The Intergenerational Transmission of Mental and Physical Health in the United Kingdom*

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Abstract

Although intergenerational health mobility is a key measure of equality of opportunity, our understanding of the topic is still limited. In this study, we estimate the degree of intergenerational health mobility in Quality Adjusted Life Years, a broad measure of health derived from the SF-12, using rich survey data from the United Kingdom. We estimate that the rank-rank slope is 0.17 and the intergenerational health association is 0.19. Breaking health down into mental and physical components, we find that both mental and physical health have a similar degree of intergenerational persistence. However, parents' mental health is much more strongly associated with broad measures of children's health than parents' physical health. The primacy of parent mental health over physical health on children's health begins during early adolescence. Finally, we construct a comprehensive measure of welfare by combining income and health and estimate a rank-rank association of 0.27. This is considerably lower than the comparable estimate of 0.43 from the US suggesting that there is greater mobility in welfare in the UK than in the US.

Key Words: intergenerational health mobility, mental health, physical health, United Kingdom

JEL Classification: J62, I14

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Estimates of intergenerational mobility in various components of socioeconomic status have been used to better understand the degree to which there is equality of opportunity across societies. A country with a very high degree of intergenerational persistence and, hence, a low degree of mobility might be indicative of a society with a dearth of opportunities for many children. In such societies there may be a particularly important role for policies that enhance equal access to opportunities for long-term socioeconomic success.

In recent years a new strand of the literature has begun to consider the intergenerational transmission of broad measures of health. This is important since health is a critical component of human welfare (Jones and Klenow, 2016; Sen, 1998) and human capital (Grossman, 1972). Moreover, childhood health also strongly influences adult economic outcomes (Case et al., 2005; Almond et al., 2018; Conti et al., 2019). Consequently, intergenerational transmission of health status also has ramifications for the transmission of economic status across generations.

Much of this new literature on intergenerational persistence in health has exploited the availability of measures of self-reported health status (SRHS) in several long-running panel datasets such as the PSID (US), SOEP (Germany) and HILDA (Australia). This has enabled researchers to assemble nationally representative intergenerational samples with broad measures of health covering many years for two generations of families. The results of these studies suggest that intergenerational transmission in health is quite low especially when compared to comparable estimates of intergenerational persistence in income.[1]

We build on this emerging new literature in several ways. First, we use a unified framework for examining how parent mental and physical health each influences children's health, both in childhood and adulthood. Mental health has been relatively less

[1]For example, these studies show that the rank persistence in health is about 0.26 in the US (Halliday et al., 2021), 0.23 in Germany (Graeber, 2020) and 0.20 in Australia (Vera-Toscano and Brown, 2021). Other studies using administrative health records have found similarly low rank-rank associations of 0.1 to 0.15 for Denmark (Andersen, 2021) and 0.22 for Taiwan (Chang et al., 2022).

studied but a number of studies suggest that it plays an important role in determining socioeconomic success.[2] Using the British Cohort Study, Johnston et al. (2013) show that maternal mental health has significant effects on children's health and other outcomes in the UK. We corroborate this finding but also go further and directly compare *the relative roles of physical and mental health* in intergenerational health transmission at different stages of the life cycle while focusing on both mothers and fathers.[3] In particular we highlight the importance of early adolescence as a potentially transformative stage where the importance of parental mental health begins to emerge. Second, we use a richer set of information on self reported health status than some previous studies such as Halliday et al. (2021) who rely on a single question on general health status. Third, we add a new country, the UK, to the set of countries where one can examine intergenerational health mobility using a broad-based measure of health. Adding evidence from another country with an entirely different institutional setting is useful for gaining further insight into the factors that affect health mobility. For example, it provides a useful contrast with the US due to having a national health insurance system. Fourth, following Halliday et al. (2021) we consider the relative importance of both parent income and parent health in determining children's outcomes. Fifth, we also combine the two distinct aspects of socioeconomic status to estimate mobility in a more comprehensive measure of social welfare and contrast our estimates from the UK with comparable estimates from the US.

Our data combines the nationally representative British Household Panel Survey and the UK Household Longitudinal Survey. Our main estimates use a 12-question health survey, the "SF-12" to construct a Quality Adjusted Life Year, or QALY, using the methods developed by Brazier et al. (2002). This data source allows us to break health

[2]Lundborg et al. (2014) show that mental health in adolescence is strongly predictive of economic outcomes later in the life-course. Biasi et al. (2020) provide plausibly causal evidence that access to medication for bipolar disorder leads to large improvements in labor market earnings. Hakulinen et al. (2019) and Hakulinen et al. (2020) show that serious mental disorders are associated with higher unemployment and lower earnings throughout the age spectrum.

[3]In work subsequent to ours Vera-Toscano and Brown (2021) also estimate intergenerational persistence in mental health.

down into mental and physical components and to track health from early childhood until late in the life-cycle. We know of no other survey in the world that permits such a breadth of health measurement.

We use two measures of intergenerational persistence. First, we estimate the intergenerational health association (IHA). This is simply the coefficient from regressing the child QALY on the parent QALY and captures the rate of regression to the mean and can be used to gauge how long it takes for health differences across families to dissipate. Second, we convert our QALYs to ranks and estimate the rank-rank slope, or the Spearman correlation. This is a measure of positional mobility and also offers a standardized way to compare coefficients across different dimensions of socioeconomic status (e.g. income, education, health).

We estimate that the IHA and rank-rank slopes are 0.19 and 0.17, respectively, suggesting a high rate of intergenerational mobility in health in the UK. When we use a comparable measure of the QALY to Halliday et al. (2021), our estimates rise a little bit but still suggest a slightly a lower degree of health persistence than in the U.S.[4] Notably, when we separate mental health from physical health, we do not see large differences in transmission estimates.[5]

With respect to gender, we generally observe greater persistence when we use mothers rather than fathers which is consistent with previous studies. We also find suggestive evidence that persistence is greater for sons than daughters. However, these differences are not statistically significant.

Our most striking finding is that when we include both parental health measures simultaneously in our statistical models, all of the intergenerational transmission loads on

[4]Specifically, using just the general health question to construct a QALY, as in Halliday et al. (2021), we estimate the IHA as 0.20 and the rank-rank as 0.21. The comparable estimates for the US are 0.23 and 0.26.

[5]We find that the IHA in mental health (0.21) is greater than that of the IHA in physical health (0.15). However, we find that the rank-rank estimate for physical health (0.20) is larger than that for mental health (0.17). The p-value of the difference between the IHA estimates is 0.16 while the p-value of the difference in rank-rank estimates is 0.06

to parental mental health rather than physical health. One caveat is that our sample of children is limited to the age range of 25 to 42 and ideally we would like to see if this pattern continues to hold as children enter the later stages of the life cycle. Nevertheless, this pattern is highly suggestive that mental health constitutes a more important transmission channel than physical health.[6]

We also investigate when this pattern emerges by extending our analysis to childhood. We find that for children ages 10 to 12, parental physical health is more strongly associated with overall health than parent mental health. However, once children enter their teenage years (13-15), parental mental health becomes more influential. Thus, we are able to show both the relative importance of parental mental health in shaping child outcomes and specifically *when* parental mental health starts to play this role – exactly as children become teenagers. To our knowledge, this is a novel finding and an intriguing new fact for future research to explore further.

We also consider the interplay between parent income and health in determining adult children's outcomes. We do this by adding parent income rank along with parent health rank in rank-rank specifications of both child health and income. We find that including the parent income rank adds very little explanatory power when predicting the child health rank. Similarly, parent health rank makes a very small contribution when explaining child income rank. Overall, this suggests that in the UK, there is a very small independent role of each of these aspects of parental socioeconomic status in explaining the other. This stands in contrast to Halliday et al. (2021) who found a more meaningful independent contribution of each dimension of socioeconomic status in the US.

Finally, we convert our QALY measure into a monetary metric, which allows us to construct a welfare measure that combines both income and health. We estimate the rank-rank slope in welfare to be 0.27 in the UK. This is a fair bit lower than the comparable

[6] One reassuring finding is that the average age of onset of mental health conditions is similar to that of many physical conditions and that the magnitude of the intergenerational associations of various health conditions does not appear to be correlated with the age of onset of these conditions (see Figure A1).

estimate of 0.43 for the US found by Halliday et al. (2021) and suggests that the UK has greater mobility in this broader measure of socioeconomic status.

The rest of this paper is organized as follows. Section 1 briefly summarizes the current literature in health mobility, then, in Section 2, we discuss the data that we use, followed by a discussion of the methods in Section 3. Our primary results are shown in Section 4. We investigate youth antecedents in Section 5. The results' robustness to alternative specifications is discussed in Section 6 and we conclude in Section 7.

1 Measuring Health Mobility: A Brief Overview

In this section, we provide a brief overview of the current state of knowledge on intergenerational health mobility. This is not meant to be a comprehensive literature review. For that, we refer the reader to survey articles by Halliday (2022) and Mazumder (2022). Rather, we discuss the nature of the intergenerational transmission literature, what methods are used in it, issues involving health measurement, and what types of data permit intergenerational research.

The intergenerational transmission literature typically regresses an outcome for children measured during adulthood on the same outcome for their parents. In fact, the term "regression" originates from research in the 19th century on the transmission of height across generations (Galton, 1886). In the many decades since Galton's work, social scientists have estimated intergenerational correlations in a variety of socioeconomic outcomes such as education, occupation, and income. Economists have tended to focus primarily on intergenerational income mobility (e.g. Solon (1992); Mazumder (2005); Chetty et al. (2014)). A recent innovation made popular by Chetty et al. (2014) estimates intergenerational regressions using the ranks of an outcome. These estimates are called rank-rank slopes or rank-rank correlations. They measure positional mobility and are particularly useful for comparing persistence estimates across various types of outcomes.

To be clear, unlike much of the literature in applied microeconomics which attempts to identify casual relationships, the intergenerational mobility literature is largely descriptive in nature and is deliberately focused on producing precise associations or correlations in order to characterize the degree of opportunity in society. Equality of opportunity is seen by many political philosophers such as Roemer and Trannoy (2015) as an important societal objective and measures of equality of opportunity are useful for comparing different societies or the same society over time.

There are a number of studies that have examined intergenerational associations in very specific health outcomes such as birth weight (e.g. Currie and Moretti (2007); Black et al. (2007); Giuntella et al. (2019)), anthropometric measures such as height, weight and BMI (Eriksson et al. (2014); Akbulut-Yuksel and Kugler (2016)) Classen (2010), mental health (Johnston et al., 2013); smoking (Darden and Gilleskie (2016), Loureiro et al. (2010); and asthma (Thompson, 2017).[7] While these studies are very valuable in understanding the transmission of specific outcomes, they produce a fairly wide range of estimates and it is not always clear how well these specific outcomes proxy for overall health.

There is also vast literature studying the intergenerational persistence in longevity that dates all the way back to Beeton and Pearson (1901) and includes a recent study by Black et al. (2022). These studies typically produce estimates of intergenerational associations in the range of 0.1 to 0.2. Longevity has important limitations as a proxy for health as well, in particular it doesn't capture the quality of health during the lifespan.

More recently studies have begun to use self-reported health status (SRHS) measured on a integer-based Likert scale as a broader measure of health. The first studies such as Kim et al. (2015) and Pascual and Cantarero (2009) used these as discrete measures at a point in time. A major innovation was by Halliday et al. (2021) who converted these measures to a continuous scale and used methods borrowed from the intergenerational

[7] See Mazumder (2022) for a a more detailed review.

income mobility literature (e.g. Solon (1992), Mazumder (2005)) to produce more reliable estimates based on long time averaging to reduce measurement error. Halliday et al. (2021) demonstrate that failure to use sufficiently long time averages for health outcomes results in significant attenuation bias.

The biggest challenge encountered when estimating intergenerational health mobility is, without question, measurement. In this literature, researchers typically attempt to measure *latent health* - an omnibus concept that captures all facets of human health in a single measure. One approach to proxying for latent health is to calculate long time averages of SRHS for both the parents' and the children's generations in a longitudinal survey. However, doing this requires a panel sufficiently long so that both generations can be linked and observed for at least five years. Very few data sources permit this. In fact, only the United Kingdom, the United States, Australia, and Germany have surveys that satisfy these requirements.

Proxies for latent health typically rely on subjective health measurements such as SRHS, the SF-12, or depression scales. There is a long and venerable literature demonstrating the validity of these measures. The strongest justification of subjective health measures is that they predict important objective health measures including mortality (Idler and Benyamini, 1997; DeSalvo et al., 2005; Halliday, 2022). Importantly, DeSalvo et al. (2005) demonstrate that SRHS predicts mortality even after adjusting for functional status, depression, and co-morbidity.[8]

Estimates of intergenerational health correlations tend to be on the order of 0.20 or smaller when estimating linear models. In the United States using omnibus measures of health from the Panel Study of Income Dynamics (PSID), Halliday et al. (2021) estimate an IHA that ranges between 0.17 and 0.23 and rank-rank correlations that range between

[8]There is a parallel discussion on the utility of happiness scales in social science research with Bond and Lang (2019) criticizing their usefulness. However, recent work by Kaiser and Oswald (2022) rebuts many of these arguments and they ultimately make arguments that are similar in spirit to those made by psychologists for many years.

0.21 and 0.29 depending on the pairing of father/mother and daughter/son. Halliday et al. (2021) also find that their persistence estimates are remarkably robust to the use of an alternative health index that uses counts of the presence of very specific health conditions such as cancer or diabetes. This suggests that despite criticisms of SRHS as a subjective measure they deliver virtually identical estimates to more objective measures of health. In addition, Halliday et al. (2020) estimate the IHA in a richer non-linear latent variable model using the same data and obtain estimates of the IHA that approach 0.30. Fletcher and Jajtner (2019) use the Add Health, an American panel that is shorter than the PSID and has a younger sample, and estimate that the rank rank correlation is 0.17.

There are a few papers that estimate intergenerational persistence in broad measures of health outside of the US. Graeber (2020) estimate rank persistence of 0.23 in Germany and Vera-Toscano and Brown (2021) find an analogous estimate of 0.20 in Australia. Johnston et al. (2013) estimate that the IHA in mental health in the UK is between 0.18 and 0.19. An emerging pattern in this literature is that intergenerational correlations in health appear to be lower than they are for income.

Neither the subjective nature of SRHS measures nor the absence of large scale administrative data is responsible for these high mobility estimates. To understand the first issue, we point to the sparse literature on intergenerational correlations in life spans (Beeton and Pearson, 1901; Ahlburg, 1998; Black et al., 2022). Life span is a completely objective outcome with little measurement error. Despite this, the best estimates of intergenerational correlations in life spans are on the order of 0.10-0.15. This is, in fact, lower than the best estimates of the IHA discussed above which are on the order of 0.20-0.30. To understand the latter issue, we point to literature that estimates intergenerational health mobility using health insurance claims data from public single payer health insurers (Andersen, 2021; Chang et al., 2022). Both of these papers extract measures of latent health by performing a principal components analysis on a battery of ICD9/10 codes and utilization variables from national claims data and then running standard intergenerational regressions on a linked parent-child sample using the principal components as outcomes. Rank-rank estimates of health persistence are on the order of 0.11-0.15 in Denmark (Andersen, 2021) and 0.15-0.20 in Taiwan (Chang et al., 2022). This suggests that the administrative data also delivers very high estimates of health mobility, albeit in different contexts.

2 Data

We combine data from the British Household Panel Survey (BHPS) and its successor, the UK Household Longitudinal Survey (UKHLS) (University of Essex, Institute for Social and Economic Research, 2020). Because our outcomes of interest appear in the UKHLS but not in the BHPS, we use the UKHLS data to estimate intergenerational relationships and to link to majority of the parent-child pairs to each other. Meanwhile, we use the BHPS to link some additional parents and children who cannot be linked in the UKHLS. Currently, nine waves of the UKHLS are available to researchers.[9] In total, the BHPS/UKHLS has been running annually for 26 years making it among the longest running *annual* longitudinal social research studies in the world. Entire households typically participate in the BHPS/UKHLS with members ages 10-15 filling out youth questionnaires and members 16 and older filling out the adult questionnaires. The surveys are representative of the population of the United Kingdom.

We use family identifiers in the data to link children to their parents. However, we only include parent-child pairs where the child responds to the survey at least once before the age of 19. This is a common restriction in the intergenerational mobility literature in order to avoid over-representing families where children continue to be co-resident with their parents at later ages.[10] Additionally, we only use health measures of children when

[9]The BHPS includes 18 rounds spanning 1991 to 2009 and approximately 10,000 households per year. The BHPS was replaced by the UKHLS in 2009 and includes roughly 40,000 households per year, including about 6,000 households from the BHPS. See more on the surveys here: https://www.understandingsociety.ac.uk.

[10]For example, in the absence of this restriction one might observe only a sub-sample of children from

they are aged 25 or older so that we observe adult health in both generations.

For our main analysis, we use the Short Form 12 Survey (SF-12) to construct three health measures.[11] First, using the algorithm provided by Brazier et al. (2002), we use all 12 questions in the SF-12 to construct a Quality Adjusted Life Year or "QALY".[12] The SF-12 includes a question on general health status that is widely collected in many surveys such as the PSID and is often referred to as "Self-Reported Health Status" (SRHS). SRHS has been validated as a strong predictor of mortality and hospitalization (DeSalvo et al., 2005; Wang et al., 2018). Halliday et al. (2021) use SRHS to construct their version of the QALY using the Health and Activity Limitation Index (HALex) transformation.[13] However, our QALY also incorporates information from the other health questions including those on mental and physical health, making it a richer measure.

Our second measure is an index of physical health that is based on five questions in the SF-12. These relate to limitations on activities of daily living and work due to problems with physical health.[14] Each question has a series of responses that vary in their severity that range from one to five for three questions and one to three for two questions. The responses to the questions are normalized so that higher numbers correspond to better health. We re-scale each outcome from one to 100. Then, we average these values for an individual-year specific physical health index (PI). Finally, we average these across years to obtain the PI index for an individual. If one or more of the five underlying questions has a missing answer, we set PI to be missing for the given year for the individual and use the remaining years to compute the index.

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older birth cohorts who happen to still live with their parents during middle age. Using only this subsample would impose the strong assumption that the rate of intergenerational health persistence for this selected group would be the same as that for individuals from the same cohort who are unobserved in the data because they no longer reside with their parents.

[11]The SF-12 is a shorter version of the 36-item SF-36. Jenkinson et al. (1997) showed that morbidity measurements from the SF-12 and SF-36 are very similar.

[12]SF-12 variables are available in all rounds of the UKHLS and rounds 9 and 14 of the BHPS.

[13]The question asked is "In general, would you say your health is excellent, very good, good, fair, or poor." The responses are then coded as a categorical variable.

[14]See Appendix Table A1.

Our third measure is a mental health index (MI) that uses a different set of five questions in the SF-12. These questions assess the degree to which mental health problems interfere with activities of daily living or work, energy levels, and whether respondents report feelings of depression or tranquility. All five questions have response values that range from one to five. Once re-scaled, MI varies between zero and 100 with higher values corresponding to better mental health. In total, our core sample consists of 1,741 parent-child pairs with valid QALY, MI, and PI measures.[15]

There is extensive evidence that the SF-12 and the scale's mental health related question block are reliable and valid. Using the test-retest approach, evidence shows high internal consistently in the general population (Ware et al., 1996) and across a range of settings, such as among the seriously mentally ill (Huo et al., 2018), older adults (Resnick and Nahm, 2001), and among those with back pain (Luo et al., 2003). The SF-12's and its mental health related question block's validity and reliability is also consistent across a range of countries (Montazeri et al., 2009; Amir et al., 2002; Kontodimopoulos et al., 2007). These findings are in line with the broader wellbeing literature finding that self-reported wellbeing measures, such as life satisfaction, are reliable too (Krueger and Schkade, 2008).

We constructed the PI and MI instead of using the SF-12's Physical Component Summary (PCS) and Mental Component Summary (MCS) for two reasons. First, both PCS and MCS include the general health question, SRHS (Lacson et al., 2010) and we wanted to avoid mechanical correlations across our measures. Second, the question "During the past 4 weeks, how much of the time has your physical or emotional problems interfered with your social activities [...]?" is only included in the MCS even though there is clear ambiguity about whether it speaks to physical or mental problems. We opt to exclude this question from both the PI and the MI measures.

Previous studies have emphasized the value of using long time averages to better

[15]See more on the sample construction in Figure A2.

capture latent health status (Halliday et al., 2020, 2021). This is analogous to the income mobility literature where more years of income better approximate permanent or lifetime income, otherwise estimates suffer from attenuation bias (Solon, 1992; Mazumder, 2005). Halliday et al. (2021) show that reliable estimates of the IHA can be obtained by using about four to five years of health status for the parents.[16]

In addition to our main measure of the QALY, we also create a version of the QALY based only on the general health question following the methodology in Halliday et al. (2021). This allows us to produce estimates for the UK that are an "apples to apples" comparison to the US estimates produced by Halliday et al. (2021). We refer to this measurement as SRHS. Furthermore, for a few exercises we also create a version of the SRHS variable that follows the same re-scaling methodology as the MI and PI to create an index that takes on values between 0 and 100. This allows us to compare the information in the SRHS to the MI and PI using an identical methodology. We refer to this index as "SRHS100".

For our heterogeneity analysis we use two categories of education.[17] The first includes those who have only attained a General Certificate of Secondary Education (GCSE) but no further educational credential. The second group includes those who have completed their A-levels (equivalent to a high school degree) or who have a tertiary education degree. For race, we split the sample into two groups. One contains white and white British respondents while the other includes Black and Black British, and Asian and Asian British (BAME) respondents.[18]

We report summary statistics in Table 1. For the child generation, we have a sample size of 1,741 and the mean QALY is 77.86. The average MI is 76.96 and the average PI is 92.39. We have an average of 3.58 different annual reports of QALYs in the child gen-

[16] Halliday et al. (2020) also show that the bias from estimating linear models (as opposed to an ordered non-linear model) is very small for rank-based estimates.

[17] We limit our analysis to 2 categories to obtain meaningful sample sizes for each group.

[18] For our heterogeneity analysis we don't include the following categories: mixed race, traveler, and those choosing the response category "other" due to small sample sizes.

Table 1: Summary Statistics

	All Children	Fathers	Mothers
QALY (Scale: 0 to 100)			
Age	28.56	57.73	54.37
	(4.31)	(7.73)	(7.23)
Overall Score	77.86	77.98	74.75
	(11.23)	(12.03)	(12.34)
Years of Health Measurement	3.58	6.05	6.45
	(2.60)	(2.32)	(2.06)
MI (Scale: 0 to 100)			
Age	28.56	57.73	54.36
	(4.31)	(7.73)	(7.24)
Overall Score	76.96	80.01	75.78
	(13.13)	(12.60)	(13.40)
Years of Health Measurement	3.59	6.08	6.47
	(2.60)	(2.32)	(2.05)
PI (Scale: 0 to 100)			
Age	28.56	57.74	54.38
	(4.30)	(7.73)	(7.23)
Overall Score	92.39	84.43	82.52
	(11.56)	(17.22)	(18.55)
Years of Health Measurement	3.58	6.04	6.44
	(2.60)	(2.32)	(2.05)
N	1,741	850	1,245

Note: Averages are reported. Standard deviations are in parentheses. This sample includes children who are observed at least once at or before 18, and have at least one health measurement observation above the age of 25 in all three health measures and are matched to at least one parent with at least one health measurement observation above the age of 25 for all three health measures. Age is the averaged for all available health measures.

eration. For the parent generation, we have 850 fathers and 1,245 mothers. Importantly, we have over six years of measurement for the parents suggesting that there should be minimal attenuation bias in our estimations.

In addition to the three subjective health indices constructed from the SF-12, we also experimented with data on biomarkers which were collected in two survey waves.[19] Unfortunately, biomarkers are only available for a very small subsample of individuals

[19]The underlying data on biomarkers is described in Appendix A6.

(N=155) and only one reading per individual was collected yielding extremely imprecise estimates. We do use them, however, in an exercise below to show how these objective measures correlate with our subjective health measures.

Specifically, following Schanzenbach et al. (2016), we construct an index by calculating the within-gender z-score for each variable (where positive z-scores indicate better health) and then aggregate these z-scores for each individual.[20] We also constructed a "stress" index comprised of four biomarkers that indicates stress and/or inflammation.[21] This is sometimes referred to as allostatic load (e.g. Chandola and Zhang (2018)).

To provide some idea of how our different health measures relate to one another in the population, Table 2 presents a correlation matrix of five of our measures which includes the SRHS100, PI, MI, the Biomarker index and the Stress index using the full sample of the UKHLS. We do not use the QALY here because it is comprised of the questions used to calculate the MI and PI and thus would be mechanically correlated. We also use the SRHS100 rather than SRHS so that it is constructed in the same way as the MI and PI. We also report the same correlation matrix on a sample restricted to respondents who have complete information across all measurements in Table A3.

Looking at the first column we find that the PI is the measure most strongly correlated with SRHS100, with a correlation of 0.68. The MI is also strongly correlated with SRHS with a correlation of 0.58. The two biomarker indices are much less correlated with SRHS with correlations of 0.31 and 0.22. We also find that the MI and PI have a quite strong correlation of 0.64.

In Figure 1, we show that the correlations of PI and MI with SRHS100 peak between the ages of 50 and 70 and find that the correlation of overall health status is higher with PI than with MI at most ages. However, we find that the age profile of the correlation of

[20] We do this separately by gender as some biomarkers (e.g. testosterone) should be interpreted differently for each gender.

[21] These include C-reactive protein (CRP), Clauss Fibrinogen, Cytomegalovirus IgG, and Cytomegalovirus IgM.

Table 2: Correlation Matrix of Health Measures

Analysis Sample	SRHS100	PI	MI	Biomarker	Stress
SRHS100	1.00				
	29,160				
PI	0.68	1.00			
	22,547	*25,654*			
MI	0.58	0.64	1.00		
	22,605	*25,605*	*25,714*		
Biomarker	0.31	0.31	0.14	1.00	
	4,570	*4,547*	*4,544*	*4,570*	
Stress	0.22	0.24	0.14	0.59	1.00
	5,004	*4,975*	*4,972*	*4,570*	*5,004*

This matrix represents the correlation between each pair-wise combination of five time-averaged health measures: Subjective Health (SRHS100), physical health index (PI), and mental health index (MI). The sample includes children and parents who had non-missing values for the specified pair of measures.

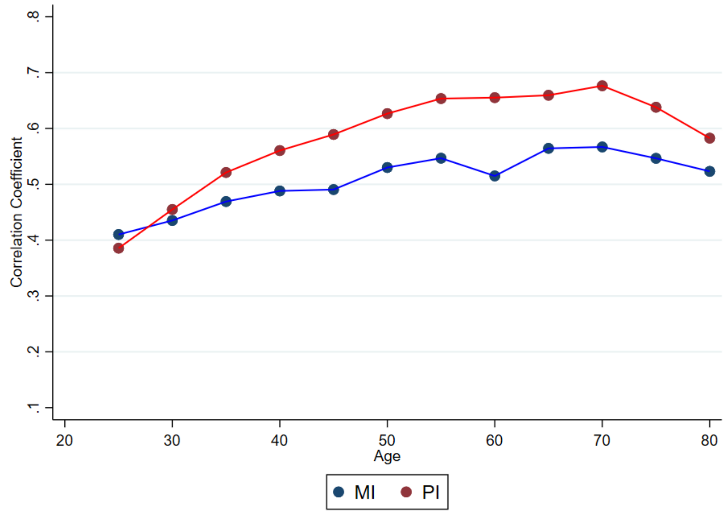
SRHS100 with MI is flatter than the correlation of SRHS100 with PI. This suggests that MI may be more uniformly informative of general health over the life-course than PI.

In addition to using the adult questionnaire which surveys people 16 years of age and older, we also use the youth survey from the BHPS/UKHLS. Importantly, youth ages 10 to 15 assess their health and other aspects of their life in their own words. The questionnaires are fielded at the same time and in the same households as the adult questionnaires. The SRHS question is identical in the youth and the adult surveys. We re-scale this also using the HALex transformation.

3 Methodology

We use standard methods from the literature (e.g. Yule (1919); Solon (1992); Mazumder (2005); Halliday et al. (2021)) to estimate intergenerational persistence in health in which we regress children's health on parents' health. Specifically, we estimate the following

Figure 1: Correlations Between SRHS100 and PI and MI Across The Lifecycle



This displays the correlation of SRHS100 and PI/MI of individuals who are within the same 5-year age span with ages above 80 bucketed together. The sample includes children and parents who had non-missing health observations for both health outcomes.

linear model:

$$y_i^C = \alpha + \beta y_i^P + X_i\theta + \epsilon_i$$

where y_i^C and y_i^P denote measurements of the health status of the child and the parent and X_i includes a parsimonious set of control variables including parent age and child age (averaged over all the years that the individual was in the panel), a quadratic in the ages of the parents and the children, and a dummy variable indicating if one parent's health outcome is missing. When y_i^C and y_i^P are averages of the health measurements for both generations, β is the Intergenerational Health Association (IHA). The IHA measures the extent to which parental health status persists across generations. Conversely, $1-\beta$ measures generational mobility or how quickly health reverts to its mean. We calculate the IHA using the different health domains discussed in the previous section. In addition to the IHA, another commonly used set of mobility measures in this literature are based on rank-rank regressions. The rank-rank slope, which is mathematically equivalent to the Spearman correlation, provides an estimate of positional mobility. The expected rank of children conditional on parent rank (e.g. at the 25th or 75th percentile) can be used to assess differences across population subgroups or for distinguishing upwards and downwards mobility patterns. Rank mobility estimates are computed by estimating a model like equation (1) except with y_i^C and y_i^P representing the rank of the child and parent's age-adjusted health within a particular group. For models where we only consider sons or daughters (mothers or fathers), the reference group is sons or daughters (mothers or fathers). We also computed "all parent" and "all children" rank measures.[22]

4 Results

4.1 Intergenerational Health Association

We begin by presenting estimates of the IHA in Table 3. We also plot estimates from the first row of the table in Figure 2. Columns 1 through 3 show the estimates for QALYs, the physical health index (PI), and the mental health index (MI), respectively. The rows show the estimates by the type of parent-child pair. The first row contains estimates of the IHA using the average of both parents and pooling all children. We treat this as the baseline estimate of the IHA. The subsequent rows show estimates for each parent-child gender combination.

Our baseline estimate for the IHA in overall health using the QALY is 0.19. When we focus on mental health and physical health our estimates are 0.21 for the MI and 0.15 for the PI.[23] This suggests that there may be more persistence in mental health than physical health across generations but we cannot reject the null hypothesis that the coefficients

[22]For the "all parent" measurement, we pooled the observations of mothers and fathers and regressed the parent health measure on a quadratic in age interacted with parent type (mother or father), indicators for missing mother and father, and fraction of the parent health observations in that family that is from the mother. The age- and gender-adjusted parent health measure is the time-average of the residuals. We then take the percentile rank of this measure. We employed a similar procedure for the "all children" measurement.

[23]Our 0.21 estimate for mental health is similar to that found by Johnston et al. (2013) who estimate an IHA of 0.19 using the British Cohort Study.

are the same.[24] We also generally find that estimates of the IHA are higher when we use mother's health rather than father's health and for sons compared to daughters. However, these gender differences are not statistically significant.

Table 3: Intergenerational Health Associations in QALY, PI, and MI

	QALY	MI	PI
Both parents- all children	0.19***	0.21***	0.15***
N=*1,741*	(0.024)	(0.026)	(0.016)
Mother-daughter	0.16***	0.18***	0.12***
N=*888*	(0.030)	(0.033)	(0.021)
Mother-son	0.19***	0.22***	0.14***
N=*741*	(0.033)	(0.035)	(0.021)
Father-daughter	0.14***	0.15***	0.10***
N=*611*	(0.038)	(0.041)	(0.029)
Father-son	0.17***	0.13***	0.16***
N=*522*	(0.038)	(0.044)	(0.023)

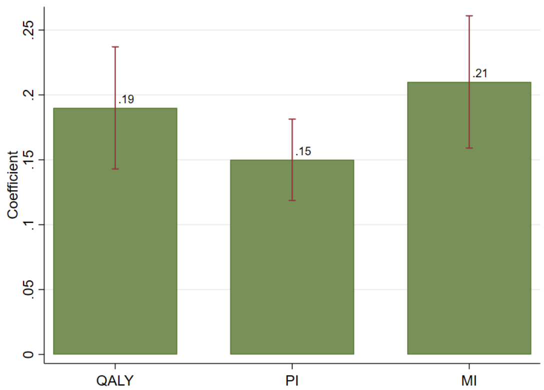
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Each cell reports the coefficient and the standard error (in parenthesis) from a separate regression specification. The main explanatory variable is the parent's averaged health measure for all available periods above the age of 25. For regressions that use both parent's health, the parent health measure is the average of the mother's and father's health if both are available. The sample is the same as the sample in Table 1.

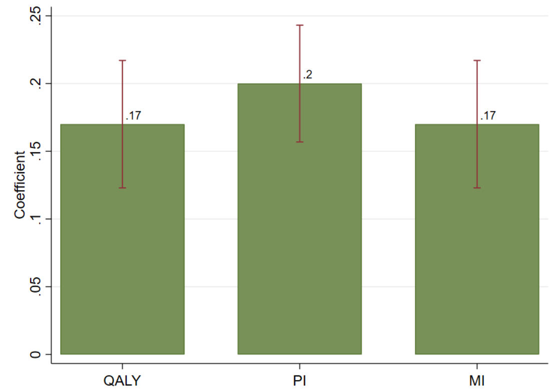
[24] To conduct this test, we estimated a SUR model using one equation for MI and another for PI. We then tested the null hypothesis that the IHA estimate from each equations is the same. Employing the system estimation allowed us to account for the covariance between the two estimates.

Figure 2: Comparison of Intergenerational Health Persistence Estimates by Domain

Panel A: Intergenerational Health Associations



Panel B: Intergenerational Rank-Rank Slopes



Panel A visually represents the results from row 1 of Table 3, while Panel B of row 1 of Table 4.

4.2 Rank-Rank Estimates

We report the rank-rank slopes in Table 4. Our baseline estimate of the rank-rank slope in overall health using the QALY is 0.17 when using both parents and pooling all children which is slightly smaller than the IHA estimate of 0.19. The point estimate of 0.20 for PI is now higher than that of the 0.17 which we find for MI, reversing the ordering we found with the IHA. A test of the difference in these estimates delivers a p-value of 0.06. Thus, although there is suggestive evidence that intergenerational persistence may be higher for MI than PI when measured in health units, we find that physical health may be more persistent than mental health when measured in ranks. This is evident in Figure 2 where we compare the main estimates of the IHA and rank-rank slope for our three primary measures. Thus, there appears to be a potential difference between the components of health that depends on the concept of mobility one is interested in measuring. Specifically the IHA captures the rate of regression to the mean in health units, while the rank-rank slope measures positional mobility.

In Figure 3, we visually show the rank-rank relationships for QALY, PI, and MI. We

Table 4: Intergenerational Rank-Rank Slopes in Health Measures

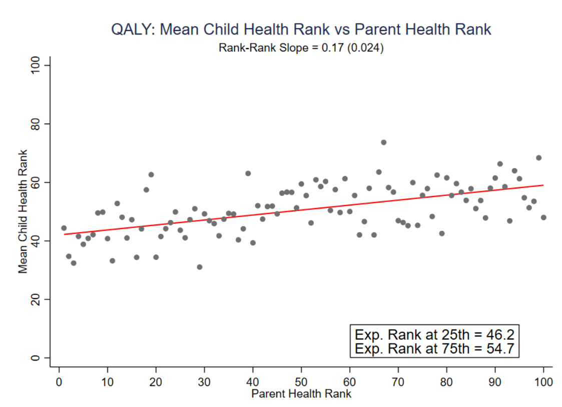
	QALY	MI	PI
Both parents- all children	0.17***	0.17***	0.20***
N=*1,741*	(0.024)	(0.024)	(0.022)
Mother-daughter	0.18***	0.19***	0.20***
N=*888*	(0.033)	(0.034)	(0.030)
Mother-son	0.18***	0.20***	0.20***
N=*741*	(0.036)	(0.037)	(0.032)
Father-daughter	0.14***	0.14***	0.15***
N=*611*	(0.040)	(0.039)	(0.035)
Father-son	0.16***	0.09**	0.15***
N=*522*	(0.040)	(0.043)	(0.035)

***$p < 0.01$,**$p < 0.05$,*$p < 0.1$

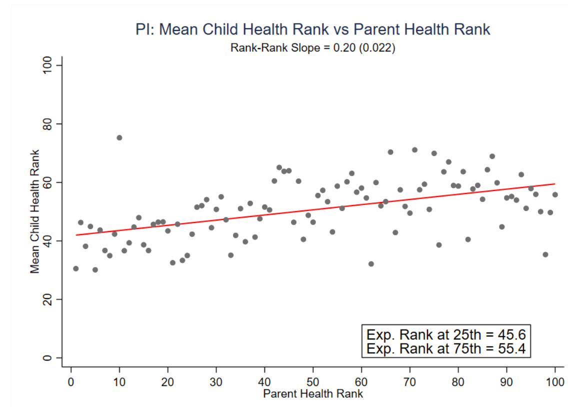
Each coefficient represents the rank-rank slope from a regression of child rank on parent rank. The ranks were generated from percentiles of an age-adjusted health measure in the respective population. Standard errors are in parentheses. The sample is the same as in Table 1.

Figure 3: Rank-Rank Relationships in Intergenerational Health

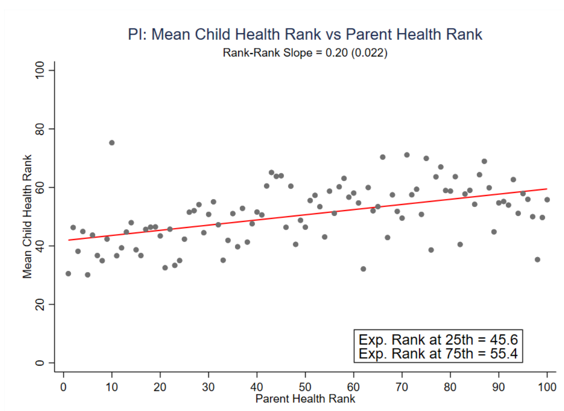
Panel A: QALY



Panel B: Physical Health Index (PI)



Panel C: Mental Health Index (MI)



The figures display the average child health rank by parent health rank. The slope and standard deviation in parentheses is from a regression of the child's health rank on the parents' health rank. The expected ranks are the expected health rank of children with parents at the 25th and 75th percentile and are estimated from that same regression specification The sample is the same as in Table 1.

also report the conditional expected ranks at p25 and p75. Conditional expected rank is another common mobility statistic that represents the degree of upward versus downward mobility. The expected rank of children when their parents are in the 25th percentile of the distribution is about the 45th percentile across all three domains. Similarly, their expected rank when their parents are in the 75th percentile is around the 55th percentile. This suggests a reasonably large degree of both upward and downward mobility in health.

4.3 The Relative Roles of Parental Mental and Physical Health

We now consider the relative impacts of parent physical and mental health on the child's QALY. To do this, we regress the child's QALY on their parents' PI and MI in the same estimation. We report the results in Figure 4. In Panel A, we estimate the model in levels and in panel B, we estimate the model using ranks. In both models we find that parents' mental health has a substantially larger association with their children's QALY than their physical health. The coefficient on MI in both models is 0.17-0.18 while the coefficient on parent PI is a precise zero.[25] This is a striking finding. It suggests that parental mental health is a better predictor of broad based health than parent physical health.

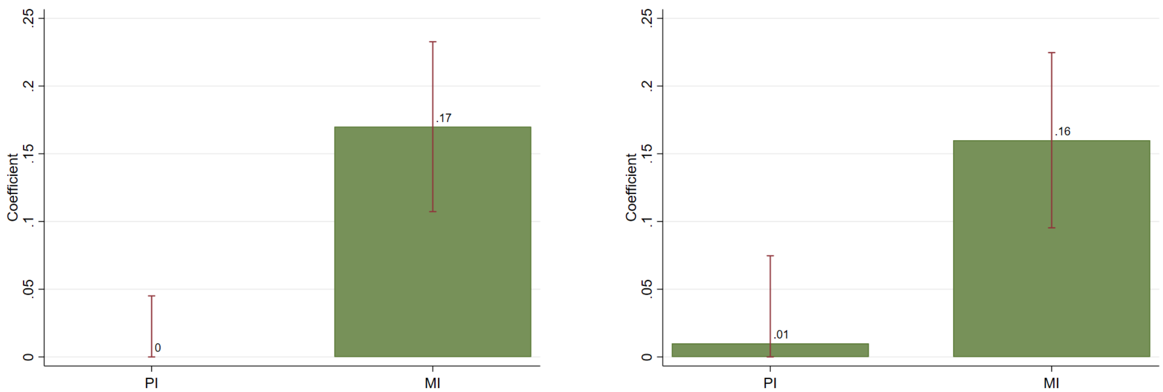
One caveat to this analysis is a possible concern that this finding is due to the relatively young age of our sample as our children are between the ages of 25 and 42 when they report their health. Specifically, one might be concerned that children's health problems tend to be more related to mental health issues rather than physical health issues and that this explains why parental mental health dominates in our regression. One way we attempt to alleviate this concern is by showing that the mean age of onset of mental health problems such as anxiety and depression is in the late 40s which is close to the age of onset of many physical health problems. This is shown in Appendix Figure A1. We note that while it is often purported that mental health issues appear well before physical health deteriorates for many in the population (e.g. during adolescence), in our sample, the average onset of mental health issues occurs in the 40s. One explanation for this might be that we use a question on "health problems" rather than whether the person "experienced any symptoms," and evidence suggests that diagnosis (the point from when on someone is likely reporting a concern as a "health problem") for mental health disorders is not far off to those for physical health disorders. We also find that the intergenerational associations across health conditions are generally not any larger based on their age of

[25]The coefficients in panel A are 0.175 for MI and 0.005 for PI. For panel B, the coefficients are 0.163 and 0.013.

Figure 4: Coefficients of Children's QALY on Parent Health Measures, Levels and Ranks

Panel A: Level of Children's QALY on Level of Parent PI & MI

Panel B: Rank of Children's QALY on Rank of Parent PI & MI



Panel A reports the coefficients of parent MI and PI from a regression of the child QALY time-averaged health measure on the parents' time averaged MI and PI health measures. Panel B reports the coefficients of parent MI and PI rank from a regression of child QALY rank on parent MI and PI rank. Ranks are percentiles of the age-adjusted health measure. The green bars are the coefficient on the variable of parent health outcome or rank, and the red lines represent the standard deviation.

onset. This suggests that our results are not driven by our relatively younger sample of adult children nor the range of conditions experienced by our sample. Nevertheless, we think that future research should verify that our findings of a stronger role for parental mental health compared to physical health, continues to hold when using older samples of adult children.

4.4 Interplay between parental income and health

We now consider how the joint distribution of income and health evolve over a generation using our rank-based framework. To do this, we add parent income rank in addition to parent health rank to our rank-rank health regressions. Similarly, we also estimate rank-rank income regressions but now we also include parent health rank. The results are shown below in Table 5.

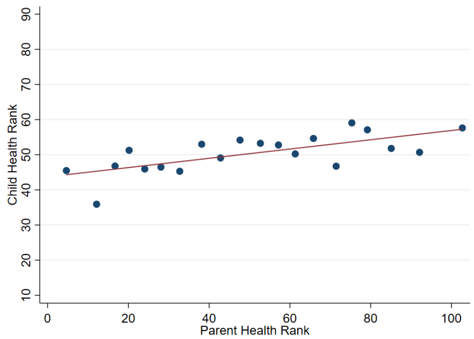
First, we consider the results with child health rank as the dependent variable. In column 1, we estimate a rank-rank slope estimate of 0.14 when only considering health in both generations. This differs slightly from our main estimates due to the changing sample that now requires information on income. In column 2, we regress child health rank on parent income rank and obtain an estimate of 0.08. These estimates are also plotted in Figure 4. When we include the two parent rank measures in the same estimation, we see a modest reduction in the coefficient on parent health rank to 0.13. We see a much larger reduction in the slope estimate for parent income rank to 0.04. We also find a slight increase in the R^2 from column 1 (0.021) to column 3 (0.022). Thus, it appears that adding parent income does not provide much more additional information than simply using parent health information.

We note that this is different from what Halliday et al. (2021) found using US data. They estimate the unconditional coefficient on parent income rank to be much larger at 0.22 and that this coefficient falls to 0.13 when they include parent health rank. They also find an increase in R-squared from 0.075 to 0.087. Therefore, it appears that parent income plays more of a distinct role in determining children's health in the US than it does in the UK.

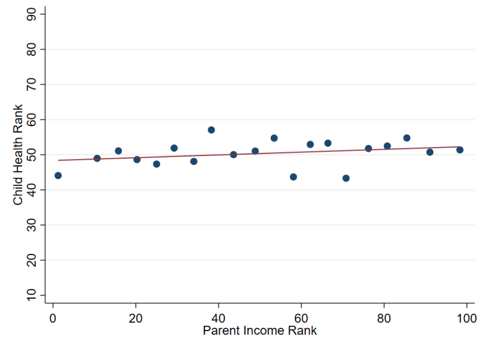
In the next three columns (4, 5 and 6), we use child income rank as the dependent variable. In column 5, the rank-rank slope in income is estimated at 0.31. This is somewhat below comparable estimates for the US (Chetty et al. (2014); Mazumder (2016); Halliday et al. (2021)). The coefficient on parent health rank alone is 0.12 as shown in column 4. When we include parent health and income rank simultaneously, we see that the coefficient on parent health rank falls to just 0.04 while the rank-rank slope in income falls very slightly to 0.30. The R^2 increases slightly from 0.095 to 0.097 moving from column 5 to column 6.

Overall, we find that the persistence in either health or income status in the UK is largely unaffected by including the other measure. This contrasts with the US, where the "cross-effects" are important. In the Appendix (see Table A7), we present similar results

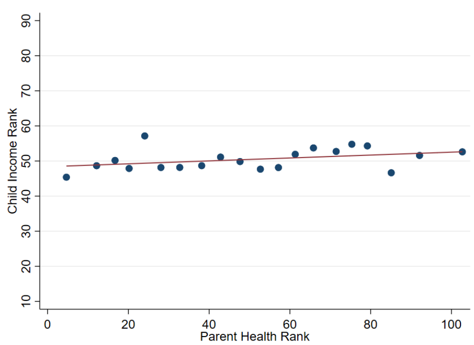
Figure 5: Interplay of Health and Income Mobility



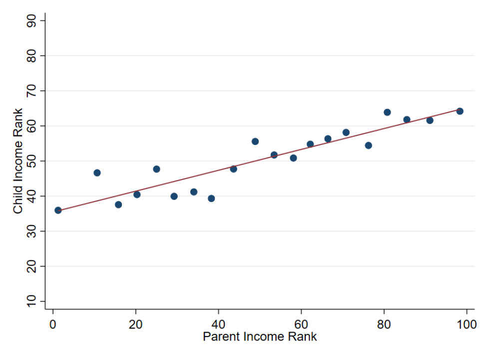
a) Child's Health versus Parent's Health Rank, controlling for parent income



b) Child's Health versus Parent's Income Rank, controlling for parent health



c) Child's Income versus Parent's Health Rank, controlling for parent income



d) Child's Income versus Parent's Income Rank, controlling for parent health

These graphs plot the average child health or income rank at each parent health or income rank, controlling for parent health or income. The sample is the same sample as in Table 5.

Table 5: Interplay of Health and Income Mobility

	Child Health Rank			Child Income Rank		
	(1)	(2)	(3)	(4)	(5)	(6)
Parent Health Rank	0.14***		0.13***	0.12***		0.04
	(0.026)		(0.027)	(0.026)		(0.026)
Parent Income Rank		0.08**	0.04		0.31***	0.30***
		(0.026)	(0.027)		(0.025)	(0.026)
Constant	43.15***	46.50***	41.70***	44.18***	34.88***	33.37***
	(1.483)	(1.494)	(1.769)	(1.490)	(1.428)	(1.704)
Observations	1499	1499	1499	1499	1499	1499
R^2	0.021	0.006	0.022	0.016	0.095	0.097

This table reports the coefficients from regressing child health or income rank on parent health rank and/or parent income rank. The sample is taken from the same sample as in Table 1, while further including only children with a non-missing income rank and had at least one parent with a non-missing income rank.

when we substitute parent physical health and mental health for the parental QALY.

4.5 Intergenerational Persistence in Overall Welfare

Given the value of considering both health and income as important measures of overall welfare, in this section we explicitly combine these two dimensions of SES into a single welfare measure. We follow Halliday et al. (2021) and first convert our QALY to a monetary metric.[26] We convert a QALY to British pounds by multiplying the QALY by 60,000 pounds (HM Treasury, 2020). We combine this monetized measure of health with annual income to construct an overall welfare measure and then estimate intergenerational persistence in two ways. First, we take logs of this measure and estimate the intergenerational elasticity. Second, we convert this measure to ranks and estimate the rank-rank slope.

The results are shown in Table 6. The intergenerational elasticity is 0.27 and the

[26] Halliday et al. (2021) only used a single question on general health status to create a QALY whereas we use a broader set of questions from the SF-12 to create our QALY based on Brazier et al. (2002).

Table 6: Welfare Regressions

	Log(Child Welfare)	Child Welfare Rank
	(1)	(2)
Log(Parent Welfare)	0.27***	
	(0.025)	
Parent Welfare Rank		0.29***
		(0.025)
Constant	8.08***	35.91***
	(0.274)	(1.438)
Observations	1499	1499
R^2	0.076	0.083

The table reports the results from a regression of the child log or rank welfare index on the parent log or rank welfare index. The welfare index was constructed by first converting the time-averaged QALY health measure into monetary units by multiplying it by 60,000. We then average the monetized health measure and real annual labor income to construct an welfare measure. The sample is the same as in Table 5.

rank-rank slope is 0.29. The corresponding estimates in Halliday et al. (2021) for the US were 0.37 and 0.43. This suggests that while persistence in health and income is broadly similar in both the UK and the US, persistence in overall welfare is much lower in the UK. *Prima facie*, this suggests that intergenerational mobility in the UK is higher than in the US. Interestingly, the difference in mobility between the US and UK is perhaps a bit higher than what one would infer from looking at income (or health) alone. Recall, that we found the rank-rank slope in income to be 0.31 in the UK. This is only modestly lower than the US estimate of 0.34 in Chetty et al. (2014) though somewhat lower than the estimate of 0.39 in Halliday et al. (2021).

5 Antecedents in Childhood

At what points in childhood does the association between parent and adult child health begin to emerge? What components of parent health matter most? When in childhood do parent mental and physical health have greater influence?

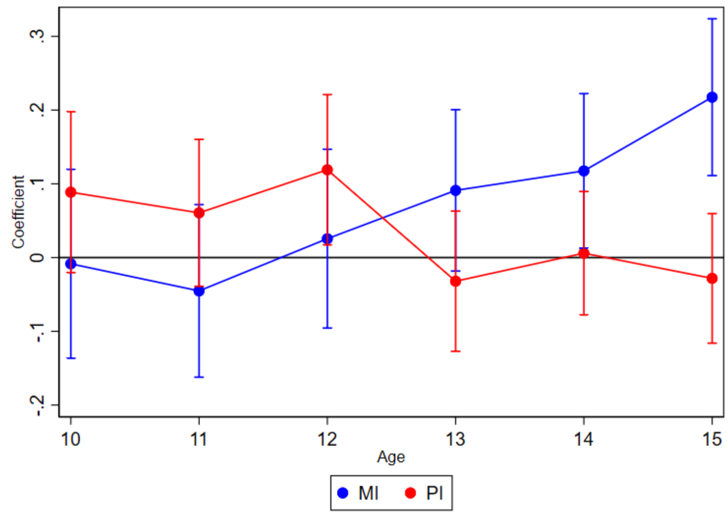
To answer these questions, we employ data on SRHS100 for children ages 10-15 and estimate similar horserace regressions as we estimated in Figure 4 where we regressed the QALY of the adult child onto parental MI and PI. As previously discussed, children older than 10 years of age report their own health status in the data. We also note that the SF12 is not asked of children under age 18 in the BPHS/UKHLS and so we cannot compute a proper QALY as we did for the results in Figure 4. In Figure 6, we plot the estimates of MI and PI where we estimated the regressions separately for each age. Figure 7 is similar except that we pooled children ages 10-12 and ages 13-15.

In both figures, we see that the relative impacts of PI and MI on the child's overall health status changes as the child ages. Parental physical health matters most for children between ages 10 and 12. However, this reverses in early adolescence; parental mental health matters more for children between ages 13 and 15. Particularly, for 15 year old children, the estimate on parental PI is zero whereas the estimate on parental MI is 0.2 and highly significant. These findings are neatly summarized in Figure 7. All told, parental mental health matters most for younger adolescents and parental physical health matters most for pre-teens.

6 Robustness checks

We now consider a number of robustness tests. First, we consider heterogeneity by parent education and race. We split the sample into two distinct parent education groups and two distinct parent racial groups as described earlier. We find that there is greater upward health mobility and greater downward mobility for families with less educated parents and with parents who are Black and Black British or Asian and Asian British (see results in Figure A5 in the Appendix). However, these differences are not statistically significant. Second, we replace our QALY measure with SRHS, which is comparable to the QALY used by Halliday et al. (2021) based only on the general health status question. We also

Figure 6: Horserace Regressions of SRHS100 onto PI and MI for Children



We regressed SHRS100 onto PI and MI for children separately for ages 10-15. Each regression included both PI and MI. The red and the blue lines plot the point estimates of PI and MI, respectively, along with their 95% confidence intervals.

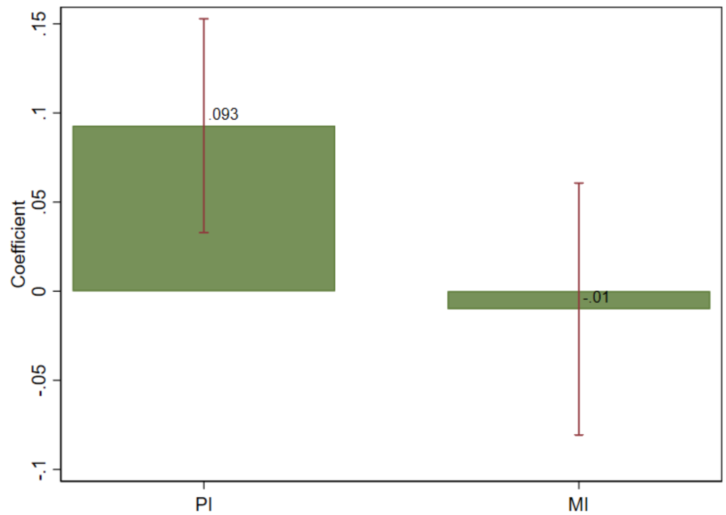
show results with the SRHS100 described earlier (see results in Table A4 for the IHA estimates and Table A5 for rank-rank estimates.) The results are similar.

We also re-define the health measures in a number of ways and show the results in Figure 8. We replace the individual's average health measure score with their minimum score, to test whether parent-child worst health years correlate similarly. We also replace the average with the earliest observation for parents and the latest observation for children to bridge the generational age gap as much as possible. Lastly, we limit the sample to children with at least four observations to reduce noise.

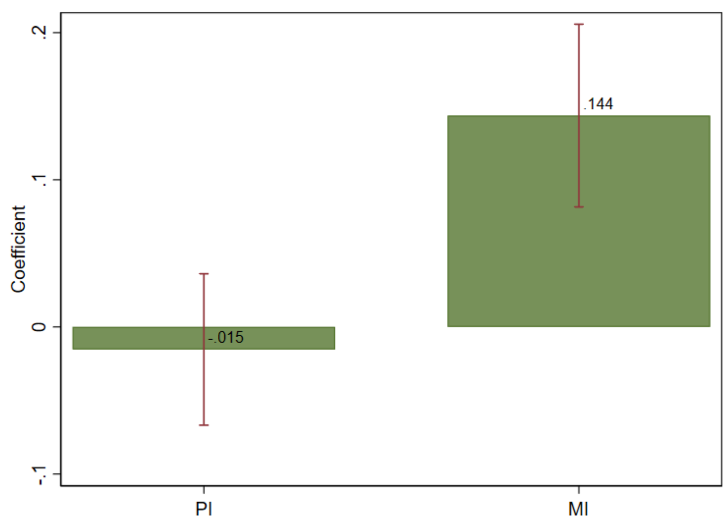
Next we check robustness to our age restriction of using the health reports when individuals are at least 25 years old in each generation. First, we expand the sample to include children's reports of their health when they are 18-24 years old. Next, we go in the opposite direction and limit the sample to children's health reports when they are 35 and above. Similarly, we check robustness to limiting parents to those below the age of 65 when they report their health. We also impose a limit of a maximum of a

Figure 7: Regressions of SRHS100 onto PI and MI for Children: Pooled Ages

Ages 10 - 12

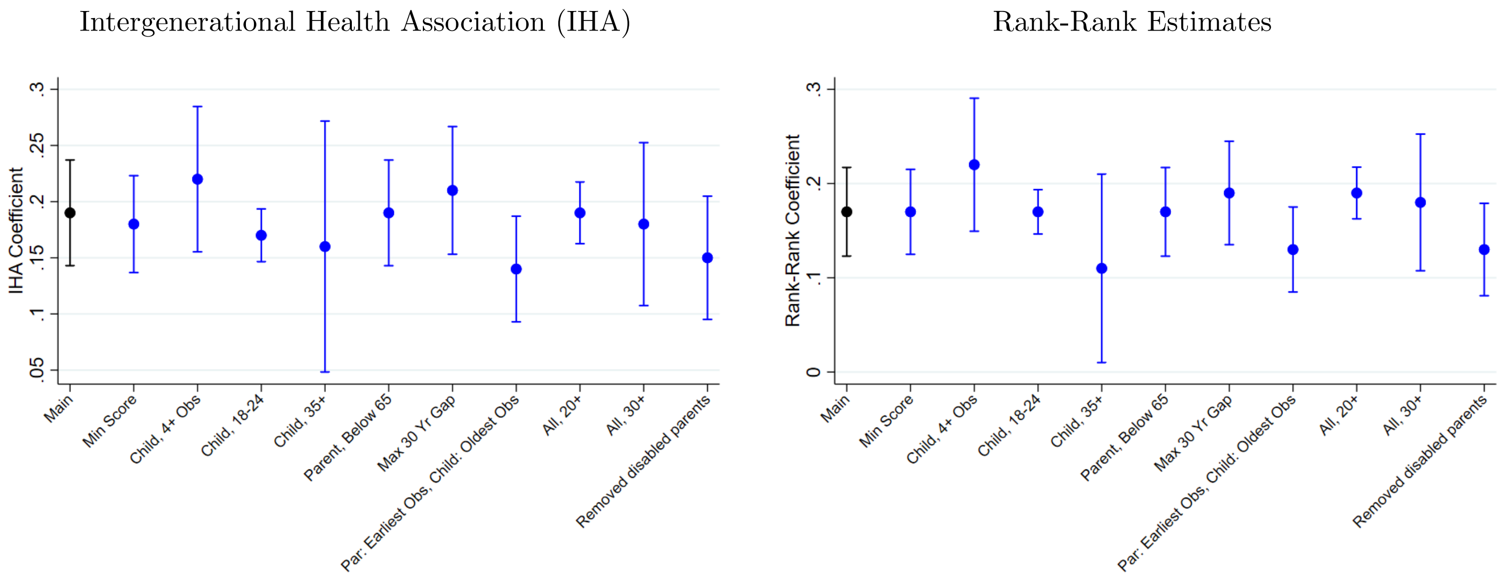


Ages 13 - 15



We regressed SHRS100 onto PI and MI for children while pooling children ages 10-12 and 13-15. Each regression included both PI and MI. The green bars plot the point estimates of PI and MI, respectively, along with their 95% confidence intervals.

Figure 8: Robustness Samples for QALY



The figures report the coefficient from the preferred IHA and rank-rank regression specifications. “Main” is our baseline sample (Tables 3 and 4). “Min Score” uses the minimum non-missing health measure for both parents and children. “Child, 4+ Obs” includes only children observed with four or more non-missing health observations. “Child, 18-24” additionally includes health observations from children when they are 18 to 24 years of age. “Child, 35+” only includes health observations from children when they are aged 35 and older. “Parent, Below 65” only includes health observations from parents when they are younger than 65. “Max 30 Yr Gap” includes children that are less than 30 years younger than their youngest parent as their average age. “Par. Earliest Obs, Child: Oldest Obs” uses the health measure that was observed at the earliest age for the parents and at the oldest age for the child. “All, 20+” additionally includes health observations from parents and children when aged 20 and older. “All, 30+” only includes health observations from parents and children when aged 30 and older. “Removed disabled parents” drops parents who have ever had a long-term sickness or been disabled.

30 year age gap (on average) between parents and children. Additional exercises use: only the health measure that was observed at the earliest age for the parents and at the oldest age for the child; health observations from parents and children when aged 20 and older, health observations from parents and children when aged 30 and older; and excluding disabled parents from the analysis. The final exercise is to address the possible concern that children who are potentially also caregivers (often informally) might have a different parent-child health relationship than those who are not. Overall, we find that the additional results are broadly in line with our main estimates. We show the same robustness checks for MI and PI in Figure A6.

7 Conclusion

We use the British Household Panel Survey and the UK Household Longitudinal Survey to study intergenerational mobility in health in the UK. We estimate that the rank-rank slope is 0.17 and the intergenerational health association (IHA) is 0.19. Both estimates suggest that about a fifth of parents' health status persists to the next generation in the UK - a relatively rapid rate of regression to the mean.

A unique contribution of our analysis is that we are able to separate physical and mental health. When considering the relative importance of mental and physical health, we show that parents' mental health is a much stronger predictor of children's health status. This is the case in both levels and ranks. Further, when using a youth supplement to the survey, we show that the primacy of parent mental health begins in the child's teen years. However, parent physical health matters relatively more during their pre-teen years.

Next, we incorporate income into our rank-rank models and show that adding parent income rank adds little additional power over and above parent health rank in predicting children's adult health rank. The same is true for children's adult income rank. This is a departure from the US, where Halliday et al. (2021) show that the two parent measures offer substantially more meaningful independent predictive power.

We combine income and health into an overall measure of social welfare and estimate the rank-rank slope in this measure to be 0.27. The comparable estimate for the US is 0.43 suggesting that there is greater intergenerational mobility in this broader measure of welfare in the UK than in the US. This gap is larger than would be inferred by simply looking at income mobility alone.

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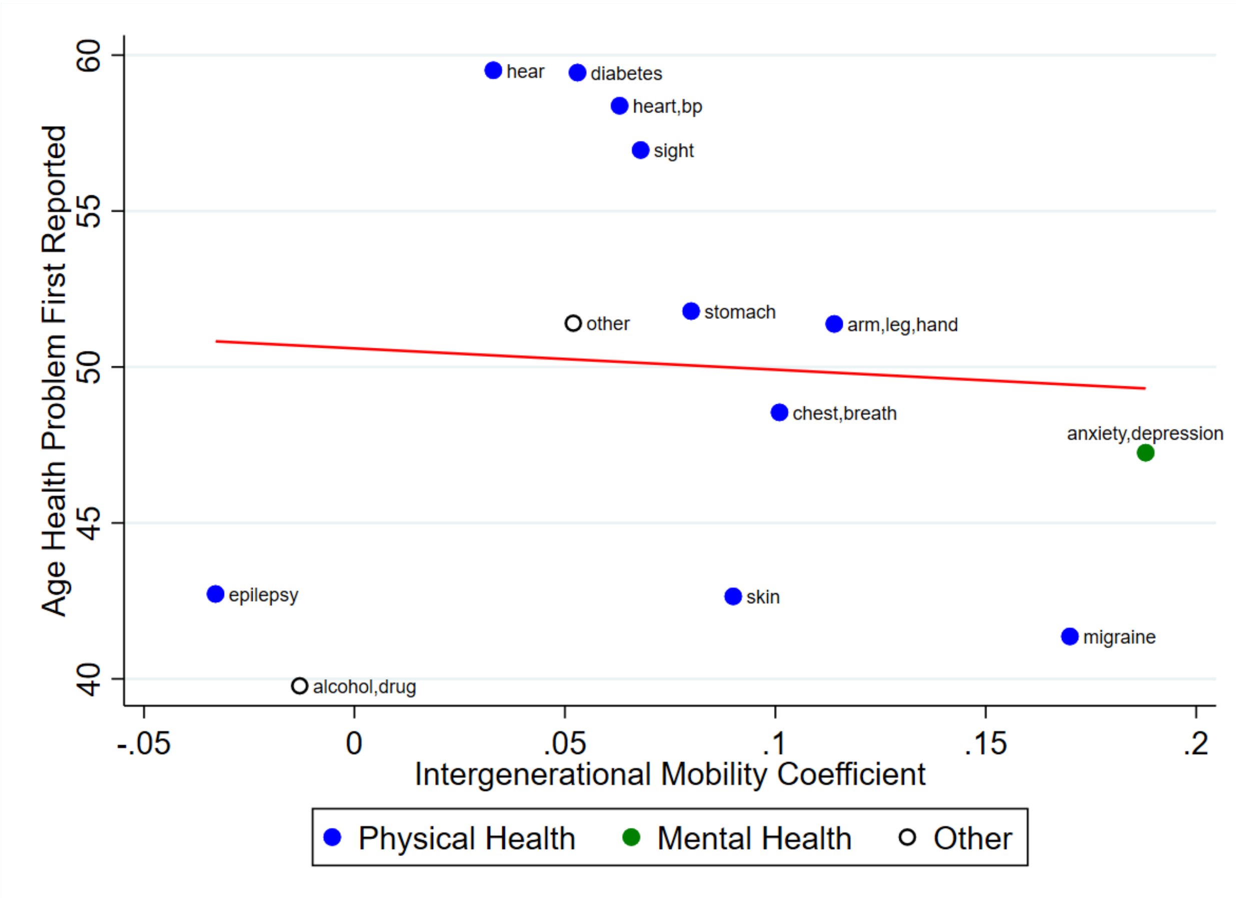
Appendix

Figure A1: Health Problems' Onset



Each point represents the intergenerational mobility coefficient from a separate regression of the child's time averaged health problem measure on the parent's time averaged health problem measure. The age the health problem was first reported is averaged across the whole survey sample.

Table A1: Construction of Health Measurements

Self-Reported Health Status (SRHS)

Question	In general, would you say your health is... Excellent (1), Very good (2), Good (3), Fair (4), or Poor (5)?
Procedure	The measure is created by following the procedure used in the PSID paper. The answer provided to the above question is rescaled to the midpoint of the appropriate HALex interval (Excellent → 97.5, Very Good → 90, Good → 77.5, Fair → 50, Poor → 15).

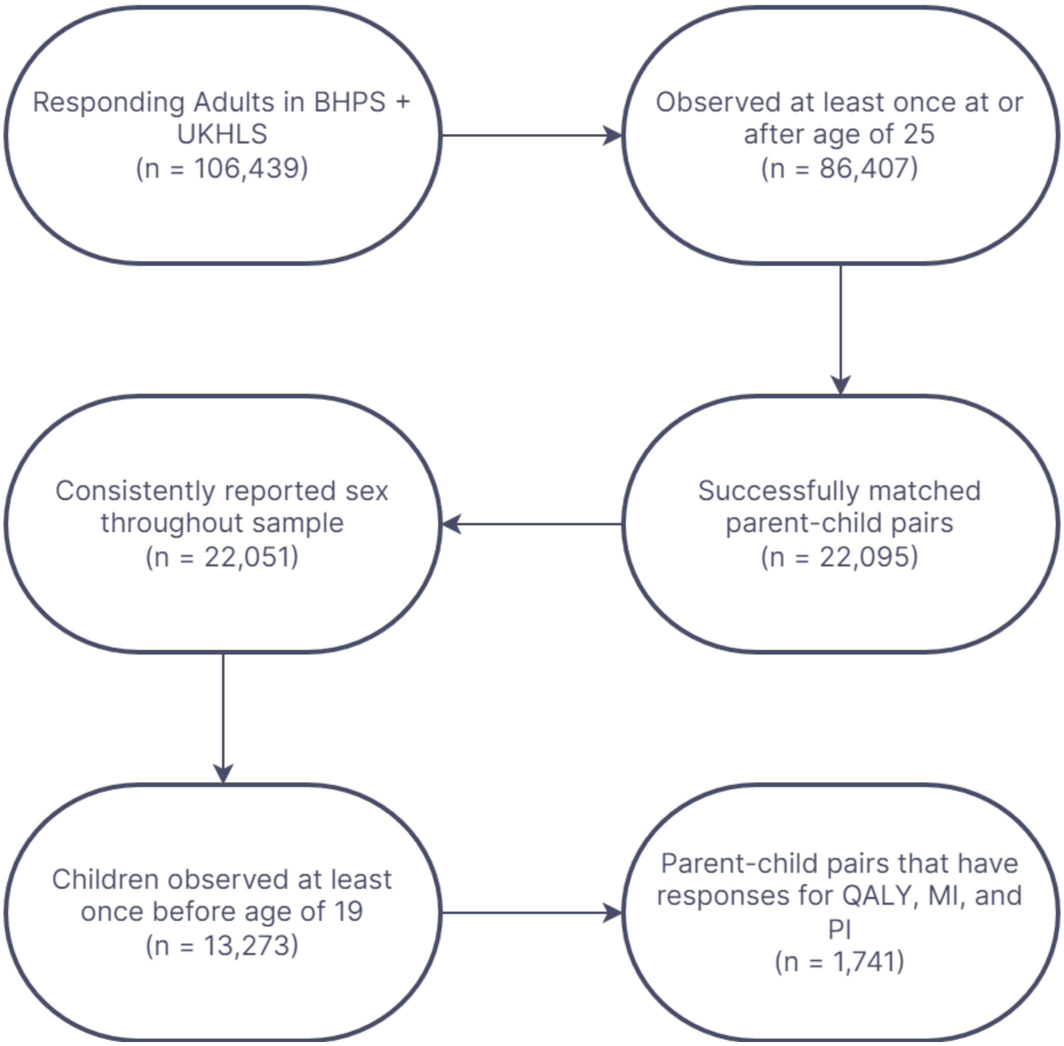
Physical Index (PI)

Question	This measure is derived from five of the SF-12 questions. These five questions are listed below: **1.** (Health limits moderate activities) The following questions are about activities you might do during a typical day. Does your health now limit you in these activities? If so, how much? Moderate activities, such as moving a table, pushing a vacuum cleaner, bowling or playing golf... Yes, limited a lot (1), Yes, limited a little (2), No, not limited at all (3) **2.** (Health limits several flights of stair) Climbing several flights of stairs... Yes, limited a lot (1), Yes, limited a little (2), No, not limited at all (3) **3.** (Last 4 weeks: Physical health limits amount of work) During the past 4 weeks, how much of the time have you had any of the following problems with your work or other regular daily activities as a result of your physical health? Accomplished less than you would like... All of the time (1), Most of the time (2), Some of the time (3), A little of the time (4), None of the time (5) **4.** (Last 4 weeks: Physical health limits kind of work) Were limited in the kind of work or other activities... All of the time (1), Most of the time (2), Some of the time (3), A little of the time (4), None of the time (5) **5.** (Last 4 weeks: Pain interfered with work) During the past 4 weeks, how much did pain interfere with your normal work (including both work outside the home and housework)? ... Not at all (1), A little bit (2), Moderately (3), Quite a bit (4), Extremely (5)
Procedure	The measure is created by taking the averages of the answers above and scaling it from 0 to 100.

Mental Index (MI)

Question	This measure is derived from five of the SF-12 questions. These five questions are listed below: **1.** (Last 4 weeks: Mental health meant accomplished less) During the past 4 weeks, how much of the time have you had any of the following problems with your work or other regular daily activities as a result of any emotional problems (such as feeling depressed or anxious)? Accomplished less than you would like... All of the time (1), Most of the time (2), Some of the time (3), A little of the time (4), None of the time (5) **2.** (Last 4 weeks: Mental health meant worked less carefully) Did work or other activities less carefully than usual... All of the time (1), Most of the time (2), Some of the time (3), A little of the time (4), None of the time (5) **3.** (Last 4 weeks: Felt calm and peaceful) These questions are about how you feel and how things have been with you during the past 4 weeks. For each question, please give the one answer that comes closest to the way you have been feeling. How much of the time during the past 4 weeks... Have you felt calm and peaceful? ... All of the time (1), Most of the time (2), Some of the time (3), A little of the time (4), None of the time (5) **4.** (Last 4 weeks: Had a lot of energy) Did you have a lot of energy? ... All of the time (1), Most of the time (2), Some of the time (3), A little of the time (4), None of the time (5) **5.** (Last 4 weeks: Felt downhearted and depressed) Have you felt downhearted and depressed? ... All of the time (1), Most of the time (2), Some of the time (3), A little of the time (4), None of the time (5)
Procedure	Same as PI.

Figure A2: Sample Construction



The flowchart represents the steps of the final analysis sample's construction, along with the sample sizes at each stage of the sample restriction. (As discussed in the main text, the sample loss between the penultimate and the final step is due to the QALY, MI, and PI questions being only asked in the UKHLS sample. The BHPS sample is used to link additional parent-child pairs.)

Table A2: Summary Statistics for Omnibus Health Measurements

	All Children	Fathers	Mothers
SRHS (Scale: 0 to 100)			
Age	28.75	55.72	52.74
	(3.25)	(7.94)	(6.98)
Overall Score	83.31	75.73	74.24
	(14.68)	(18.25)	(18.73)
Years of Health Measurement	2.95	4.56	4.72
	(1.66)	(1.90)	(1.69)
SRHS100 (Scale: 0 to 100)			
Age	28.75	55.72	52.74
	(3.25)	(7.94)	(6.98)
Overall Score	74.71	65.80	64.27
	(17.79)	(18.12)	(18.60)
Years of Health Measurement	2.95	4.56	4.72
	(1.66)	(1.90)	(1.69)
N	1,371	686	920

Note: Averages are reported. Standard deviations are in parentheses. This sample includes individuals who have at least one health measurement observation above the age of 25 and are matched to at least one parent with at least one health measurement observation above the age of 25. Age is the averaged for all available health measures.

Table A3: Correlation Matrix of Health Measures in the Restricted UKHLS

Complete UKHLS	SRHS100	PI	MI	Biomarker	Stress
SRHS100	1.00				
PI	0.71	1.00			
MI	0.59	0.64	1.00		
Biomarker	0.31	0.31	0.14	1.00	
Stress	0.22	0.25	0.13	0.59	1.00

Reports the correlation matrix from Table 2 restricting the sample to the same number of observations ($N = 4543$) across measurements.

Table A4: Comparing Intergenerational Health Associations in Various Measures of SRHS

	SRHS	SRHS100
Both parents- all children	0.20***	0.25***
N=*1,371*	(0.024)	(0.030)
Mother-daughter	0.14***	0.18***
N=*650*	(0.030)	(0.036)
Mother-son	0.16***	0.21***
N=*643*	(0.030)	(0.037)
Father-daughter	0.09***	0.16***
N=*490*	(0.036)	(0.044)
Father-son	0.14***	0.16***
N=*494*	(0.033)	(0.042)

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Each cell reports the coefficient, standard error, and number of observations of the parent mental health measure from a separate regression specification. The main explanatory variable is the parent's averaged health measure for all available periods above the age of 25. For regressions that use both parent's health, the parent health measure is the average of the mother's and father's health if both are available. Standard errors are in parentheses. The number of observations are in italics. The sample is the same as the sample in Table A2.

Table A5: Comparing Rank-rank slopes in Various Measures of SRHS

	SRHS	SRHS100
Both parents- all children	0.21***	0.23***
N=*1,371*	(0.027)	(0.028)
Mother-daughter	0.20***	0.21***
N=*650*	(0.039)	(0.039)
Mother-son	0.22***	0.22***
N=*643*	(0.039)	(0.039)
Father-daughter	0.15***	0.17***
N=*490*	(0.043)	(0.046)
Father-son	0.17***	0.16***
N=*494*	(0.042)	(0.044)

Each coefficient represents the rank-rank slope from a regression of child rank on parent rank. The ranks were generated from percentiles of an age-adjusted health measure in the respective population. Standard errors are in parentheses. Sample size is in italics. The sample is the same as the sample in Table A2.

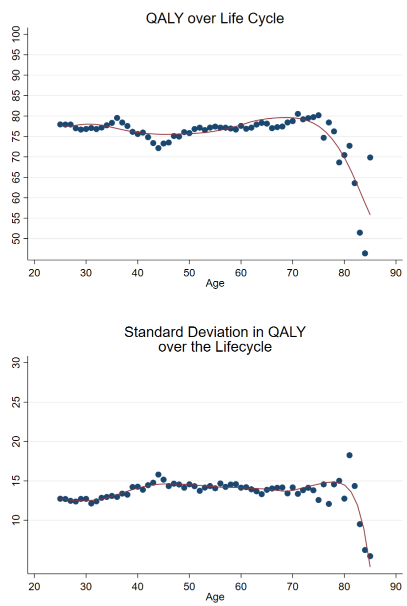
Table A6: Biomarkers in UKHLS

Biomarker Group	Health Outcome/Applications	Specific variable
Cholesterol	Cardiovascular disease (CVD)	Cholesterol HDL cholesterol
Triglycerides	CVD	Triglycerides
Glycated hemoglobin (HbA1c)	Diabetes, used to identify those who have undiagnosed diabetes or do not manage their diabetes well	Glycated haemoglobin
Ferritin	Lower measures indicate poor nutrition, anemia. Higher measures indicate haemochromatosis (associated w/ heart disease + diabetes)	Ferritin
Hemoglobin	Poor nutrition, anemia	Hemoglobin
Liver function tests	How well liver functions, Linked to alcohol, drugs, obesity + other diseases	Albumin Alkaline phosphatase Alanine transaminase Aspartate transaminase Gamma glutamyl transferase
Creatinine	Kidney diseases (chronic kidney disease)	Creatinine
Urea	Kidney diseases (acute or chronic kidney disease)	Urea
Insulin-like growth factor 1 (IGF-1)	Growth + development, diet, diabetes, cancer, heart disease	Insulin-like growth factor 1
Dihydroepiandrosterone sulphate (DHEAs)	Cardiovascular disease (CVD), muscle strength, cognition	Dihydroepiandrosterone sulphate
C-reactive protein (CRP)	Measure of inflammation (due to injury/infection, response to stress), CVD, mortality	**C-reactive protein**
Fibrinogen	Measures of inflammation (due to injury/infection, response to stress)	**Clauss fibrinogen**
Cytomegalovirus (CMV) seropositivity	"wear + tear" on immune system, chronic stress, diabetes	**Cytomegalovirus IgG** **Cytomegalovirus IgM**

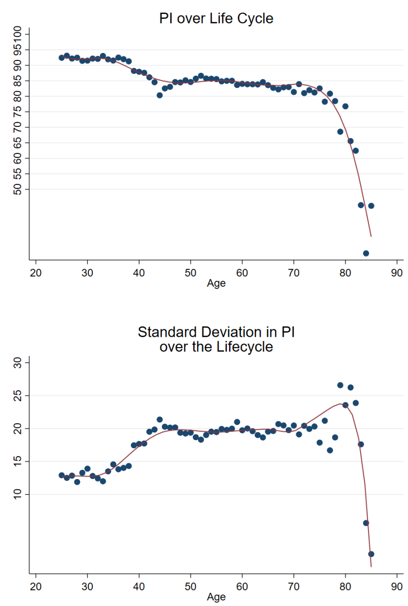
Biomarkers are from waves 2 and 3 of the UKHLS. Those denoted in **bold** are also part of the Stress Index

Figure A3: Health Measures Over the Lifecycle

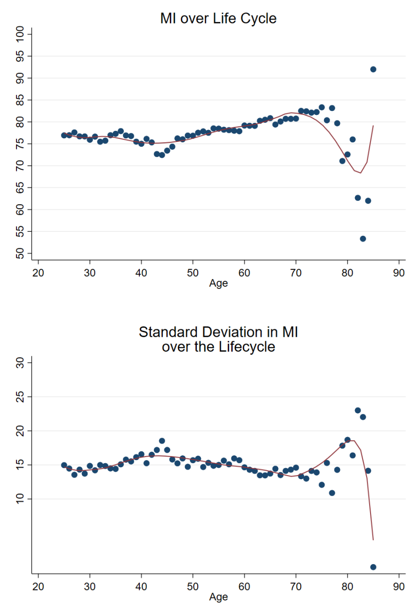
Panel A: QALY



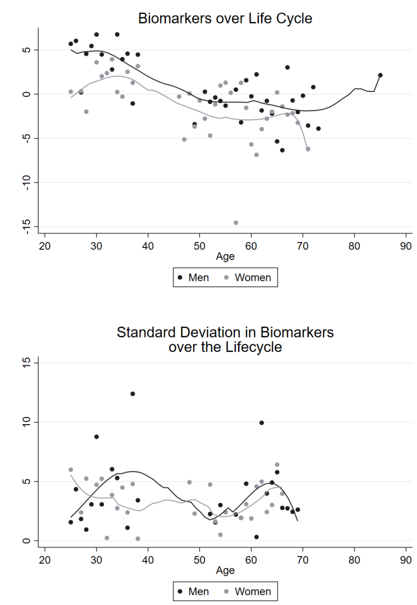
Panel B: PI



Panel C: MI



Panel D: Biomarker Index



Panels A to C display the average health outcome by age group. Panel D displays the average Biomarker value by age and gender. Ages are each individual are averaged for all available health measures. Ages 85 and above are binned together. The sample includes observations from both children and parents found in the same sample as in Table 1.

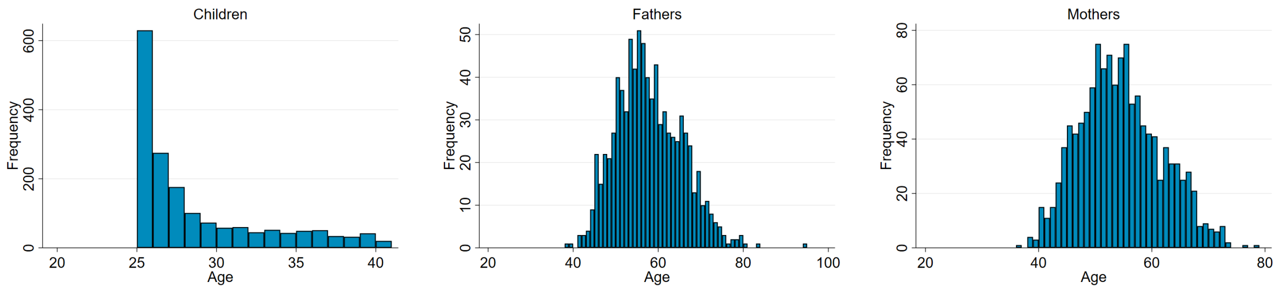
Table A7: Interplay of Health and Income Mobility Controlling for MI and PI

	Child Health Rank			Child Income Rank		
	(1)	(2)	(3)	(4)	(5)	(6)
Parent PI Rank	0.00		-0.00	0.11**		0.05
	(0.034)		(0.034)	(0.034)		(0.033)
Parent MI Rank	0.13***		0.12***	0.04		0.00
	(0.036)		(0.036)	(0.036)		(0.035)
Parent Income Rank		0.08**	0.05		0.31***	0.29***
		(0.026)	(0.027)		(0.025)	(0.026)
Constant	43.41***	46.50***	41.85***	42.61***	34.88***	32.78***
	(1.626)	(1.494)	(1.858)	(1.626)	(1.428)	(1.785)
Observations	1499	1499	1499	1499	1499	1499
R^2	0.016	0.006	0.018	0.021	0.095	0.099

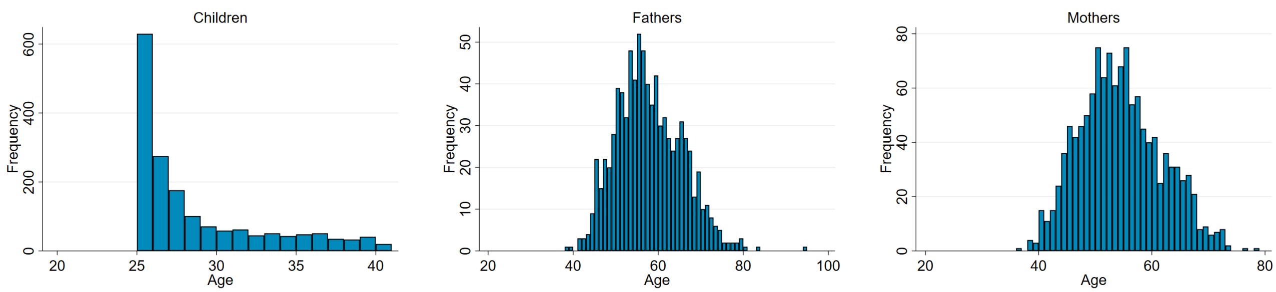
This table reports the results from regressing child health or income rank on parent PI/MI and/or income rank. The sample is the same as in Table 5.

Figure A4: Age Distribution of Children, Mothers, and Fathers

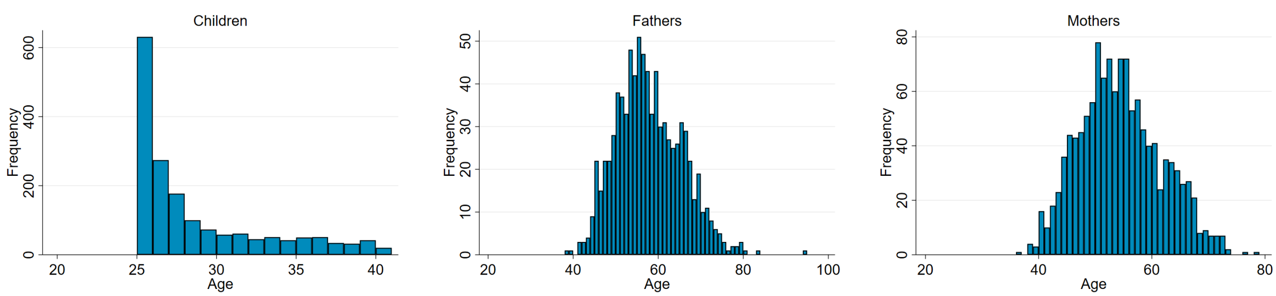
QALY



Physical Health Index (PI)

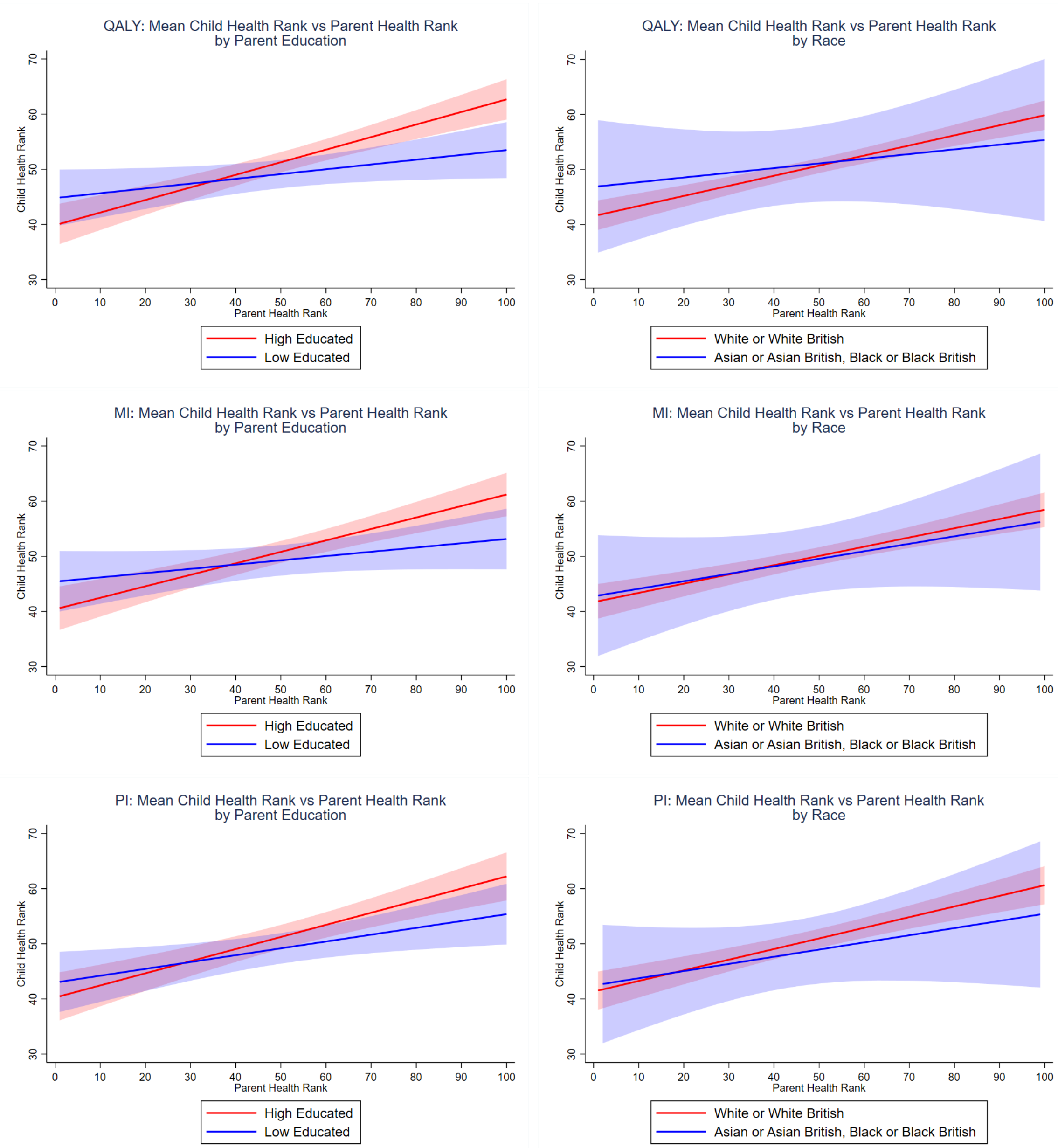


Mental Health Index (MI)



Ages for each individual are averaged for all available health measures. Ages are binned by year. The sample is the same as in Table 1.

Figure A5: Rank-Rank Relationships by Education and Race



These graphs show the slope from a regression of the child health rank on parent health rank by the parent's education and the child's race. 95% Confidence bands are represented by the dashed lines. Education is defined as the highest level across both parents for the most recent survey period. The child's race is taken from the most recent survey period.

Figure A6: MI & PI: Robustness Samples