words, for men, income is potentially more likely to enable the maintenance or rise in quantity of connections; for women, income may be more helpful with regard to improving or creating higher quality connections.

We also find that neighbourhood deprivation is most strongly related to social isolation for both men and women. Deprived neighbourhoods can impede social activities, through for example having limited safe, public and free spaces to commune and socialise (e.g. Finlay and Kobayashi, 2018). Education, on the other hand, appears to impact women's perceptions of loneliness and (especially) social support, but only perceptions of support among men. This is consistent with the literature that human capital attainment – which involves non-cognitive skills – is important for social functioning, among other outcomes (Heckman et al., 2006; Smithers et al., 2018). Naturally, this would include the ability to develop and nurture high-quality relationships (Qualter et al., 2015).

This paper has confirmed and strengthened the evidence base on the substantive link between economic status and poor social health in Great Britain, additionally illustrating that the extent of the gradients does differ between men and women. The large sample available in the UK Biobank has enabled us to more precisely identify the independent roles that household income, educational attainment, recent financial stress, and local area deprivation can have in explaining inequalities in social health. Identifying those individuals most at risk of poor social health can help inform interventions and policies aimed at reducing the substantial inequalities that exist.

Credit author statement

Claryn S. J. Kung: Formal analysis, Writing – original draft, Writing – review & editing. Stephen E. Pudney: Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Visualization: Michael A. Shields: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2022.115122.

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