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Daniel Graeber

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German Socio-Economic Panel (SOEP)
DIW Berlin
Mohrenstrasse 58
10117 Berlin, Germany
Contact: soeppapers@diw.de

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We describe the joint permanent health distribution of parents and children in Germany using 25 years of data from the Socio-Economic Panel. We derive three main results: First, a ten percentile increase in parental permanent health is associated with a 2.3 percentile increase in their child's health. Second, employing our anchoring method, we find that a percentile point increase in permanent health ranks is associated with a 0.8% to 1.4% increase in permanent earnings. Additionally, we conclude that health is particularly important for earnings at lower levels of health. We argue that our anchoring method has great potential to enhance the comparability of the literature across data sets and countries. Third, a more favorable socioeconomic status of the parents is predominantly associated with higher upward mobility in health.

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1. Introduction

The stock of health capital is an important determinant of the time an individual can allocate to welfare enhancing market and home production. In addition, a high stock of health capital exhibits consumption value (e.g. Grossman 1972; Dalgaard and Strulik 2014; Galama and Van Kippersluis 2019).[1] Yet, even though health is inarguably a central determinant of individual well-being and its inequality, the literature on intergenerational mobility mainly focuses on mobility in income (e.g. Solon 1992; Chetty et al. 2014; Bratberg et al. 2017; Corak 2019; Mazumder 2005), occupational prestige (e.g. Long and Ferrie 2007, 2013; Modalsli 2017), and education (e.g. Blanden 2013; Couch and Dunn 1997; Alesina et al. 2021).

The difficulties in advancing the economic literature on intergenerational health mobility are threefold: First, few data sets contain rich health information in conjunction with socioeconomic information over long periods. Second, the data must allow for linking children in adulthood with their parents. Third, health is a latent concept, like ability, that is inherently difficult to measure. For instance, if we focus solely on mortality, we would discard all health conditions that are not associated with a shortened life expectancy. Moreover, if we focus on in- and outpatient care only, we would discard all health conditions that do not result in medical treatment. [2]

We address these issues in this paper by estimating the intergenerational positional mobility in permanent health for Germany using the Socio-Economic Panel (SOEP). The SOEP provides more than 25 years of rich health information for children in adulthood and their parents. We focus on permanent health because the contemporary literature on health and earnings emphasizes that it is permanent health differences, not transitory health differences, that matter (Blundell et al. 2016; Keane, Capatina, and Maruyama 2018; Britton and French 2020). For example, permanent health differences are typically explained by long-lasting cardiovascular diseases. In contrast, transitory differences

[1]Dalgaard and Strulik (2014) deviate from the classical health-capital theory by modeling the development of health as the accumulation of health deficits over time. A further deviation of Dalgaard and Strulik (2014) is that the deficit index does not enter utility directly. The only way through which Dalgaard and Strulik (2014) hypothesize that health affects life-time utility is through expanding the individual's life expectancy and, thus, the time horizon over which individuals can consume goods.

[2]Another important shortcoming, which might hinder the advancement of the literature, could be the lack of an economic theory rationalizing the emergence of intergenerational health persistence. However, such a model can derived if parental sick times diminish market time available, and hence, resources available to child investments. Such a model is depicted in Section A of the Online Appendix. We relegated the model to the appendix because we are not able to test the mechanisms directly. However, we are confident that this may be a promising starting point for future endeavors into the important topic of intergenerational health transmission.

are typically temporary illnesses, like the flu or broken limbs, which normally heal within weeks or months. Furthermore, we apply an intuitive way to capture these multidimensional, objective, and subjective data on health in a single index via Item Response Theory (IRT).[3] That is, we model the responses to our battery of health items as a function of a latent health index. Since this health index does not exhibit a natural scale, we perform an anchoring procedure to link changes in the health distribution to a metric that allows us to describe the welfare consequences of changes in health beyond the direct consumption value of health. This anchoring metric is permanent earnings, which is of central interest in the economic literature on intergenerational mobility (Becker and Tomes 1979; Solon 1999).[4] Thus, we also bridge the gap between the literature on economic and health mobility. We organize our analysis into three parts.

In the first part, we present estimates of intergenerational positional mobility in health for Germany. Our main analysis focuses on a representative sample of children born in 1945 or later, who are between 30 and 65 years of age, alongside their parents. This, along with our preferred measure of mobility, helps us to account for life-cycle biases.[5] We show that the variation across SOEP health items can be explained by a single factor, i.e., latent health capital. Based on these data, we construct a continuous index reflecting the latent health capital of the respondents based on a wide range of health measurements using methods from IRT.[6] To capture permanent health, we calculate individual level averages of the latent health status to eliminate transitory health shocks. We then perform rank-rank regressions to estimate intergenerational

[3] We choose IRT Model over principal component analysis simply because of the finite scale of our items. However, we do not expect meaningful differences between results based on a principal component analysis and IRT models.

[4] In other studies, authors rely on Quality Adjusted Life Years (QALY) derived from preference based evaluations of health states. These studies rely on the self-rated health status or related measures, such as the Short Form 12-questionnaire, as their measure of health (Halliday, Mazumder, and Wong 2021; Bencsik, Halliday, and Mazumder 2023). For these measures, there exists an established correspondence between responses to the item on self-rated health status and QALY. However, for our measure, there exists no such correspondence. This is why we rely on permanent earnings. As a consequence, we discard the “non-monetary” or consumption value of health. However, as we argue, our method could be applied in future studies to make studies comparable in the absence of self-reported health measures, such as administrative data.

[5] In fact, in Section C of the Online Appendix, we show that differences in average latent health between high and low socioeconomic status individuals do not emerge before age 30. Thus, estimates that include measurements *before* the age of thirty are prone to life-cycle biases since a clear ordering with respect to the health status cannot be established before the age of 30. This is analogous to the life-cycle bias in the literature on the intergenerational earnings mobility (Nybom and Stuhler 2016; Haider and Solon 2006, e.g.).

[6] Details on the method are available in Section B of the Online Appendix.

positional mobility in permanent health. Stemming from the literature on income mobility, Dahl and DeLeire (2008) pioneered this method. We find support for this linear specification by running local linear regressions. The resulting rank-rank slope is the central statistic describing relative positional mobility in permanent health. The estimate of the intercept informs about the expected rank of the children if their parents are located at the bottom of the distribution of permanent health. In addition, we also calculate measures for absolute upward and downward mobility, i.e., the expected rank of children that have parents that are located at the 25th and 75th percentile, respectively.

Our central findings in this part are as follows: A 10 percentile point increase for the parents is associated with an expected increase in the child's percentile rank of 2.32 points. This is smaller than the comparable figure for permanent income in Germany, which corresponds to 2.45 (Bratberg et al. 2017; Kyzyma and Groh-Samberg 2018). In addition, our estimates reveal that up- and downward mobility are 44.43 and 56.54.[7]

In the second part, we contribute to the literature by anchoring the distribution of permanent health in permanent earnings. This allows us to overcome the lack of a natural metric for permanent health. To our knowledge, this has not been shown in the literature until today. This method is common in the literature of skill-production (e.g. Cunha and Heckman 2008; Cunha, Heckman, and Schennach 2010; Cunha 2011; Bond and Lang 2018). Thus, we provide guidance on how to overcome the lack of a natural metric for the health economics literature. This is important since studies in health economics increasingly rely on latent variables models (e.g. Andersen 2021; Halliday and Mazumder 2017; Halliday, Mazumder, and Wong 2020; White 2023) and established survey instruments, such as the Short-Form 12 questionnaire (e.g. Marcus 2013; Eibich 2015), the Kessler Scale (e.g Adhvaryu, Fenske, and Nyshadham 2019), and the Center for Epidemiological Studies Depression Scale (e.g. Papageorge et al. 2021; Fruehwirth, Iyer, and Zhang 2019). While these are readily available in data sets, they often lack a natural scale and, hence, movements along the distribution cannot be evaluated.[8] Every measure that has (1) a natural metric and (2) is correlated with health qualifies as anchor metric (Cunha 2011). Permanent earnings is such a metric (e.g. Grossman 1972; Currie

[7] We also present results for the children's probability of having a higher health rank in Section H in the Online Appendix.

[8] For many of these measures, preference based measures to evaluate health states have been developed (e.g. Brazier, Roberts, and Deverill 2002; Torrance et al. 1995). However, preferences could change over time or such measures may not be available for different countries or institutional settings, limiting their use to certain settings. In contrast, contemporaneous earnings or other life outcomes, such as educational attainment, are often readily available in data sets that include health measures.

and Madrian 1999). We show that an increase of a percentile point in the distribution of permanent health is associated with a 1.3% and 0.8% increase in permanent earnings for daughters and sons, respectively. For parents, we estimate that these associations correspond to 0.8% and 1.4% for mothers and fathers, respectively.[9]

However, deviating from the assumption of linearity, we find evidence for strong non-linearities in the association between permanent health and earnings. In all generations, the association between the percentile rank in the distribution of permanent health and earnings is highly non-linear and stronger in the bottom quintile of the distribution of permanent health. Thus, changes in permanent health are particularly consequential for individuals at the bottom of the health distribution. This points to strong incentives to escape the bottom of the health distribution across generations. Therefore, altruistic parents with higher socioeconomic status (SES), who are located at the bottom of the health distribution, have strong incentives to invest in their children's health. A direct implication is that a more advantageous socioeconomic background of children should be associated with higher upward mobility in health. We also test this hypothesis in the third part.

In the third part, we test the implication derived in the second part of this study by testing how intergenerational health mobility interacts with the parental socioeconomic background. Here, we expect that children of parents with a more favorable socio-economic background are more upwardly mobile. For this, we compare children's up- and downward mobility with respect to the health of their parents, who are located at the same percentile rank of the parental distribution of permanent health, i.e., parents with the same health endowment, but have different socioeconomic characteristics. Strikingly, we find that improvements in the socioeconomic background are associated with higher upward mobility in health.[10] This is consistent with our conjecture that the high non-linearities in the association between permanent earnings and health creates strong incentives to escape the bottom of the health distribution. The evidence also stands in clear contrast to findings for the U.S. (Halliday, Mazumder, and Wong 2021), where children of parents with more "favorable" socioeconomic characteristics are better off across the entire parental health distribution.[11]

[9] The mean of the permanent earnings, measured in 2010 Euros, is 18,301.58 and 30,342.46 for daughters and sons, respectively. For parents, the mean of the permanent earnings is 15,547.78 for mothers and 35,478.19 for fathers.

[10] In six out of eight cases, or 75%, differences in health mobility are characterized by higher upward mobility in health.

[11] An important caveat of this comparison are differences in methodology and cohorts under consideration.

Our study relates primarily to the burgeoning literature on intergenerational mobility in health: Halliday, Mazumder, and Wong (2021), Halliday, Mazumder, and Wong (2020), and Fletcher and Jajtner (2021) estimate the intergenerational positional mobility in health in the U.S. using the Panel Study of Income Dynamics and the National Longitudinal Study of Adolescent to Adult Health. All three of these studies focus on self-rated health. Halliday, Mazumder, and Wong (2021) estimate a rank persistence in health of about 0.261 for the full sample. Halliday, Mazumder, and Wong (2020) build on Halliday, Mazumder, and Wong (2021) and apply a non-linear latent variable model using the self-rated health status of the individuals. They estimate a rank persistence across generations of about 0.281.[12] Fletcher and Jajtner (2021) estimate a rank persistence of about 0.174.[13]

Our work differs from that of Halliday, Mazumder, and Wong (2021), Halliday, Mazumder, and Wong (2020), and Fletcher and Jajtner (2021) by considering a wider range of health outcomes. In addition, we also employ a non-linear latent variable framework, like Halliday, Mazumder, and Wong (2020), but use more health outcomes, which allows us to provide a richer characterization of the health distribution. The reason why the consideration of more health information is important is that the "actual" health trait is an infinite dimensional object. Therefore, any modeling attempt of health is a mapping of this complex object onto a much simpler space. Using very sparse sets of discrete states to represent health, such as the five categories of self-rated health, can cause misrepresentation of the health state across groups, especially in the presence of measurement or reporting error. In the case of the self-rated health status, much of the relevant variation in health between individuals, within a health state, is not observed. In contrast, small differences, i.e., transitory shocks, in health that cause the health trait to cross the line from, i.e., "good" to "bad," hence causing categorical differences between individuals in the discrete health mapping, are observed (White 2018, 2023). Relying on a wider range of health items and, hence, a finer mapping between the latent health trait and the health items, allows to better capture differences in health that are meaningful.

Another important study is Bencsik, Halliday, and Mazumder (2023). Bencsik, Halliday, and Mazumder (2023) evaluate the intergenerational transmission individuals'

[12] For rank-rank slopes, Halliday, Mazumder, and Wong (2021) find no differences in the estimate using either self-rated health or the non-linear latent variable model based on self-rated health. The reason is that the latter is only a positive monotone transformation of self-rated health while rank correlations are invariant to monotone transformations (Halliday, Mazumder, and Wong 2021).

[13] Fletcher and Jajtner (2021) emphasize that their estimates are heavily attenuated since parental health is only observed once.

SRHS, mental health and physical health in the U.K. using the British Household Panel/U.K. Household Longitudinal Study. They find that the intergenerational transmission of SRHS is 0.19, 0.15 for mental health, and 0.22 for physical health. The corresponding rank-rank slopes are 0.19, 0.20, and 0.17, respectively.

Further evidence stems from Andersen (2021), who estimates the intergenerational mobility of health in Denmark using administrative data on hospitalizations and general practitioner visits. Andersen (2021) characterizes the health distribution by the first principal component derived from this health information. Based on this metric, Andersen (2021) estimates rank correlations ranging from 0.112 to 0.145. However, Andersen (2021)'s primary goal is to compare the intergenerational transmission of health with sibling correlations. In contrast to Andersen (2021), we use subjective assessments of health, together with objective measures, to measure health, thus allowing us to consider differences in health that do not result in immediate treatment but affect individual welfare. In addition, the association between health and health care usage varies over time, potentially biasing the relationship of interest if we would rely on indicators of healthcare usage only (Tysinger et al. 2019). Lastly, in contrast to Andersen (2021), we also anchor our permanent health distribution in permanent earnings. This allows us to evaluate changes in permanent health.

Related, Chang et al. (2023), using administrative data from Taiwan and a methodology similar to Andersen (2021), found a rank-rank correlation of approximately 0.218. Notably, Chang et al. (2023) exploit the presence of same-sex siblings to contrast the intergenerational transmission of certain diagnoses with their genetic heritability and can reject the hypothesis that the intergenerational transmission of health is driven by genes. They put forward the hypothesis that this could be caused by the polygenic nature of many of the relevant health conditions, such as cardiovascular diseases.[14]

With Germany, we add an interesting country case to this literature. The U.S. is a country characterized by a mixture of public and private health care providers as well as high income inequality and immobility. At the opposite end, Denmark is typically described as a country with universal public health care as well as low income inequality and immobility. Along these dimensions, Germany is located between the U.S. and Denmark (Corak 2013). Our estimates show that Germany also ranks between the U.S. and Denmark when it comes to health mobility, constituting a new stylized fact to the mobility literature.[15]

[14] For an overview of this literature, which is still at it's infancy, please refer to Halliday (2023).

[15] However, since all three of these studies rely on different health measures and cohorts, this comparison must be made with caution.

Moreover, our study also relates to the economic literature on intergenerational associations in health outcomes, such as birth weight (Currie and Moretti 2007), mental health (Johnston, Schurer, and Shields 2013), longevity (Ahlburg 1998; Björkegren et al. 2019; Hong and Park 2015; Lach, Ritov, and Simhon 2006), asthma (Thompson 2017), and self-rated health (Kim et al. 2015; Pascual and Cantarero 2009). In contrast to all these studies, we consider a broader measure of health capital instead of a single specific expression of it.[16]

For Germany, Coneus and Spiess (2012) estimate the intergenerational health association between children up to age two and their parents. Our study adds to the evidence on this important topic from Coneus and Spiess (2012) in three important ways: First, we concentrate on children in adulthood. Second, in contrast to Coneus and Spiess (2012), our health measures are reported by the children themselves.[17] Third, and this point applies to all studies on intergenerational health associations, our measure of health mobility avoids ambiguous welfare implications in two ways: First, from simple intergenerational health associations, we are not able to conclude whether changes over time or across groups correspond to Pareto improvements or not. The second aspect is related to the interpretation of intergenerational health associations. Standard OLS regressions of children's health on their parental health outcome vary with varying degrees of health inequality across generations. This is not the case for rank-rank slopes, which are scale invariant.

In sum, our contributions are as follows: First, we are the first to study intergenerational mobility in *permanent* health in Germany. In the intergenerational mobility literature, in which country comparisons are an important sub-field, Germany is typ-

[16] A common theme in the literature on the intergenerational transmission of health is to what extent health is genetically determined by parents. So far, the accumulated evidence is highly ambiguous. Thompson (2017) concludes that pre-birth factors account for 20-30% of the intergenerational associations in chronic conditions. However, adoption studies, such as Thompson (2017), can only plausibly distinguish between pre- and post-birth factors. For instance, a large literature on the effects of in-utero exposure to adverse conditions shows that long-run health is malleable during the fetal period (Almond, Currie, and Duque 2018). Fletcher and Jajtner (2021) conclude that their health mobility estimates are attenuated by 32% for self-rated health in the adoptee sample. At the opposite end, using adoptee samples, Classen and Thompson (2016) and Björkegren et al. (2019), respectively, provide evidence that BMI and mortality are largely determined by pre-birth factors. In contrast, in the biological literature, estimates of the genetic heritability of longevity range from 15 to 30%, with evidence emphasizing that this figure is inflated by a factor of up to three by positive assortative mating of the parents (Ruby et al. 2018). In conclusion, we argue that approximately 70% percent of children's health is determined by the family environment. This provides a large scope for policy interventions.

[17] Parental reports of child health could bias estimates of the intergenerational health associations by either systematic reporting differences between high and low SES individuals or the fact that low SES is potentially associated with undiagnosed health conditions of the children (Case, Lubotsky, and Paxson 2002).

ically characterized as a “median” country when it comes to earnings inequality and mobility (Corak 2013). Second, we introduce an anchoring procedure to the literature that eases the interpretation of the results in the literature by allowing for comparisons across countries and data sets, i.e., admin and survey data. By choosing earnings as the anchoring metric, we are also the first to connect the literature on intergenerational health with the literature on the intergenerational earnings mobility. Third, we provide statistical evidence that the rank-rank regression is indeed linear, validating the empirical approach of studies so far.[18]

Further, this study relates also to the more established literature on intergenerational income mobility. Existing studies in economics focus on relative income mobility, estimating intergenerational earnings elasticities (e.g. Solon 1992; Mazumder 2005; Haider and Solon 2006; Schnitzlein 2016). A second generation of the literature focuses on positional mobility in income (e.g. Dahl and DeLeire 2008; Chetty et al. 2014; Bratberg et al. 2017; Corak 2019; Markussen and Røed 2020; Bell, Blundell, and Machin 2199; Blundell and Risa 2019). We relate to this literature by estimating rank-rank regressions.

Lastly, our approach to measure the latent health status relates to the literature on the estimation of the latent health status (White 2023; Halliday 2011; Halliday and Mazumder 2017; Halliday, Mazumder, and Wong 2020, e.g,). In contrast to these studies, I rely on multiple items instead on the SRHS only. Moreover, (White 2023) models latent health as an autoregressive model of order one and explicitly models reporting error. We, in contrast, do not model the health dynamics, but account for transitory shocks and (classical) reporting errors by relying on individual level time averages.

2. Methodology

2.1. Measuring health

In the literature on health and life-cycle labor supply or earnings, authors typically summarize health in a single index, either by relying on the self-reported health status or summarizing the available health information in a summary index, e.g., a principal component analysis of a group of health items (French 2005; French and Jones 2011; De Nardi, Pashchenko, and Porapakkarm 2017; Braun, Kopecky, and Koreshkova 2017; Blundell et al. 2021). Since health is often measured with (classical) measurement errors,

[18] We also derive an economic model that can explain the emergence of intergenerational persistence in health across generation’s as the utility maximizing behavior of altruistic parents. The model is depicted in Section A of the Online Appendix for the above mentioned reasons.

more health proxies typically lead to improved estimates of earnings or employment elasticities with respect to health (Blau and Gilleskie 2001; Blundell et al. 2021; Britton and French 2020).[19]

Consequently, we first summarize health in a single index, relying on item response theory (IRT). While the intuition is similar to a factor analysis, i.e., a single trait explains the common variation across items, we are convinced that IRT improves upon commonly applied factor analyses since it explicitly accommodates the discrete and finite nature of our data, i.e., the non-linear association between the trait and the items. The usage of multiple items, with many realizations, also improves upon previous approaches, which relied on single items with few realizations (Halliday, Mazumder, and Wong 2020, 2021), by allowing for a less coarse mapping between the complex health trait and the items. Other applications of IRT in economics include Ronda (2016) and Del Boca et al. (2019). To be more specific, we use the Graded Response Model (GRM) suggested by Samejima (1969), which is appropriate for multidimensional ordinal items. Details on the method are depicted in Section B of the Online Appendix.

However, contemporaneous observations of health are only an imperfect measure for permanent health. If we do not account properly for transitory health shocks, we would expect that any coefficient of a linear regression of children's on parents' contemporaneous health status suffers from attenuation bias (Hausman 2001; Solon 1992). Additionally, we must account for biases that could arise due to potential heterogeneous changes in health over the life-cycle (Galama and Van Kippersluis 2019; Haider and Solon 2006). To accommodate for the presence of transitory shocks, we take the average of individuals' health observations. In the next section, we explain how we address potential life-cycle biases.

2.2. Rank mobility measures

To quantify intergenerational health mobility we perform rank-rank regressions. Formally, rank mobility measures are estimated as the intercept and slope of the following linear projection:

$$r_{1iz} = \delta + \zeta r_{0z} + \eta_{zi}. \tag{1}$$

In Equation 1, r_{1iz} and r_{0z} are the percentile rank in the distribution of permanent

[19]Importantly, Blundell et al. (2021) find that a single index can indeed capture important health variations for employment.

health of child i and parents in family z, respectively. By construction, the error term η_{zi} is orthogonal to the rank of the parents r_{0z}. This rules out unobserved factors that jointly determine the parents' and child's health rank and that would bias our estimates. This is an assumption typically invoked in the literature on intergenerational mobility (e.g. Nybom and Stuhler 2016). [20]

Then, the estimate of the intercept δ is the expected percentile rank of a child in the children's distribution of permanent health whose parents are at the bottom of the parental distribution of permanent health. The rank-rank slope ζ reflects the relative positional persistence in permanent health across generations. That is, the rank-rank slope, multiplied by 100, indicates the expected difference in the children's percentile ranks of parents who are located at the bottom and the top of the parental distribution of permanent health. Therefore, the scalar $1 - \zeta$ reflects the degree of relative positional mobility in health.

Rank-rank regressions are very popular in the literature on economic mobility (e.g. Dahl and DeLeire 2008; Chetty et al. 2014; Bratberg et al. 2017; Corak 2019; Bell, Blundell, and Machin 2199; Blundell and Risa 2019). Four reasons underlie the popularity of rank-rank regressions: First, positional mobility measures are well suited for welfare comparisons. For instance, if intergenerational health associations change over time, it is not clear whether this change corresponds to a Pareto improvement or not. As an example, suppose that the intergenerational health association decreases over time or across groups. In this case, we do not know whether the narrowing of this health gap occurs due to the children from the family with the worse health status improving or because the health status of the children of the family with the better health status deteriorates across generations. The latter case would not correspond to a Pareto improvement. Clearly, similar considerations apply to rank-rank slopes, which are also measures of relative mobility. But the estimates of the intercept and the slope of Equation 1 allows us to circumvent the problem of ambiguous welfare implications by calculating measures for absolute intergenerational rank mobility in health, similar to, e.g., Chetty et al. (2014) or Halliday, Mazumder, and Wong (2021). Thus, we calculate the expected percentile rank in the distribution of permanent health of a child stemming from a family whose percentile rank in the distribution of permanent health is $r_{0z} \in \{25, 75\}$. We refer to these measures as absolute up- and downward mobility,

[20]Clearly, while this assumption is standard in the literature on intergenerational mobility, it does not necessarily have to hold true. Thus, future research would have to gauge to what extent the relationship of interest is indeed causal. For this analysis, we assume that the conjecture of orthogonality indeed holds true, in line with the literature on intergenerational mobility in general.

respectively.

Second, every intergenerational health association depends highly on the cross-sectional inequality in the health outcome in the children's and parents' generation. To see this, the OLS coefficient of a bivariate regression of Y_{1iz} on Y_{0z} can be decomposed as follows:

$$b_{ols} = \frac{Cov(Y_{1iz}, Y_{0z})}{Var(Y_{0z})} = \frac{Cov(Y_{1iz}, Y_{0z})}{\sigma_0 \sigma_1} \frac{\sigma_1}{\sigma_0} = Corr(Y_{1iz}, Y_{0z}) \frac{\sigma_1}{\sigma_0}, \tag{2}$$

with σ_0 and σ_1 being the standard deviation in the health outcome in the parents' and children's generation. Further, $Cov(\cdot)$ and $Corr(\cdot)$ correspond to the covariance and correlation. For a fixed correlation in health outcomes across generations, a doubling of the cross-sectional inequality across generations doubles the intergenerational health association. This change would also increase differences in health outcomes between individuals in the children's generation and the associated consumption possibilities. Without normative foundations, it is not clear whether a measure of intergenerational health association should capture this or not.[21] In contrast, rank mobility measures are invariant in the scale of the underlying outcome.

The third reason for the popularity of rank-rank regressions is the fact that the estimates have more desirable statistical properties than intergenerational health associations. For instance, the variance of the true percentile rank and estimated percentile rank in the respective distributions of permanent health are equal by definition. Consequently, attenuation bias due to i.i.d. shocks is less of a concern (Nybom and Stuhler 2017). Nevertheless, we show that i.i.d. health shocks could bias our estimates and that taking individual time averages is a remedy to this.

Fourth, starting from age 30, estimates of rank-rank slopes tend to show no life-cycle biases in the case of permanent income in Sweden (Nybom and Stuhler 2017). In Section C of the Online Appendix, we depict the life-cycle properties of the latent health status for high and low SES individuals. Similar to the case for earnings, early health observations could lead to misleading conclusions. However, after the age of 30, a clear ordering emerges. Therefore, we restrict our sample to the 30-65 age range. Moreover, the inequality in health increases with age. This could also cause life-cycle biases. However, rank-rank slopes are invariant to mean preserving spreads. This would not be the case for OLS estimates. Further, in Section 4.2, we test the robustness of

[21] Landersø and Heckman (2017) put this argument forward for the case of intergenerational income mobility.

our estimates to life-cycle biases and can reject the presence of life-cycle biases in our application.

We calculate the percentile ranks in permanent health separately for all genders and generations. Before that, we partial out a second order polynomial of age as well as year of birth fixed effects for males and females as well as the child and parent generations. Lastly, we calculate the percentile ranks separately for each gender and generation. In addition, we average the latent health status of both parents and partial out quadratic age terms and year of birth fixed effects for both parents as well as indicators that indicate whether the mother or the father is missing and the share of observations contributed by the mother. If the father or mother is missing, we set the respective age and year of birth equal to zero. Then, we calculate the respective permanent health of the parents jointly based on this latent health status.[22]

In addition to our main analysis based on the rank-rank regressions displayed in Equation 1, we also provide alternative estimates of upward mobility in Section H in the Online Appendix. These additional analysis complements the primary analysis by providing estimates for the share of children that have a higher health rank than their parents.

2.3. Anchoring

After measuring the degree of health mobility, we still do not know how to interpret changes in the distribution of permanent health. Therefore, we anchor permanent health in an anchoring metric that exhibits a natural scale. Every outcome that (1) exhibits a natural metric and (2) is correlated with permanent health qualifies as anchoring metric (Cunha 2011). We use permanent earnings as such a natural metric. Permanent earnings are (1) measured in Euro and health are (2) correlated with earnings, as described in the first part of this section.

In our case, the anchoring equation takes the form

$$y_i = \alpha + \gamma r_i + \phi_i. \tag{3}$$

[22] We emphasize that health is not equivalent to earnings if we focus on the permanent health of the parents jointly. Consequently, the interpretation might change accordingly. However, many processes adhere to a regression to the mean. As an example, children tend to be of average parental height (Tanner, Goldstein, and Whitehouse 1970). Therefore, we believe that the average health is indeed of relevance for children's health in our setting. However, where necessary, we always show also the estimates separately for all combinations of children and parents.

In Equation 3, y_i is permanent earnings, adjusted for age and year of birth, while γr_i is referred to as the anchoring function (Cunha 2011). However, the anchoring Equation 3 implies a linear relationship between the percentile rank in the distribution of permanent health and permanent earnings. As we show in Section 4.1, the relationship between the percentile rank in the distribution of permanent health and permanent earnings is non-linear. Thus, we also display a nonparametric specification.[23]

3. Data

We use 25 waves of the SOEP to estimate the intergenerational mobility in permanent health. The SOEP is a representative panel of households in Germany that is administered to individuals and households annually since 1984. The SOEP contains rich information on occupational biographies, education, household composition, and health, among others. As of today, about 15,000 households and 30,000 persons are interviewed on an annual basis.[24] For more detailed information, see Goebel et al. (2018).

Most important for our study, we can link parents and their adult children in the SOEP. Children in each SOEP household are first surveyed when they turn eleven or twelve years old and followed thereafter, even if they leave the parental household and form new households.[25] Thus, we are able to link parents with their adult children, even if the children no longer live in the parental household.

For the IRT model to summarize health, we make use of all health items administered between 1992 and 2017 in a consistent way.[26] There exists no comparable data that contains consistent health information over so many years in Germany. These items

[23]We only show OLS associations of the underlying relationship. However, we argue that the estimated association corresponds to an upper bound. The reasons for this are twofold: First, the presence of a justification bias could bias our estimates downward (e.g. Blundell et al. 2021; Currie and Madrian 1999). The explanation is that individuals who work fewer hours or do not work at all could be hypothesized as justifying this reduction of labor supply by their poor health status. If this is the case, we would expect that any association between subjective health proxies and labor supply or earnings is biased upwards. Second, the existence of classical measurement error in health measurements could attenuate OLS estimates, biasing estimates of the underlying relationship downwards. We discuss the relevance of classical measurement error in Section 4.2 and conclude that measurement error is present and that individual time averages account for most of the classical measurement error. Thus, we face two sources of bias that work in opposing directions. However, since we account for classical measurement errors, we are left with justification bias as the only source of bias. Therefore, we argue that our estimates are either not biased or biased upward. Therefore, we conclude that our estimate represents an upper bound.

[24]We use SOEPv34. DOI: 10.5684/soep.v34.

[25]Until 2013, children in each household were surveyed first in the year in which they turned 17 years old. Since 2014, the SOEP also administers questionnaires to individuals aged eleven and twelve.

[26]We do not use the 1993 wave since the self-rated health status was not inferred in 1993.

are: The self-rated health status, satisfaction with health, number of doctor visits within the last three months, number of hospital admissions in the previous year,[27] and the degree of disability or reduced earnings capacity[28] as assessed by a physician.[29]

Detailed information on the health items and their operationalization as well as the IRT analysis are available in Table A1 and Section D in the Online Appendix. Next, we implement the age restrictions and calculate the permanent health measure as explained in Section 2. The age distribution of the final sample is displayed in Figure A1. [30] Figure A2 displays the unadjusted and adjusted distribution of permanent health of the children and their parents, respectively. The unadjusted distributions of permanent health in Figure A2A suggest that the children have better permanent health, on average, than their parents. However, the difference is accounted for completely by age and year of birth fixed effects, as the adjusted distributions of permanent health in Figure A2B suggest. Based on this permanent health measure, we calculate the respective percentile rank in the distributions of permanent health. The summary statistics for our main sample are displayed in Table A2.

Overall, we observe 3536 mother-child pairs with 2604 distinct mothers, 1940 of which are sons and 1596 which are daughters. In addition, we observe 3090 father-child pairs for 2360 distinct fathers: 1689 of these are associated with sons and 1401 with daughters. The distribution of children's gender is clearly skewed toward sons, which is consistent with the sex specific birth numbers for these cohorts.[31]

We also construct a subsample to investigate the influence of parental socioeconomic

[27]We use hospital visits of the previous year since most interviews are conducted in the first half of the year. Therefore, we argue that hospital visits of the previous year are more reflective of the health status at the time of the interview than the number of hospital visits in the contemporaneous survey year.

[28]In the U.S., individuals who apply for benefits from the Social Security Disability Insurance program must be unemployed or have very low earnings. In fact, these earnings have to be lower than the substantial gainful activity threshold for at least 5 months before the receipt of the benefits can occur (e.g. Hosseini, Kopecky, and Zhao 2021; Social Security Disability Insurance 2021). This reinforces any negative correlation between application status and earnings. In contrast, there exists no formal earnings threshold in Germany. On the contrary, applicants must have contributed to the German statutory pension insurance scheme for at least three years in the five years prior to the application for retirement benefits because of reduced earnings capacity (Deutsche Rentenversicherung 2021). Therefore, there exists no formal earnings threshold. We imputed zeros for individuals who reported the absence of disabilities or reduced earnings capacities.

[29]Table A1 includes detailed information on the health items and our recoding.

[30]The analysis of the attrition for each of the relevant concepts as well as the representativeness of our sample with respect to the population of interest is described in Section E in the Online Appendix. The analysis of representativeness in Section E suggests that our sample is representative of the hypothesized underlying population.

[31]For instance, the number of births given to sons was about 7% higher for males than females in the years after the second World War (Statistisches Bundesamt 2022). In general, we perform all analysis also sex specific to account for potential gender imbalances.

characteristics on the degree of intergenerational health mobility.[32] For this, we restrict the parental observations to provide information on education, the individual time average of the occupational prestige score, and permanent earnings. We also retain information on the parental migration background.

The educational background is captured by the school leaving degrees.[33] For our analysis, we collapse the school leaving degree into two categories: The first category consists of individuals with no or a basic school leaving degree. The second category consists of individuals with an intermediate or high school leaving degree.

Permanent earnings is calculated as the individual average of the yearly labor earnings. The yearly labor earnings comprises wages and salary from all employment and self-employment as well as earnings from bonuses, overtime, and profit-sharing.[34] We partial out a second order polynomial of age and year of birth fixed effects from the logarithm of yearly labor earnings and calculate the individual time average of the parents between the age 30 and 65.[35] Our analysis then compares individuals whose parents have permanent earnings above and below the median.[36]

Occupational prestige is summarized by the Magnitude-Prestige Scale (MPS), developed by Wegener (1988). For the development of the MPS, a representative sample of Germans first associated a number with an initial occupation, representing the associated prestige. Then, the respondents were asked to rate other occupations relative to this initial occupation. After that, these occupational scores were averaged across all individuals. This results in a quasi-continuous scale with higher scores reflecting

[32]We rely on a separate sample to avoid selection bias in the main sample since it can be hypothesized that individuals with non-missing information on background characteristics are different than the whole sample. This is already reflected in the higher health status, on average, and higher labor earnings for the parents in our subsample.

[33]In Germany, for the generations under consideration, tracking typically starts after grade four. Children are then allocated to one of three different school tracks, according to their ability, as reflected in the children's GPA. Children with the lowest school grades are allocated to the basic school ("Hauptschule"), preparing the students for vocational education. Students with intermediate grades are allocated to the intermediate school ("Realschule"), comprising a more academic curriculum than the basic school, preparing their students for more demanding vocational training. The best students are typically allocated to the high school ("Gymnasium"), preparing the students for an academic education.

[34]Monthly labor earnings stem from the Cross National Equivalence Files, an international project that provides internationally harmonized household panels. For further details, see Frick et al. (2007).

[35]We proceed this way separately for each gender and generation. To calculate the joint permanent earnings of the parents, we proceed similarly to permanent health.

[36]Haider and Solon (2006) and Nybom and Stuhler (2016) highlight the relevance of life-cycle biases in the approximation of permanent earnings. The parents in our analysis are not in the recommended age range of 30 to 45 for the approximation of life-time earnings. However, since the median is an order statistic, we are confident that a median split of this measure avoids any life-cycle related problems with this measure since the median is robust to any spread of the distribution.

higher occupational prestige. As a result, the MPS reflects perceived social prestige of occupations and associated social capital, beyond the information that is conveyed by education and income (Lin 2008). Again, we calculate the individual time average of the MPS of parents of age 30 through the age of 65.

Lastly, parental migration background is summarized by an indicator that is equal to one if the respective parent has a direct migration background, e.g., if a parent is born outside of Germany. We show the corresponding summary statistics of the sample for the heterogeneity analysis in Table A3.

4. Results

4.1. Main results

In Table A4, we display the results of the rank-rank regressions as well as the up- and downward mobility in permanent health. Throughout, robust standard errors are clustered on the family level. In addition, Figure A3 displays the rank-rank regression for children and their parents jointly. The rank-rank slope of the sample combining both parents and all children is 0.232. That is, if two children's parents are 10 percentile points apart in the parental permanent health distribution, this gap is expected to decrease 2.32 percentile ranks in the children's permanent health distribution. From Figure A3, it becomes immediately apparent that the relationship between children's and the parents' percentile rank is indeed linear. In Section 4.2, we provide further evidence for the linearity assumption. Further, the rank-rank slope is 0.219 for the mother-son and 0.233 for the mother-daughter relation. Lastly, the rank-rank slopes are 0.193 and 0.198 for the father-son and father-daughter relation, respectively.

Two patterns become apparent in Table A4: First, the rank-rank slopes are higher for the mother-child than for the father-child relations. This suggests a higher relative positional mobility in percentile ranks in the permanent health distribution across generations for father-child than for mother-child relations. Second, the estimates for the parent-child estimates are always higher for the daughters than for the sons, pointing to higher relative positional persistence in the distributions of permanent health across generations for daughters than for sons.[37] These observations are consistent with the findings of Halliday, Mazumder, and Wong (2021) and Andersen (2021). However, Andersen (2021) does not find any differences comparing the rank-rank slopes of father-daughter and mother-daughter relations. Notwithstanding, the rank-rank slopes suffer from ambiguous welfare implications. Therefore, we investigate the degree of up- and downward mobility in health.

We estimate an upward mobility of 44.74, as depicted in column (2) of Table A4. The estimate for downward mobility is 56.34, as depicted in column (3) of Table A4. Thus, if the parents are located at the 25th (75th) percentile, their children are expected to be at percentile 44.74 (56.34) in the corresponding permanent health distribution. Focusing on gender differences, we conclude that our estimates suggest that children display a higher absolute positional upward mobility in percentile ranks based on the

[37] However, these differences are not statistically significant.

rank-rank regressions for the father-child than for the mother-child relations. Focusing first on the measurement of upward mobility, we estimate that the degree of upward mobility is 45.87 and 45.96 for the father-daughter and father-son relations, respectively. For mothers and their children, we estimate that the upward mobility is 44.99 and 44.97 for the mother-daughter and mother-son relations, respectively. Our estimates for downward mobility are 55.76 and 55.60, for the father-daughter and father-son relations, respectively. Lastly, the estimates for downward mobility are 56.61 and 55.90 for the mother-daughter and mother-son relations, respectively.

4.2. Sensitivity analysis

To investigate the sensitivity of our results to the presence of transitory health shocks in the explanatory variable, we construct estimates for different samples with at least z years of observations on the latent health capital per each parent. We choose z such that $z \in \{5, 7, 10, 14\}$ per parent. For each of these samples, we construct permanent health measurements based on 1 to z observations separately. Then, we perform rank-rank regressions for the z permanent health measurements in each sample. The results are displayed in Figure A4, in which we plot the rank-rank slope as a function of the number of observations.

Clearly, attenuation due to transitory health shocks is highly relevant. Throughout, we observe that the estimates increase with increasing numbers of observations per permanent health measurement of the parents. This confirms Halliday, Mazumder, and Wong (2021)'s findings. However, the relevance varies across samples. Most prominently, the number of observations per average is more relevant for rank-rank regressions for sons than daughters. For sons, the estimates tend to converge if the estimates of the permanent health measurements includes at least ten observations, as displayed in Figures A4B and A4D. In contrast, the gradients are much smaller for daughters, as can be inferred from Figures A4A and A4C.

A further observation is a permanent shift in the rank-rank slopes for mother-daughter and father-son samples if the sample restrictions require a higher number of observations for each parent. One possible explanation is that conditioning on the availability of at least z observations introduces unobserved heterogeneity between groups. For instance, those families that are able to contribute more observations per permanent health measurement and which are potentially positively selected, could be hypothesized as showing less persistence in health across generations. However, unfortunately, the exploration of these heterogeneities is beyond the scope of this paper.

In conclusion, one should not put too much emphasis on the levels of the rank-rank slopes in this sensitivity analysis, rather it should be on the changes as a function of the number of observations within each sample.

Next, we thoroughly investigate to what extent the assumption of linearity is warranted. Therefore, we estimate rank-rank regressions using local linear regressions. We use an Epanechnikov kernel with bandwidth w and determine the optimal bandwidth via cross-validation.[38]

Figure A5 displays the fit of the local linear rank-rank regressions and the corresponding 95% percentile bootstrap confidence intervals, based on 50 repetitions each, for the mothers, for the fathers, and their children, respectively. As it becomes immediately apparent, the estimates suggest that the association between parental and the children's percentile ranks in the respective distributions of permanent health is indeed linear. This is even more so for the case of fathers and their children in contrast to mothers and their children. This is a result that is not yet shown in the literature on intergenerational mobility in health. This result clearly supports the linear specification of rank-rank regressions, as in Equation 1.

To quantify the sensitivity of our estimates to potential life-cycle biases, we consider two different age groups in both the parental and children's generation. These age groups are 30-45 and 46-65. The age range 30-45 is based on the recommendation that emerged from the literature on intergenerational income mobility (Haider and Solon 2006; Nybom and Stuhler 2016). Then, we test the stability of our estimates for all possible combinations of these age ranges across children and their parents.[39] The resulting estimates are displayed in Table A5.[40]

Overall, we find little evidence for life-cycle biases in our estimates. We find that ten out of twelve estimates are comparable to each other.[41] The two exceptions are the estimates for the sons when sons and their respective parents are 30-45, as depicted

[38]We perform cross-validation for the sample of mothers and their children as well as fathers and their children separately to determine the optimal bandwidth. For mothers and their children, the optimal bandwidth is 5.79. For fathers and their children, the optimal bandwidth is significantly larger. In fact, the optimal bandwidth so large that it will always include the full support. We conclude that this is indicative of the fact that the true relation is, indeed, linear. For illustrative purposes, we impose a bandwidth of six for both samples.

[39]Since parents are older than their children and we do not have complete life-time profiles for both generations, we are not yet able to test the stability of the estimates for the sample when children are of age 46-65 and parents are of age 30-45.

[40]Please note that the estimates for the sample in which the children and the parents are of age 30-45 and 46-65, respectively, largely coincide with our main sample. Thus, large deviations are not expected.

[41]We do not count in the estimates for the main sample in this comparison since the overlap with the sample of parents of age 46-65 and children of age 30-45 is very large.

in Table A5. However, while these point estimates are clearly attenuated compared to those for the other sub-samples, a formal test of equality of estimates across samples does not allow us to reject the hypothesis of equality of the estimates across samples.[42] One potential explanation for the stability of the rank-rank slopes across samples could be the fact that rank-rank slopes are stable to any mean preserving spread, i.e., increase of the variance with age.

When we pool all birth cohorts, we estimate the average correlation between intergenerational health across all birth cohorts. However, this masks potential heterogeneity across generations. In addition, we would like to mute the variation caused by survey year effects by focusing on distinct cohorts that are observed over a similar range of survey years.

To allow for heterogeneity across cohorts, we distinguish three birth cohorts: The first cohort was born from 1945 until 1965, the second cohort was born from 1966 to 1975, and the third cohort was born from 1976 through 1987. Table A6 presents the rank-rank slopes and the estimates for up- and downward mobility for the different cohorts. In addition, Table A6 contains p-values of tests of equality of the estimates across cohorts. Table A7 displays gender specific results.

Clearly, the estimates for the rank-rank slopes suggest that there is no variation in relative positional health mobility across generations. The estimates in Table A6 range from 0.257 for the 1945-1965 cohort, to 0.237 for the 1966-1975 cohort, and 0.229 for the 1976-1987 cohort. Moreover, these differences are not jointly statistically significant as the p-value of 0.892 suggests. In addition, we find no differences in our measures for absolute positional up- and downward mobility in health across cohorts. The estimate for upward mobility is 45.94 for the 1945-1965 cohort, 44.97 for the 1966-1975 cohort, and 43.70 for the 1976-1987 cohort. Further, we cannot reject the null hypothesis of no differences across estimates, as indicated by Table A6. The associated p-value is 0.411. Moreover, the estimates for downward mobility are 58.80 for the 1945-1965 cohort, 56.83 for the 1966-1975 cohort, and 55.13 for the 1976-1987 cohort. Again, we find no significant differences across estimates. The corresponding p-value is 0.122, as shown in Table A6. Turning to gender differences, as shown in Table A7, we also do not detect any significant differences in health mobility across cohorts.

[42] The test also includes the restriction that the estimate of the main sample are similar to those of the other subsamples. However, the null cannot be rejected in all comparisons if we exclude the latter restriction.

4.3. Returns to permanent health

Since our health metric exhibits no natural scale, it is impossible to evaluate movements along the health distribution. Therefore, we anchor permanent health in permanent earnings. To minimize potential life-cycle biases, we restrict the age range in both the children's and parents' samples to 30-45, following Haider and Solon (2006). Figure A6 displays the association between permanent earnings and the percentile rank in the distribution of permanent health for daughters, sons, mothers, and fathers.

Clearly, we observe a non-linear and positive relation between permanent earnings and the percentile rank in the permanent health for the children and their parents. The non-linearity would have been masked if we had only relied on a linear functional form. Throughout, the relation appears to be linear from approximately the 20th percentile rank up to the top of the distribution of permanent health in all subsamples. In contrast, the association is stronger and highly non-linear between the bottom of the distribution of permanent health and the 20th percentile rank of the distribution of permanent health. Thus, changes in the distribution of permanent health are more consequential in the first quintile of the distribution than in other parts of the distribution of permanent health. This is consistent with Hosseini, Kopecky, and Zhao (2021), who also find that it is mainly individuals scoring above the 75th percentile (individuals with worse health) in their frailty index, an alternative aggregate health measure, whose earnings are affected by changes in health.

Assuming linearity, we anchor the percentile rank in the distribution of permanent health in the metric of permanent earnings. Consequently, we can describe the percentage change in permanent earnings associated with a one percentile point increase in the distribution of permanent health. A one percentile point change in the distribution of permanent health is associated with an approximate 1.3% change for daughters and a 0.8% change for sons, as inferred from Figures A6A and A6B, respectively. For parents, a one unit change in the percentile rank in the distribution of permanent health is associated with an approximate 0.8% change for mothers and 1.4% change for fathers in permanent earnings, respectively.

4.4. The influence of the parental SES

In the previous section, we presented evidence that it is primarily individuals at the bottom of the health distribution for whom changes in health are very consequential, measured in permanent earnings. Hence, the incentives are very large to help one's children to escape the bottom of the health distribution. Thus, children of parents with more resources at the bottom of the health distribution should be more mobile than children of parents with fewer resources. In this section, we investigate differences in health mobility with respect to the parents' socioeconomic background and show that an advantageous socioeconomic background is indeed associated with higher upward mobility in health. These proxies for the socio-economic background are permanent earnings, education, and occupational prestige. We also check for the association of our mobility estimates with the parental migration background. We provide a short literature overview about these four proxies in Section F in the Online Appendix.

Tables A8 to A10 show the corresponding estimates for the rank-rank slopes, upward and downward mobility, as well as p-values for tests of equality of estimates across samples. The corresponding mobility curves are displayed in Section G of the Online Appendix.[43]

Table A8 shows no difference between children of parents with high and low permanent earnings. However, we find that the daughters' health mobility depends on mother's permanent earnings. Table A9 shows that daughters of mothers with high earnings have better health throughout. The differences in the estimates for upward and downward mobility are 4.90 and 4.50, respectively, and significant in a SUR framework, as the p-value in Table A9 indicates. This result suggests that the distribution of permanent health of daughters of mothers with permanent earnings above the median first-order stochastically dominates the distribution of permanent health of daughters of mothers with permanent earnings below the median.[44] Thus, under reasonable assumptions about individual preferences, daughters would prefer to be born into families in which mothers have permanent earnings above the median. This is a result that would have been masked if we would have only focused on the rank-rank slope or intergenerational health associations. The rank-rank slope of daughters of mothers with high and low permanent earnings are 0.226 and 0.218, respectively. The difference of these estimates is small and not statistically significant, as Table A9 shows.

Turning to differences in parental education, we distinguish children of parents

[43]In addition, we provide a similar analysis for our complementary measure of upward mobility, i.e., the share of parents who have a higher health rank than their children, in Section H in the Online Appendix.

[44]If we compare two cumulative distribution functions, e.g. $F_a(x)$ and $F_b(x)$, and suppose x is a desirable outcome, such as health, then we say that option a first-order stochastically dominates b if $F_a(x) \leq F_b(x)$. An immediate consequence is that for any utility function $u(\cdot)$, we have that $\int u(x)dF_a(x) \geq \int u(x)dF_b(x)$. To put it differently, every utility maximizing individual should choose option a over b since option a maximizes the expected utility of this individual.

who have at least an intermediate school leaving degree from parents who have at most a basic school leaving degree. Table A8 displays no difference between children of parents with a high and low school leaving degree. Further, if we additionally distinguish between genders, we conclude that sons of fathers with higher education experience a greater upward mobility in health than sons of fathers with lower education. The difference in upward mobility amounts to 4.82 and is statistically significantly different from zero, as Table A10 suggests.[45]

Analyzing differences with respect to parental occupational prestige, we distinguish between children whose parents' occupational prestige score is below and above the median. Indeed, daughters of fathers with occupational prestige above the median are more upwardly mobile, as Table A9 shows. The difference in percentile ranks is 4.85 and statistically significantly different from zero.

Lastly, we investigate differences with respect to parental migration background. In our analysis, we compare children of parents who are and who are not born in Germany. The difference amounts to 5.05 and is statistically significant in a SUR framework, as presented in Table A8. A gender specific analysis reveals that this is mainly driven by sons and their parents. Table A10 shows that the difference in upward mobility is 5.88 for the mother-son and 5.30 for the father-son relation.

[45]At first glance, this contrasts with evidence by Huebener (2022), who reports no effect of paternal years of schooling on their children. However, this could be explained by the fact that Huebener (2022) exploits a reform that increased the number of compulsory years of schooling from eight to nine years. Formally, these parents were still only entitled to a basic school leaving degree. Thus, the corresponding local average treatment effect applies to individuals at the lower end of the educational hierarchy. In contrast, we compare children of parents with different school leaving degrees.

5. Discussion and conclusion

We provide the first complete description of intergenerational mobility in permanent health for Germany. For this, we capture latent health from 25 years of health information in the SOEP via an IRT model. To account for transitory health shocks that would attenuate our estimates and capture permanent health, we calculate individual-level averages of these health measurements. Then, we perform rank-rank regressions. On average, we find that intergenerational health mobility in Germany amounts to 0.232.

We also contribute to the literature with our anchoring of permanent health into permanent earnings. In the absence of preference-based evaluation of health states or the absence of subjective indicators, this allows us to quantify the relevance of permanent health and compare estimates across studies. We find that permanent health matters for permanent earnings, especially so at the bottom of the permanent health distribution. Since this creates large incentives to escape the bottom of the health distribution, we find that a more favorable SES for the parents is associated with higher upward mobility for the children.

How do our health mobility estimates compare to the results on income mobility for Germany? Comparing our results to the most recent estimates, we conclude that intergenerational health mobility is higher than income mobility in Germany (Bratberg et al. 2017; Kyzyma and Groh-Samberg 2018). One possible explanation for this could be that Germany has a highly formalized labor market. Access to vocational tracks and, thus, earnings prospects, is determined by the school leaving degrees. Since students are typically tracked after the fourth year of school, parents and their teachers largely determine in which kind of occupations the children work by choosing the school track. Consequently, intergenerational persistence of economic status, mediated via education, tends to be high in Germany compared to other countries (Lange and von Werder 2017). In contrast, the transmission of health, to be precise, the part which is mediated through school, is potentially lower. While evidence exists that one's own schooling has a positive effect on one's own health in Germany (Kemptner, Jürges, and Reinhold 2011), a meta-analysis suggests that, taken together, the published body of research on education and health indicates the absence of any effect (Xue, Cheng, and Zhang 2021).

A naturally arising question is: How does health mobility inform us about the state of societies? Good health is the precondition for individuals to exert any effort aiming at increasing income and consumption possibilities (Sen 2002). Therefore, one could certainly consider intergenerational health mobility a characteristic of an egalitarian society. For earnings, a mobile society can additionally be considered to be a society that rewards effort. This also applies to health to the extent that good health increases individual productivity. However, while most studies acknowledge a role for productivity effects of health, most studies conclude that it is the employment channel that drives the association between earnings and health (e.g. Britton and French 2020; French 2005; Hosseini, Kopecky, and Zhao 2021). This aligns more closely with the notion that bad health limits individual capabilities to exert any effort. Therefore, we argue that health mobility is more a sign of an egalitarian society rather than a sign of a society that rewards effort.

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TABLE A1. Health items for calculation of latent health status

Item (1)	Wording of question (2)	Potential answers (3)	Recoding (4)
Self-rated health status	"How would you describe your current health?"	5-point Likert-scale ranging from 1 "Very good" to 5 "Bad"	None
Satisfaction with health	"How satisfied are you with your health?"	11-point Likert-scale ranging from 0 "completely dissatisfied" to 10 "completely satisfied"	Scale reversed so that higher values indicate worse health
Doctor visits last 3 months	"Have you gone to a doctor within the last three months? If yes, please state how often."	Open answer	Indicator for having visited the doctor more than three times in the last three months
Hospital visits previous year	"What about hospital stays in the last year - were you admitted to a hospital for at least one night in $t-1$?"	Open answer	Indicator for being admitted at least twice in the previous year
Degree of disability	"Have you been officially assessed as being severely disabled or partially incapable of work for medical reasons?"	Open answer	Discretized to eleven values ranging from 0 to 100 in increments of 10.

Note: Table A1 displays the health items in the SOEP used to predict the latent health status. Column (1) displays the title of the health item. Columns (2) and (3) display the exact wording of the item as well as the potential answers. Column (4) displays the recoding of the health item.

TABLE A2. Summary statistics

	Parents		Children	
	Father (1)	Mother (2)	Son (3)	Daughter (4)
Outcomes:				
Permanent health (standard deviations)	-0.308	-0.331	0.279	0.218
	(0.766)	(0.752)	(0.717)	(0.751)
Years of health measurement	11.742	12.884	8.698	8.365
	(6.784)	(7.091)	(6.800)	(6.231)
Permanent earnings (2010 Euros)	30235.980	11595.393	32096.969	18668.463
	(28419.007)	(14202.182)	(20552.206)	(15162.707)
Health items:				
Self-rated health status	2.862	2.900	2.312	2.363
	(0.728)	(0.715)	(0.653)	(0.689)
Satisfaction with health	4.929	4.935	3.847	3.963
	(1.757)	(1.716)	(1.570)	(1.634)
Degree of disability	10.999	8.172	3.559	3.013
	(21.194)	(18.719)	(14.548)	(13.565)
More than 3 doctor visits last 3 months	0.248	0.282	0.115	0.215
At least 2 hospital visits in previous year	0.034	0.029	0.015	0.024
Additional characteristics				
Age	55.937	54.690	34.478	34.189
	(5.835)	(6.015)	(3.927)	(3.664)
Year of birth	1944.758	1946.860	1972.115	1974.077
	(8.603)	(8.985)	(7.959)	(7.408)
Number of individuals	3090	3536	2012	1643

Note: Table A2 displays summary statistics of the sample for the main analysis. Standard deviations are in parantheses.

TABLE A3. Summary statistics for the sample for the analysis of the interaction of the parents' socioeconomic background with health mobility

	Parents		Children	
	Father	Mother	Son	Daughter
	(1)	(2)	(3)	(4)
Outcomes:				
Permanent health (standard deviations)	-0.275	-0.273	0.294	0.227
	(0.732)	(0.726)	(0.705)	(0.738)
Years of health measurement	12.251	13.748	8.614	8.249
	(6.677)	(6.914)	(6.757)	(6.134)
Health items:				
Self-rated health status	2.829	2.841	2.295	2.353
	(0.696)	(0.692)	(0.642)	(0.678)
Satisfaction with health	4.866	4.837	3.824	3.943
	(1.692)	(1.639)	(1.555)	(1.605)
Degree of disability	9.583	6.866	3.196	2.709
	(18.983)	(15.972)	(13.502)	(12.608)
More than 3 doctor visits last 3 months	0.242	0.271	0.113	0.214
At least 2 hospital visits in previous year	0.028	0.026	0.014	0.024
Additional characteristics:				
Age	55.686	53.900	34.275	34.004
	(5.677)	(5.815)	(3.712)	(3.433)
Year of birth	1945.042	1948.417	1972.579	1974.419
	(8.497)	(8.538)	(7.819)	(7.177)
Parental background characteristics:				
Basic school leaving degree or less	0.430	0.423		
Intermediate school leaving degree	0.364	0.448		
Academic school leaving degree	0.206	0.129		
Occupational prestige	58.824	56.319		
	(29.140)	(23.808)		
Migration Background	0.226	0.192		
Permanent earnings (2010 Euros)	32386.796	15126.383		
	(28231.922)	(14480.915)		
Number of individuals	2853	2703	1822	1545

Note: Table A3 displays summary statistics of the sample for the analysis of the interaction of the parents' socioeconomic background with health mobility. Standard deviations are in parantheses.

TABLE A4. Health rank mobility by parent-child relation

	Rank-rank slope	Child's exp. rank if parent(s) are at 25th percentile	Child's exp. rank if parent(s) are at 75th percentile	Observations
	(1)	(2)	(3)	(4)
Mother-son	0.219	44.971	55.896	1940
	(0.023)	(0.930)	(0.824)	
Mother-daughter	0.233	44.987	56.613	1596
	(0.025)	(0.955)	(0.979)	
Father-son	0.193	45.960	55.601	1689
	(0.025)	(0.964)	(0.940)	
Father-daughter	0.198	45.866	55.758	1401
	(0.027)	(1.030)	(1.044)	
Both parents-all children	0.232	44.735	56.338	3655
	(0.017)	(0.657)	(0.647)	

Note: Each row of Table A4 displays the estimate of rank-rank slope, up- and downward mobility for different parent-child relations. The estimates are based on a regression of the children's percentile rank in the children's permanent health distribution on the parents' percentile rank in the parents' permanent health distribution. Robust standard errors, in parantheses, are clustered on the family level. Column (1) displays the estimates of the rank-rank slope. Columns (2) and (3) display the children's expected percentile rank if the parents' percentile rank would have been 25 and 75, respectively. Column (4) displays the number of observations.

TABLE A5. Life cycle bias

Age group (1)	All children-both parents (2)	Daughter-mother (3)	Daughter-father (4)	Son-mother (5)	Son-father (6)
30-45/30-45	0.200	0.218	0.190	0.157	0.147
	(0.027)	(0.038)	(0.047)	(0.036)	(0.047)
46-65/46-65	0.250	0.208	0.182	0.246	0.216
	(0.038)	(0.059)	(0.076)	(0.055)	(0.058)
30-45/46-65	0.233	0.227	0.200	0.222	0.188
	(0.017)	(0.026)	(0.027)	(0.024)	(0.025)
30-65/30-65	0.232	0.233	0.198	0.219	0.193
	(0.017)	(0.025)	(0.027)	(0.023)	(0.025)
P-value	0.576	0.974	0.294	0.993	0.775

Note: Table A5 displays life-cycle patterns in the rank-rank slope for different samples. Column (1) indicates the ages under consideration for the children/parent-combination. Column (2) to (6) display the estimates for the different age combinations for the respective child-parent combination. Robust standard errors, clustered on the family level, are displayed in parantheses. The p-values in the last row are based on a Chi-square distribution, with three degrees of freedom, for a test of equality of estimates within each column. All results are based on seemingly unrelated regressions to account for potential correlation of coefficients across samples.

TABLE A6. Health mobility of children by cohort for all children

	Cohort			
	1945-1965	1966-1975	1976-1987	P-value
	(1)	(2)	(3)	(4)
Rank-rank slope	0.257	0.237	0.229	0.828
	(0.038)	(0.026)	(0.027)	
Upward mobility	45.940	44.974	43.698	0.411
	(1.323)	(0.974)	(1.101)	
Downward mobility	58.796	56.831	55.126	0.122
	(1.642)	(1.004)	(0.924)	
Observations	685	1511	1459	

Note: Table A6 displays the estimate of rank-rank slope, up- and downward mobility for different cohorts of children. The estimates are based on a regression of the children's percentile rank in the children's permanent health distribution on the parents' percentile rank in the parents' permanent health distribution. Upward and downward mobility are the children's expected percentile rank in the children's permanent health distribution if the parents are located at the 25th and 75th percentile rank of the parental permanent health distribution. Robust standard errors, clustered on the family level, are in parentheses. Each column corresponds to a different cohort of children. The p-values are based on a Wald Chi-square test of equality of the respective estimates based on seemingly unrelated regressions in which each cohort resembles one equation and are displayed in column (4).

TABLE A7. Health mobility of children by cohort for different subsamples

		Daughters				Sons			
		Cohort				Cohort			
		1945-1965 (1)	1966-1975 (2)	1976-1987 (3)	P-value (4)	1945-1965 (5)	1966-1975 (6)	1976-1987 (7)	P-value (8)
	Rank-rank slope	0.244	0.232	0.230	0.983	0.212	0.212	0.234	0.904
		(0.065)	(0.040)	(0.037)		(0.051)	(0.035)	(0.037)	
	Upward mobility	43.796	45.632	44.767	0.779	46.492	44.655	44.279	0.643
Mothers		(2.390)	(1.446)	(1.436)		(1.957)	(1.384)	(1.534)	
	Downward mobility	55.994	57.225	56.280	0.875	57.108	55.270	55.968	0.696
		(2.787)	(1.567)	(1.372)		(1.803)	(1.271)	(1.309)	
	Observations	218	648	730		418	816	706	
	Rank-rank slope	0.252	0.190	0.190	0.750	0.233	0.209	0.154	0.442
		(0.078)	(0.042)	(0.039)		(0.054)	(0.037)	(0.040)	
	Upward mobility	43.486	46.550	45.912	0.598	45.994	45.367	46.734	0.811
Fathers		(2.679)	(1.544)	(1.566)		(2.077)	(1.437)	(1.580)	
	Downward mobility	56.105	56.038	55.422	0.952	57.644	55.825	54.421	0.449
		(3.318)	(1.654)	(1.429)		(2.101)	(1.408)	(1.468)	
	Observations	165	572	664		327	720	642	

Note: Table A6 displays the estimate of rank-rank slope, up- and downward mobility for different cohorts of children. The estimates are based on a regression of the children's percentile rank of the children in the children's permanent health distribution on the parent's percentile rank in the parent's permanent health distribution. The p-values are based on a Wald Chi-square test of equality of the respective estimates based on seemingly unrelated regressions in which each cohort resembles one equation. Columns (1) to (4) displays estimates for daughter samples and columns (5) to (8) display estimates for son samples. Robust standard errors, in parentheses, are clustered on the family level.

TABLE A8. Health mobility by education, occupational prestige, permanent earnings and migration background of both parents

	Rank-rank slope	Upward mobility	Downward mobility	N
	(1)	(2)	(3)	(4)
Educational degree of the parents:				
Basic or less	0.224	44.611	55.788	1165
	(0.031)	(1.056)	(1.292)	
Intermediate or more	0.221	45.211	56.279	2202
	(0.022)	(0.887)	(0.793)	
P-value test of equality	0.954	0.664	0.746	
Occupational prestige of the parents:				
Below median	0.215	45.014	55.742	1740
	(0.025)	(0.851)	(1.063)	
Above median	0.231	44.878	56.415	1627
	(0.027)	(1.125)	(0.876)	
P-value test of equality	0.658	0.923	0.625	
Permanent earnings of the parents:				
Below median	0.242	44.635	56.743	1745
	(0.025)	(0.844)	(1.090)	
Above median	0.201	45.691	55.739	1622
	(0.027)	(1.143)	(0.861)	
P-value test of equality	0.265	0.457	0.470	
Migration background of the parents:				
No migration background	0.244	43.733	55.926	2543
	(0.021)	(0.811)	(0.752)	
Migration background	0.185	47.787	57.028	824
	(0.035)	(1.237)	(1.547)	
P-value test of equality	0.150	0.006	0.521	

Note: Each row of Table A8 displays the estimate of rank-rank slope, up- and downward mobility for different subsamples, stratified according to socioeconomic characteristics of the parents. The estimates are based on a regression of the children's percentile rank in the children's permanent health distribution on the parents' percentile rank in the parents' permanent health distribution. The p-values are based on a Wald Chi-square test of equality of the rank slopes or predicted ranks across groups after a seemingly unrelated regression model, in which each subgroup corresponds to a separate equation in the seemingly unrelated regression model. Throughout, robust standard errors, in parentheses, are clustered on the family level.

TABLE A9. Health mobility of daughters by education, occupational prestige, permanent income and migration background of the mother or father

	Mother-daughter				Father-daughter			
	Rank-rank slope	Upward mobility	Downward mobility	N	Rank-rank slope	Upward mobility	Downward mobility	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Educational degree of parent:								
Basic or less	0.232	43.689	55.276	496	0.181	45.863	54.911	549
	(0.046)	(1.607)	(1.886)		(0.044)	(1.594)	(1.779)	
Intermediate or more	0.242	44.857	56.960	763	0.196	46.857	56.636	758
	(0.036)	(1.416)	(1.357)		(0.037)	(1.417)	(1.386)	
P-value test of equality	0.860	0.585	0.468		0.799	0.641	0.443	
Occupational prestige of parent:								
Below median	0.241	43.409	55.448	630	0.140	46.017	52.999	654
	(0.041)	(1.413)	(1.729)		(0.042)	(1.395)	(1.750)	
Above median	0.231	45.537	57.092	629	0.219	46.899	57.848	653
	(0.040)	(1.610)	(1.426)		(0.039)	(1.628)	(1.400)	
P-value test of equality	0.866	0.320	0.463		0.168	0.680	0.030	
Permanent income of parent:								
Below median	0.226	42.331	53.647	622	0.185	45.632	54.863	645
	(0.040)	(1.350)	(1.773)		(0.041)	(1.299)	(1.819)	
Above median	0.218	47.228	58.142	637	0.179	47.673	56.646	662
	(0.042)	(1.702)	(1.398)		(0.044)	(1.852)	(1.371)	
P-value test of equality	0.889	0.024	0.046		0.931	0.366	0.433	
Migration background of parent:								
No migration background	0.240	43.984	55.961	1029	0.192	46.111	55.715	1031
	(0.032)	(1.212)	(1.191)		(0.032)	(1.253)	(1.190)	
Migration background	0.262	45.752	58.843	230	0.203	47.289	57.447	276
	(0.066)	(2.235)	(2.885)		(0.061)	(2.000)	(2.781)	
P-value test of equality	0.759	0.486	0.354		0.872	0.617	0.566	

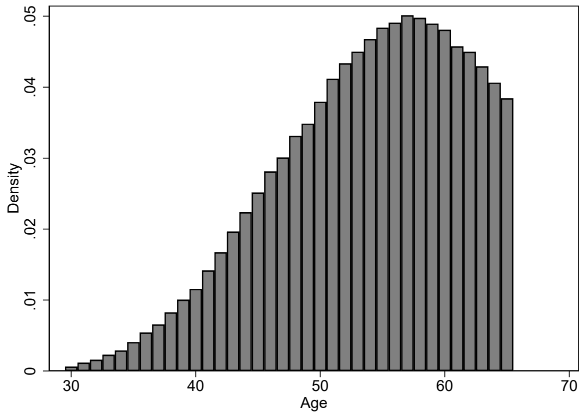
Note: Each row of Table A9 displays the estimate of rank-rank slope, up- and downward mobility for different subsamples, stratified according to background characteristics of the respective parent. The estimates are based on a regression of the percentile rank of the daughter's permanent health distribution on the percentile rank of the parent in the parent's permanent health distribution. The p-values are based on a Wald Chi-square test of equality of the rank slopes or predicted ranks across groups after a seemingly unrelated regression model, in which each subgroup corresponds to a separate equation in the seemingly unrelated regression model. Robust standard errors, in parentheses, are clustered on the family level.

TABLE A10. Health mobility of sons by education, occupational prestige, permanent earnings and migration background of the mother or father

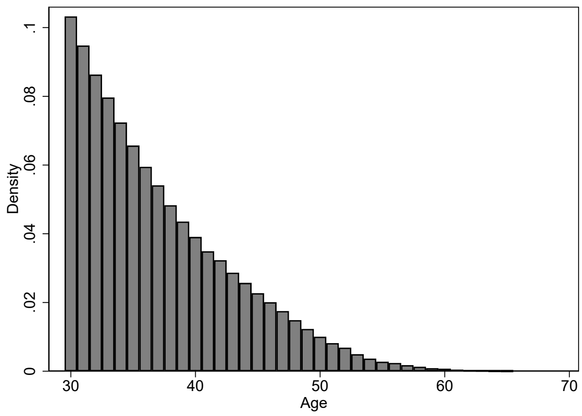
	Mother-son				Father-son			
	Rank-rank slope	Upward mobility	Downward mobility	N	Rank-rank slope	Upward mobility	Downward mobility	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Educational degree of parent:								
Basic or less	0.236	42.801	54.597	647	0.218	43.890	54.785	677
	(0.040)	(1.449)	(1.557)		(0.039)	(1.345)	(1.628)	
Intermediate or more	0.180	45.517	54.495	797	0.145	48.711	55.973	869
	(0.036)	(1.489)	(1.210)		(0.036)	(1.470)	(1.221)	
P-value test of equality	0.288	0.191	0.959		0.170	0.015	0.559	
Occupational prestige of parent:								
Below median	0.227	43.938	55.281	760	0.162	46.646	54.737	810
	(0.037)	(1.387)	(1.416)		(0.037)	(1.278)	(1.492)	
Above median	0.187	44.503	53.852	684	0.209	45.601	56.073	736
	(0.038)	(1.571)	(1.298)		(0.038)	(1.604)	(1.290)	
P-value test of equality	0.449	0.788	0.456		0.368	0.610	0.498	
Permanent earnings of parent:								
Below median	0.225	43.314	54.566	761	0.213	46.998	57.623	788
	(0.037)	(1.328)	(1.517)		(0.038)	(1.260)	(1.611)	
Above median	0.177	45.651	54.514	683	0.183	45.005	54.150	758
	(0.039)	(1.670)	(1.225)		(0.038)	(1.633)	(1.219)	
P-value test of equality	0.372	0.273	0.979		0.581	0.333	0.085	
Migration background of parent:								
No migration background	0.240	42.568	54.581	1154	0.204	44.772	54.985	1178
	(0.029)	(1.180)	(1.030)		(0.030)	(1.169)	(1.087)	
Migration background	0.114	48.449	54.134	290	0.149	50.068	57.500	368
	(0.062)	(2.162)	(2.536)		(0.053)	(1.909)	(2.228)	
P-value test of equality	0.062	0.017	0.870		0.360	0.018	0.309	

Note: Each row of Table A10 displays the estimate of rank-rank slope, up- and downward mobility for different subsamples, stratified according to background characteristics of the respective parent. The estimates are based on a regression of the percentile rank of the daughter's permanent health distribution on the percentile rank of the parent in the parent's permanent health distribution. The p-values are based on a Wald Chi-square test of equality of the rank slopes or predicted ranks across groups after a seemingly unrelated regression model, in which each subgroup corresponds to a separate equation in the seemingly unrelated regression model. Robust standard errors, in parentheses, are clustered on the family level.

FIGURE A1. Age distributions



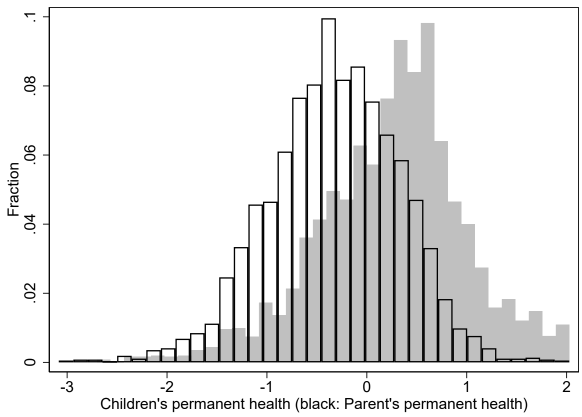
A. Parents



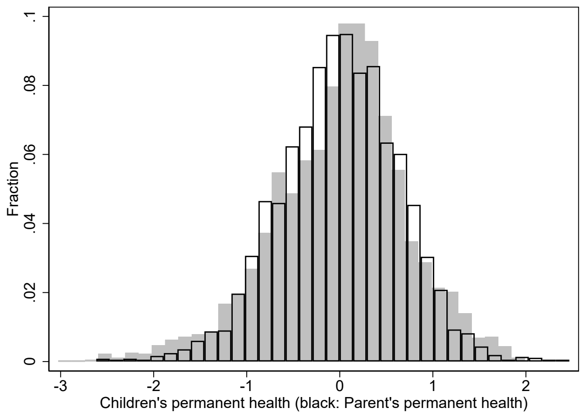
B. Children

Note: Figures A1A and A1B display the age distribution in the parent and child sample.

FIGURE A2. Distribution of permanent health



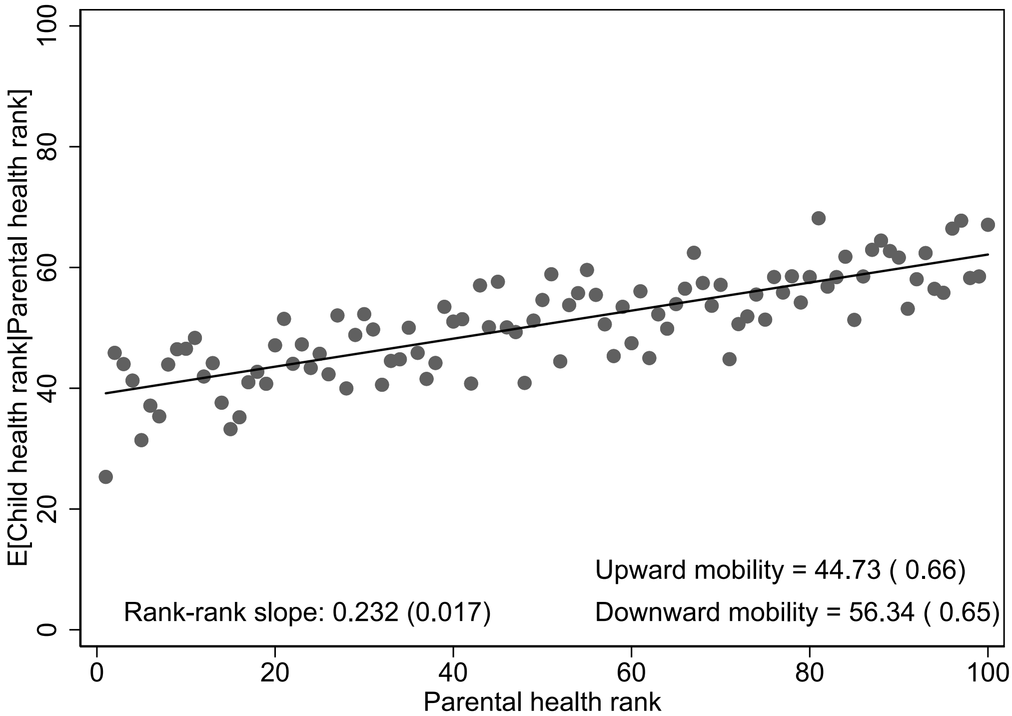
A. Unadjusted



B. Adjusted

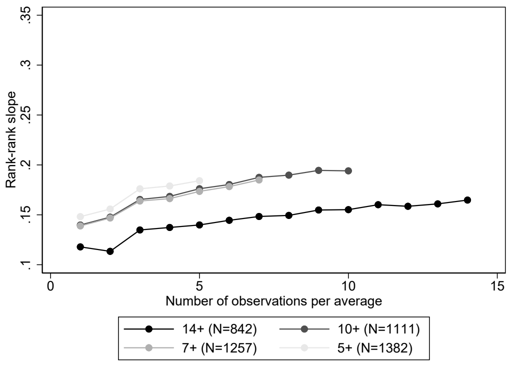
Note: Figures A2A and A2B display the unadjusted and adjusted distribution of permanent health of parents and their children, respectively. Higher value correspond to better permanent health. Bars without a filling color correspond to the parent's permanent health. Grey bars correspond the children's permanent health. Figure A2A displays the unadjusted distributions of permanent health. Figure A2A displays the distributions of permanent health, adjusted for a second order polynomial in age and year of birth fixed effects.

FIGURE A3. Rank mobility in permanent health

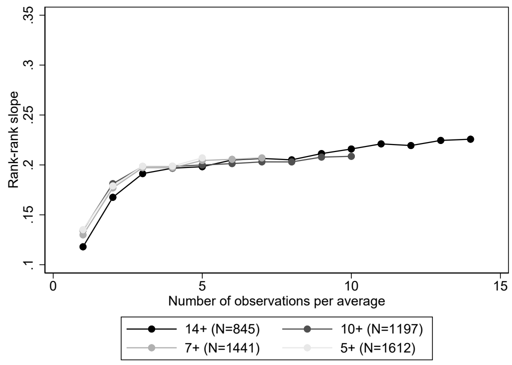


Note: Figure A3 presents nonparametric binned scatter plots and a plot of a linear regression of the relationship between children's and parents' percentile rank in the distribution of permanent health. Each dot corresponds to the children's average percentile rank, conditional on the parents' percentile rank. The linear fit is based on a regression of the children's percentile rank on the parents' percentile rank. Upward and downward mobility correspond to the children's expected percentile rank of parents who are located at the 25th and 75th percentile rank of the distribution of permanent health. Throughout, robust standard errors are clustered on the family level.

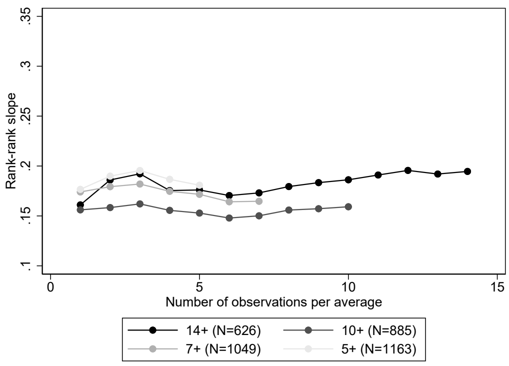
FIGURE A4. Association of rank-rank slopes and the number of observations per permanent health measurement



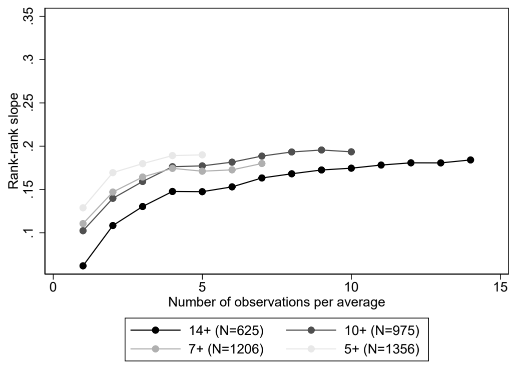
A. Mothers and daughters



B. Mothers and sons



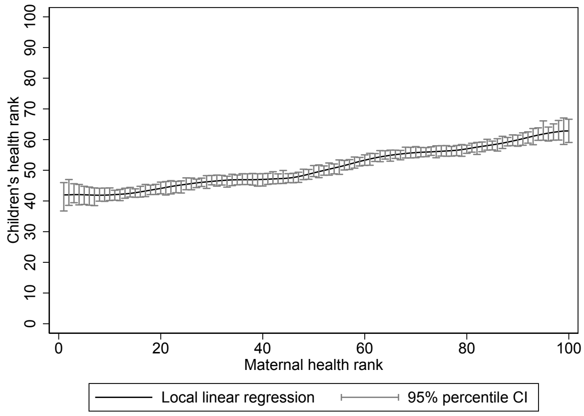
C. Fathers and daughters



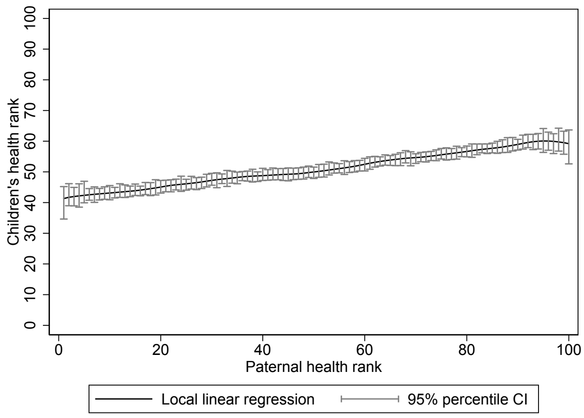
D. Fathers and sons

Note: Figures A4A to A4D illustrate how the rank-rank slope depends on the number of observations for the parental measurement of permanent health. The figures display the rank-rank slope of regressions of the children's percentile rank on the parents' percentile rank in the respective distribution of permanent health for different number of health observations per measurement of the permanent health per sample. The samples correspond to samples in which parents have at least 5, 7, 10, or 14 health observations available. Each figure presents results for a different parent-child sample.

FIGURE A5. Non-linear rank-rank regressions



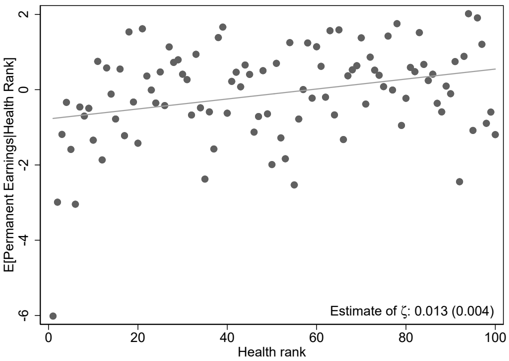
A. Mothers



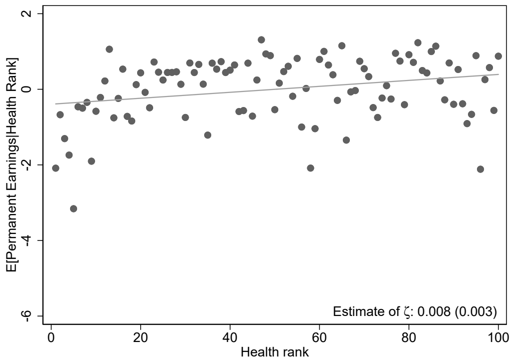
B. Fathers

Note: Figures A5A to A5B display the fit of a local linear rank-rank regression and the corresponding 95% percentile confidence intervals, based on bootstrapped standard errors with 50 replications each, for mothers as well as fathers and their children, respectively. We used an Epanechnikov kernel with bandwidth $w = 6$.

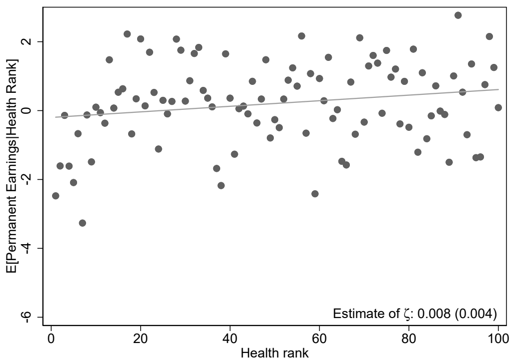
FIGURE A6. Anchoring the distribution of permanent health in permanent earnings



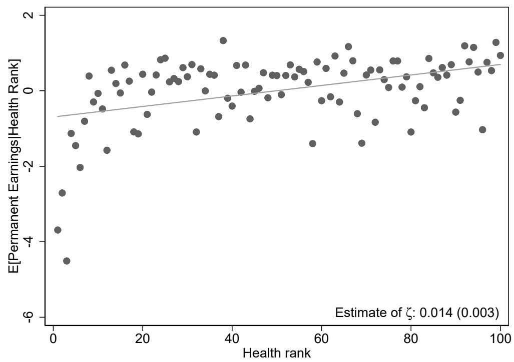
A. Daughters



B. Sons



C. Mothers



D. Fathers

Note: Figures A6A to A6D present the association between permanent earnings and percentile rank in the distribution of permanent health. The gray dots correspond to nonparametric binned scatter plots, displaying the sample equivalent of the population mean of the permanent earnings, conditional on the own percentile distribution of permanent health. The linear fit corresponds to a regression of the permanent earnings on the own percentile rank. Robust standard errors, in parentheses, are robust to heteroscedasticity.

Intergenerational Health Mobility in Germany: Online Appendix

Daniel Graeber

October 31, 2023

Contact: Daniel Graeber, SOEP at DIW Berlin, IZA Bonn & CEPA. dgraeber@diw.de.

Appendix A. A theoretical model on intergenerational health mobility

In this section, we show that the intergenerational persistence of health can be derived as the result of the utility maximizing behavior of a representative altruistic parent. In the following, we build on Solon (1999) to illustrate this. We assume that the parent's lifetime utility $U(\cdot)$ depends on the parent's own lifetime consumption in period $t-1$, C_{t-1}, and her child's lifetime health in period t, H_t:[1]

$$U(C_{t-1}, H_t). \tag{A1}$$

We further assume that the parent's lifetime budget constraint is

$$w_{t-1}h^{w} = p_{t-1}C_{t-1} + m_{t-1}, \tag{A2}$$

with w_{t-1} being the market wage and h^w the hours that the parent spends in market production. Thus, $w_{t-1}h^w$ is the parent's lifetime or permanent earnings. The parent spends this income either on consumption, paying p_{t-1} per consumption unit or service, and on investments into the child's health, m_{t-1}. For simplification, all prices are expressed relative to the price for investments in health goods.

The parent's time budget is

$$1 = h^{w} + h^{sick}. \tag{A3}$$

That is, the parent spends her time either working or being sick, h^{sick}. The time spent sick is a function of the parent's permanent health status, i.e., $h^{sick} = f(H_{t-1})$. We assume that $f' < 0$.

The health investments translate into child's health in the following manner:

$$H_t = (1+r)m_{t-1} + E_t, \tag{A4}$$

where r is the return on health investments and E_t corresponds to the health endowments of the child. The implied Lagrangian function, after substituting in Equation A4

[1]For the sake of brevity, we assume that the discount factor is equal to one.

and A3, looks as follows:

$$\mathcal{L} = U(C_{t-1}, m_{t-1}) + \lambda(w_{t-1}(1 - h^{sick}) - p_{t-1}C_{t-1} - m_{t-1}). \tag{A5}$$

From the parent's optimization problem, the following optimality condition results:

$$\frac{\frac{\partial U}{\partial C_{t-1}}}{\frac{\partial U}{\partial m_{t-1}}} = \frac{p_{t-1}}{1}. \tag{A6}$$

The optimality condition A6 implies that, in the optimum, the marginal rate of substitution of the parent's health investments and consumption equals the ratio of the respective prices. If we assume convex preferences, i.e., the parent prefers a mix of own consumption and child's good health over only one or the other, the usage of additional income is determined by the marginal rate of substitution. If additional utility derived from investing one unit into child's health exceeds the additional utility from own consumption, the parent will invest into the child's health and vice versa.

Let us assume that the parent's preferences imply a Cobb-Douglas utility function:[2]

$$U(C_{t-1}, H_t) = (1 - \alpha)log(C_{t-1}) + \alpha log(H_t), \text{ with } \alpha \in (0, 1). \tag{A7}$$

In this case, the parent's optimal demand for health is

$$m_{t-1} = \alpha w_{t-1}(1 - h^{sick}) - \frac{1 - \alpha}{1 + r}E_t. \tag{A8}$$

Plugging A8 into A4, we have

$$H_t = (1 + r)\alpha w_{t-1}(1 - h^{sick}) + \alpha E_t. \tag{A9}$$

Note that the parent's time sick is a function of their own permanent health. Further, let's assume that

$$h^{sick} = f(H_{t-1}) = \sigma H_{t-1}^{-\delta}, \text{ with } \sigma > 0 \text{ and } \delta > 0. \tag{A10}$$

Then, it follows that

$$H_t = (1 + r)\alpha w_{t-1}(1 - \sigma H_{t-1}^{-\delta}) + \alpha E_t. \tag{A11}$$

[2]For the sake of brevity, we assume the parent's discount factor is equal to one.

Equation A11 implies that the first derivative of the child's health with respect to the parent's health is positive:

$$\text{(A12)} \qquad \frac{\partial H_t}{\partial H_{t-1}} = (1 + r)\alpha w_{t-1}\delta H_{t-1}^{-\delta-1} > 0.$$

To our knowledge, the fact that the intergenerational transmission of health arises as a result of the optimizing behavior of a representative parent, who is altruistic towards their own child but restricted by a monetary and time budget constraint, has not yet been shown in the economic literature. While important previous studies investigate how parents invest in their children's health (see the overview in Currie and Almond 2011; Heckman and Mosso 2014), no previous study rationalizes intergenerational transmission of health. The strength of the transmission of health depends on the parameters of the child's health production function, the strength of the parent's altruism toward their child, wages, and how the parent's health translates into sick days, which depends on the parent's occupation. While this model shows that the strength of the transmission, i.e., the coefficient for the parent's health status, depends on socio-economic factors, it also encompasses the possibility that the child's health is shaped by factors that children share with their parents, such as genetics. This would be captured in E_t. The relative importance of these factors is an empirical question, ultimately depending on society's social stratification and the health outcome(s) under consideration (Björkegren et al. 2019).

Appendix B. Details on the IRT model

In this section, we provide details on the IRT model. Let $A_{ij} = k$ correspond to the answer to item j given by individual i, with $k \in M_j = \{m_1, m_2, \ldots, m_{h_j}\}$, such that $m_1 < m_2 < \cdots < m_{h_j}$. M_j is of cardinality h_j. The scalar $H \in \mathbb{N}$ is the number of health items. The GRM explicitly models the probability of observing answer m_k or higher for item j for individual i as a non-linear function of the latent health status θ_i. Thus, in a first step, we estimate the parameter space $\mathbf{B} = \{\mathbf{a}, \mathbf{b} \mid \mathbf{a} \in \mathbb{R}^H, \mathbf{b} \in \mathbb{R}^P\}$, in which $\mathbf{a}$ corresponds to vector $(\alpha_1, \ldots, \alpha_H)$ and $\mathbf{b}$ to vector $(b_{11}, b_{12}, \ldots, b_{1h_1}, b_{21}, \ldots, b_{Hh_H})$, and P is the sum over all h_j, of the model

$$P(A_{ij} \geq m_k \mid \theta_i) = \frac{\alpha_j exp(\theta_i - b_{jk})}{1 + \alpha_j exp(\theta_i - b_{jk})}. \tag{A13}$$

In Equation A13, parameter α_j describes the discriminatory power of item j and b_{jk} is the difficulty parameter associated with each potential response for each item. The probability of observing answer k to item j for each respondent i is then given by the empirical mean of

$$P(A_{ij} = m_k \mid \theta_i) = P(A_{ij} \geq m_k \mid \theta_i) - P(A_{ij} \geq m_{k+1} \mid \theta_i). \tag{A14}$$

After estimating the parameters in $\mathbf{a}$ and $\mathbf{b}$, we estimate the value of the latent health status θ_i in a second step by the empirical Bayes method. Assuming that $\theta_i \sim \mathcal{N}(0, 1)$, it follows that

$$\hat{\theta}_i = \int_{-\infty}^{\infty} \theta_i \prod_{j=1}^{H} \frac{P(A_{ij} = k \mid \theta_i, \hat{\alpha}_i, \hat{b}_{jk}) f(\theta_i)}{\int_{-\infty}^{\infty} \prod_{j=1}^{H} P(A_{ij} = k \mid \theta_i, \hat{\alpha}_i, \hat{b}_{jk}) f(\theta_i) d\theta_i} d\theta_i. \tag{A15}$$

The resulting estimate $\hat{\theta}_i$ proxies the contemporaneous latent health status or health capital of the individual i.

Appendix C. Life-cycle profile of the latent health status

The literature on intergenerational income mobility emphasizes that is of utmost importance to take earnings observations from an age range between the early thirties and mid-forties (Haider and Solon 2006; Nybom and Stuhler 2016, 2017). Otherwise, earnings observations or averages of multiple earnings observations are likely to be a biased proxy for permanent income or life-time earnings. The sources of these biases are heterogenous earnings growth rates over the life-cycle across individuals. For instance, individuals with higher permanent income typically have lower earnings at the beginning of their life but steeper earnings growth rates later in the life-cycle than individuals with lower permanent income. One reason for these heterogenous growth rates are different propensities to invest in human capital (Mincer 1958; Ben-Porath 1967; Becker 1962).

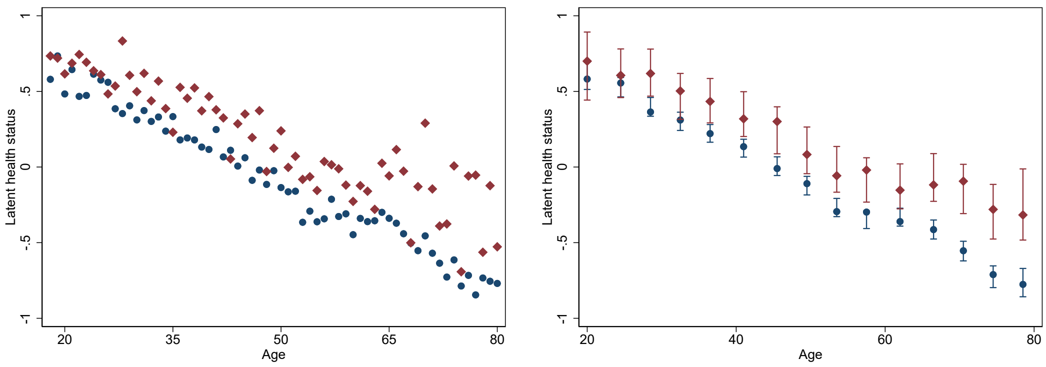
Similar to earnings, health is also potentially prone to heterogeneous changes over the life-cycle across individuals with different SES. Therefore, we illustrate the life-cycle pattern in health in this section. To be precise, we lay out some life-cycle facts of our health measure, focusing specifically on a single cross-section in year 2007. We restrict the age range to observations between age 18 and 80. Next, we calculate the mean for each age-paternal education-cell. The resulting plot is displayed in Figure A1A. Figure A1B corresponds to the binned scatter plot based on the data for Figure A1A.[3] Figure A1A and A1B together lead to our first observation:

(a) *Differences that are traced back to the parental background stay latent until midlife and become salient thereafter.*

Clearly, in Figure A1A, the averages of both groups largely overlap. Further, the confidence intervals in Figure A1B suggest that the health status is statistically indistinguishable between groups until the age of thirty. Thus, like earnings, no clear ordering of the two groups with respect to health can be established until approximately age 30. After the age of 30, a clear ordering emerges, with rather stable differences between groups until the retirement age. Thus, relying on observations before age 30 could result in misleading conclusions. This is similar to the problem with early observations for earnings, when orderings are not well established. This is why we take observations starting from 30 until retirement.

[3] We use the Stata package **binsreg**. For the documentation, please refer to Cattaneo et al. (2019).

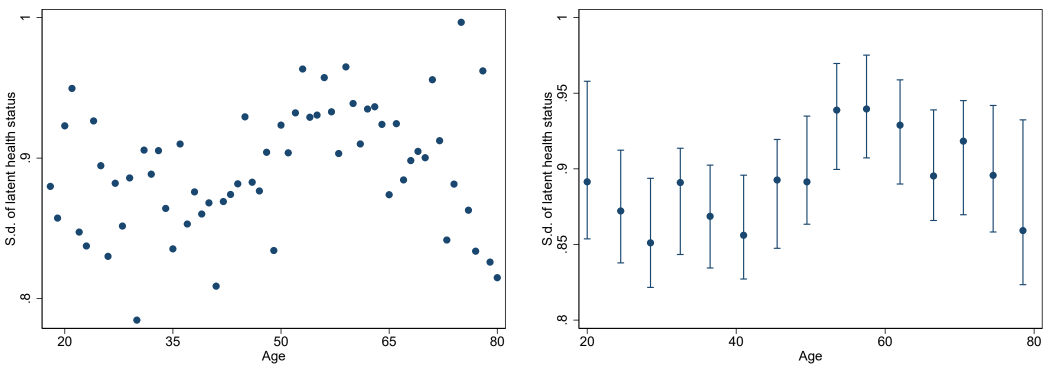
FIGURE A1. Life-cycle profile of the latent health status



A. Raw data B. Binscatter

Note: Figures A1A to A1B display the life-cycle trajectories in latent health by age and paternal education. Figure A1A displays the average latent health status by age and education level. Figure A1B displays binned scatter plots with 15 bins. In Figure A1B, the dots correspond to means of the bins. The vertical bars correspond to 95% confidence intervals, based on robust standard errors for polynomials of degree three with three smoothness constraints. Blue dots correspond to the averages of children whose fathers have no or only a basic school leaving degree. Red dots correspond to the averages of individuals whose fathers have a tertiary school leaving degree.

FIGURE A2. Inequality in health over the life-cycle



A. Raw data B. Binscatter

Note: Figures A2A to A2B display the standard deviation in the latent health status over age. Figure A2A displays the standard deviation of the latent health status by age. Figure A2B displays the corresponding binned scatter plot with 15 bins. In Figure A2B, the dots correspond to means of the respective ages. The vertical bars correspond to 95% confidence intervals, based on robust standard errors for polynomials of degree three with three smoothness constraints.

Moreover, in Figure A2A and A2B, we display the standard deviation in latent health by age. Clearly, the standard deviation in latent health increases with age. Therefore, we summarize the following:

(b) *Health inequalities increase with age.*

This is consistent with previous evidence on health inequalities over the life-cycle (Timothy 2011; Deaton and Paxson 1998; Halliday, Mazumder, and Wong 2020), resulting in important implications for the measurement of intergenerational persistencies in health. If one regresses children's on parental health, results will clearly depend on the age range at which parents' or children's health is measured. If health inequalities increase with age, as shown in Figures A2A and A2B, health associations decrease as we take parental observations from older than younger ages, *ceteris paribus*. Similarly, OLS associations will increase as we take observations from higher ages than lower ages for children. This is a direct consequence of the observation that the OLS coefficient corresponds to the linear correlation between the two outcomes, rescaled by the ratio of the standard deviation of the children's and parents' health outcomes. This is not the case for rank-rank regressions, which are invariant to any mean preserving spread. This is a direct consequence of the fact that, for the uniform distribution, with lower and upper bound equal to zero and one, the variance is equal to $\frac{1}{12}$. Thus, changes in the variance with age are not relevant for rank-rank regressions.

Appendix D. Detailed information on the utilized health information in the SOEP and the calibration of the IRT model

In this section, we provide more detail on the health items as well as the calibration of the IRT model. The self-rated health status is inferred by the answer to the question, "How would you describe your current health?" Answers are given on a five-point Likert-scale ranging from one "Very good" to five "Bad." The self-rated health status is shown to be highly predictive for illnesses and mortality, even after conditioning on objective health information (see van Doorslaer and Gerdtham (2003), Pijoan-Mas and Ríos-Rull (2014), Miilunpalo et al. (1997) for an overview; Schwarze, Andersen, and Anger (2000) provide evidence for the SOEP).

A related subjective measure of the current health status is satisfaction with health. Satisfaction with health is inferred by the answer to the question "How satisfied are you with your health?" Answers are given on an eleven point Likert-scale ranging from zero "Completely dissatisfied" to ten "completely satisfied."[4]

The two reported objective measures for in- and outpatient care are doctor visits within the last three months and hospital admissions in the previous year. Note that we dichotomize the number of hospital visits and the number of doctor visits within three months prior to the interview. The reason is that we want to ensure that the items are reflective of health and not a formative factor of health. One could, for instance, argue that preventive care can be a cause of good health. Thus, for hospital visits, we construct an indicator that is equal to one if an individual has been admitted to the hospital at least twice in the previous year.[5] For doctor visits, we construct an indicator that is equal to one if an individual visited the doctor more than three times in the last three months.

The objective measure for health is the degree of disability or reduced earnings capacity. In Germany, individuals can apply to have their disability ascertained by a medical reviewer. The degree of disability is then documented, allowing the individual to access compensation, including tax allowances, additional vacation days, and early retirement, among others. The process is highly formalized and documented in a law enacted by the federal government.[6] The degree of disability starts at 0, indicating the

[4] We reverse the scale such that all scales of the health items have the same polarization.

[5] We use two hospital visits since giving birth is associated with hospital stays for females. We argue that this is not necessarily related to health.

[6] "Verordnung zur Durchfuehrung des §1 Abs. 1 und 3, des §30 Abs. 1 und des §35 Abs. 1 des Bundesversorgungsgesetzes (Versorgungsmedizin-Verordnung - VersMedV)"

absence of disabilities, and ranges to 100 in increments of 10. Additionally, the reduced earnings capacity captures the degree to which individuals are incapacitated for work. Again, this is highly regulated and exact formulations are found in the social security code[7]. Realizations of the degree of reduced earnings capacities can potentially range from 0 to 100.[8] We discretize the degree of disability into eleven categories.

We calibrate the IRT model for the full population of the SOEP in 2006, the middle of the observation period, and for all respondents providing answers to all items. [9] However, in a first step, we show that the correlation between the five health items is consistent with a unique trait causing the co-movement of the health items.

A principal component analysis of the health items for the population of the SOEP in 2006 shows that the items load unambiguously on one factor. Based on that, we conclude that the items are reflective of an underlying trait, which we refer to as latent health status. For instance, Figure A3 plots the factors and their corresponding Eigenvalues in descending order according to the magnitude of the respective Eigenvalue. While the first factor has an Eigenvalue of 2.37, the second factor has an Eigenvalue of 0.94, which is below the threshold of 1 implied by the Kaiser criterion (Kaiser and Dickman 1959). Lastly, the second factor is the factor at which the curve in the scree-plot levels off, leaving the first factor as the only significant factor (Cattell 1966).[10] Further, the factor loadings, depicted in Table A1, range from 0.87 for the self-rated health status to 0.36 for the hospital visits in the previous year. Three out of five items are associated with factor loadings of 0.85 or higher. Throughout, the self-reported health measures and the degree of disability are associated with higher factor loadings than the reports of out- and inpatient care.

In a second step, we calibrate the GRM model and predict the latent health status for all individuals in all years for which we observe full item response on the five health items. In a third step, we keep all individuals in the age range 30 to 65 in the children's and parent's generation. Then, in a last step, we take the individual time average using all available observations for individuals, after accounting carefully for age as well as year of birth fixed effects. The last step accounts for transitory shocks to health. Otherwise, our estimates may suffer from attenuation bias, as shown in the sensitivity analysis.

[7]"Sozialgesetzbuch 6, §43"

[8]The degree of disability and the degree of reduced earnings capacity are assessed within the same item in the SOEP.

[9]This procedure is similar to the routine to calibrate the physical and mental scale of the SF12v2 in the SOEP (Nuebling et al. 2007).

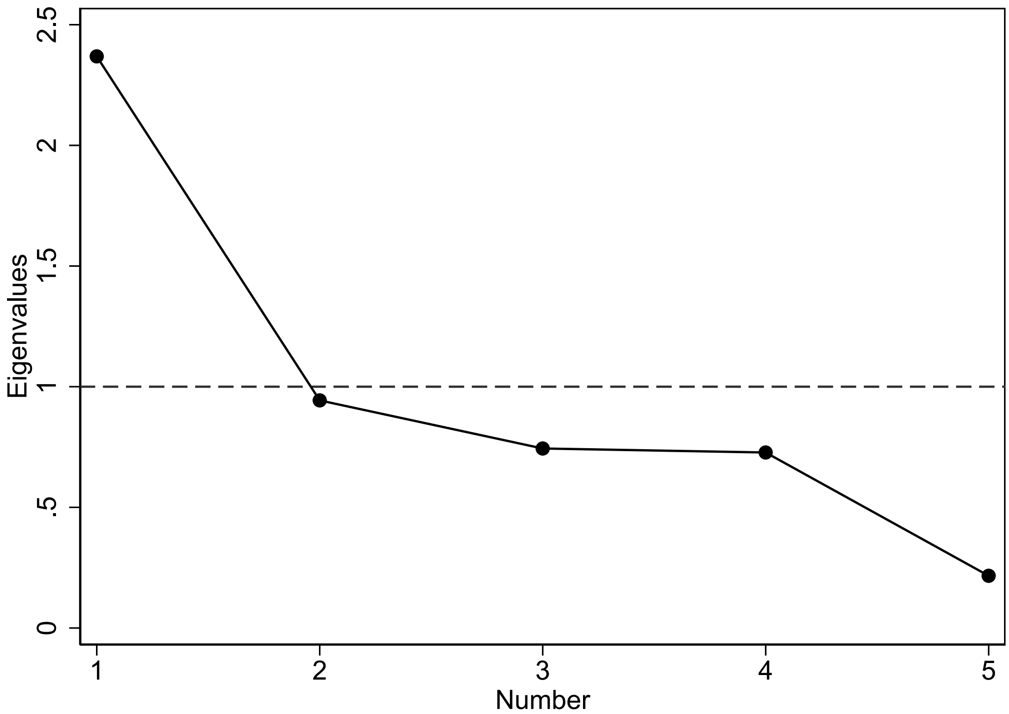
[10]This is the intuition of the "Elbow-criterion."

TABLE A1. Factor loadings of a principal component analysis of health items of the SOEP population in the survey year 2006

Item (1)	Factor loading (2)
Self-rated health status	0.87
Satisfaction with health	0.85
More than three doctor visits in last three months	0.61
More than one hospital visit in previous year	0.36
Degree of disability	0.87

Note: Table A1 displays the factor loadings of a principal component analysis of the recoded health items in the SOEP survey year 2006. The sample is restricted to full response on the five health items. Column (1) shows the recoded health item. Column (2) displays the corresponding factor loadings for the first factor.

FIGURE A3. Screeplot of principal component analysis of health items in 2006



Note: Figure A3 plots the Eigenvalue of a principal component analysis of self-rated health status, satisfaction with health, an indicator for having visited the doctor more than three time in the last three months, an indicator for being admitted to the hospital for at least two times in the previous year, and a discretized version of the degree of disability against the corresponding factors, with the factors being ordered in descending order. The dashed horizontal line indicates Eigenvalues with a value of one.

Appendix E. Description of attrition and representativity

In the following, we describe the degree of attrition and analyze the representativeness of our sample. We find the that our sample is representative of the relevant population. This allows us to conclude that attrition does not threaten the validity of our results. As a consequence, our estimates can be interpreted as reflecting the population parameters.

E.1. Attrition

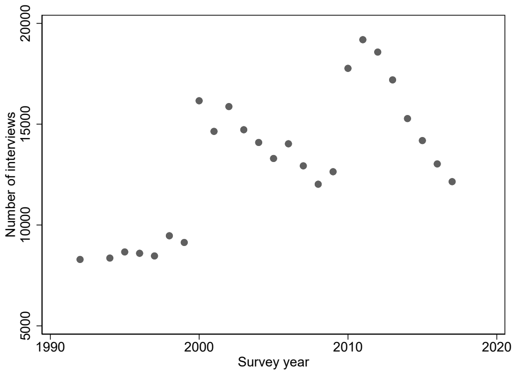
Attrition is common in panel analysis. This phenomenon compounds when we link two generations. For this reason, we describe the attrition in our sample for all relevant variables. These are the number of interviews within the age range 30 to 65 over the years 1992 and 1994 to 2017. Among these observations, we count the number of observations with parental identifier(s) in the relevant age and year cells. Then, we show the number of observations in the relevant age and year cells for which we observe parental identifier(s) and parental health information. Finally, we count the number of observations that have all necessary information, i.e., the correct age-year cells, parental identifiers(s), the parents' health information and information about one's own health. This analysis is displayed in Panel A4.[11]

Figure A4A displays the number of observations in the age range 30 to 45 over the years 1992 and 1994 to 2017 with completed interviews. The number of observations vary over time. For the observations from 1992 to 1999, the number of observations is about 8,700. For the years 2000 to 2009, the number of observations per year increases to an average of 14,000. For the years 2010 to 2017, the average numbers of observations per year increases to 16,000. The explanation for the discontinuous increase in the number of observations in the years 2000 and 2010 is the fact that, in this years, refreshments or additional samples were added to the SOEP so that the data maintains representativity. This is typically caused by changes of the underlying population, such as immigration due to the eastward enlargement of the European Union or the need of larger samples. Most of the time, this is a steady process, with the refreshments in 2000 and 2010 being particular large. For an overview of the development of the samples in the SOEP, please refer to Figure 1 on page 33 in Siegers, Steinhauer, and Dührsen (2021).

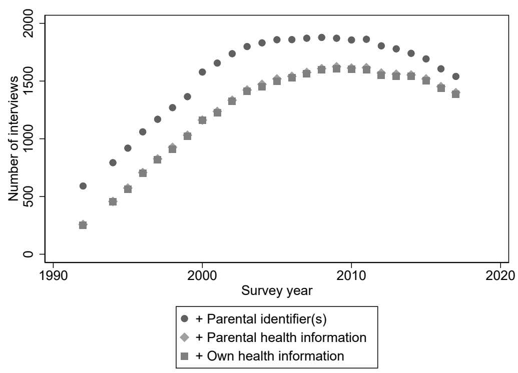
Figure A4B displays the number of observations with parental identifiers in the age range 30 to 65 over the relevant years. These numbers are indicated by the dots. This

[11]We neglect attrition because of non-available demographic information such as year of birth and sex. Among all observations, this information is missing only for about 0.5% of all observations.

FIGURE A4. Attrition analysis



A. Realized personal interviews



B. Observations with required information

Note: Figures A4A and A4B illustrate the number of observations with available information. Figure A4A displays the share of realized personal interviews of respondents in the age range 30 to 65 over the years for whom we have potential health information. Figure A4B shows the yearly number of observations in the age range 30 to 65 over the years for which we have potential health, parental identifier(s), associated parents with the required health information, and information about the respondents' own health.

number is increasing over the years as the number of children who become old enough to join the SOEP increases. This number ranges from 591 in 1992 to 1,878 in 2008. The other two time series reflect the number of children in the SOEP who have parents in the SOEP, who provide the necessary health information at the right age, as well as the same number restricted to children who also provide information about their own health status. Those time series are displayed by the diamonds and squares in Figure A4B. The number of observations for which we have the required information on the parents ranges from 259 in 1992 to 1,624 in 2009. If we further require that the children also provide information on their own health status, this number varies from 249 in 1992 to 1,607 in 2009.

Panel A5 display the available observations per year for both mothers and fathers.[12] Figure A5A displays the analysis for all fathers of children who are also part of the SOEP. The round dots indicate the number of fathers with at least one child who is part of the SOEP. Clearly, that number varies over time. Again, discontinuities are associated with this time series. These discontinuities correspond to the introductions of large

[12] Note that the parental identifiers also include parents who provide proxy information about their children if these children are not old enough to respond to the questionnaire or if the children are surveyed with the youth questionnaire. Hence, the degree of attrition, if we analyze how many children provided the required health information, can be interpreted as an upper bound.

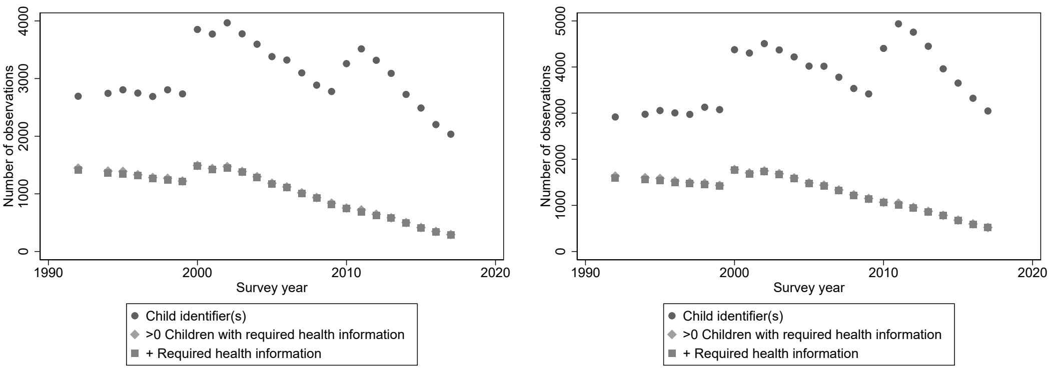
refreshments to the SOEP (Siegers, Steinhauer, and Dührsen 2021). For the years 1992 to 1999, the number of fathers who have at least one child that is part of the SOEP ranges from 2,693 in 1992 to 2,734 in 1999. For the years 2000 to 2009, the number of fathers who have at least one child that is part of the SOEP goes from 2,776 in 2009 to 3,852 in 2000. The same number varies from 3,259 in 2010 to 2,035 in the year 2017. The diamonds in Figure A5A indicate the number of observations that have children in the SOEP that are observed in the age range 30 to 65 and who provided the required health information. This figure ranges from 1,450 in 1992 to 294 in 2017. Relative to the times series of the number of fathers with at least one child that is part of the SOEP, this corresponds to about 54% in 1992 and about 14% in 2017. These dynamics are a result of the combination of fathers becoming older and, hence, dropping out of the sample, children not being old enough or too old to be included in the sample, and panel attrition. The squares in Figure A5A correspond to the number of fathers that have children who are part of the SOEP and are observed in the age range 30 to 65, with valid health information, and for which we observe the fathers' health information. This number goes from 1,415 in 1992 to 289 in 2017. These numbers correspond to about 98% of the fathers in the SOEP for which we have the children's health information in the age range 30 to 65.

Figure A5B repeats the analysis for all mothers of children who are also part of the SOEP. We count 2,917 mothers of children that are part of the SOEP in 1992. This number increases to 3,076 in 1999. For the years 2000 and 2009, these numbers correspond to 4,376 and 3,417, respectively. For the years 2010 and 2017, these numbers are 4,404 and 3,047, respectively. The diamonds in Figure A5B indicate the number of mothers who have children in the SOEP that are observed in the age range 30 to 65 and that provided the required health information. This number goes from 1,638 in 1992 to 522 in 2017. That corresponds to about 56% of the initial number of mothers of children who are part of the SOEP in 1992 to 17% in 2017. The squares in Figure A5B correspond to the number of mothers who have children that are part of the SOEP and are observed in the age range 30 to 65 and for which we observe the mothers' health information. These numbers are 1,593 in 1992 and 517 in 2017. These numbers correspond to about 97% and 99% of the observations for which we have the children's health information in the age range 30 to 65, respectively.

E.2. Representativity

The SOEP is the only panel in Germany that allows for intergenerational analysis with adult children in Germany. The only data from administrative sources that would allow

FIGURE A5. Attrition analysis for parents



A. Fathers

B. Mothers

Note: Figures A5A and A5B illustrate the number of observations with available information for fathers and mothers, respectively. In each figure, the dots correspond to the number of mothers and fathers in the age range 30 to 65 with children who are part of the SOEP, respectively. The diamonds represent the number of mothers and fathers in the age range 30 to 65 with children that are part of the SOEP of the SOEP and whose children are observed over the age range 30 to 65 over the years 1992 as well as 1994 to 2017. The squares show the number of mothers and fathers in the age range 30 to 65 with children who are part of the SOEP and whose children are observed over the age range 30 to 65 over the years 1992 as well as 1994 to 2017 and that provide health information in the respective year.

such an analysis would be the German census because it also interviews the children within the target households, i.e., around the age of 17. In addition, the health information in the German census is very limited, e.g., the German census only collects information about weight and height as well as smoking and drinking behavior. In addition, this data is still based on surveys. While it is mandatory to respond and non-compliance can be sanctioned with a penalty of up to 5,000 Euro according to §23 of the Federal Statistics Act (BStatG), non-response is still possible. For instance, respondents could prefer to pay the fee if they have very high opportunity costs of responding to the census.

Alternative data for such an intergenerational analysis are the "National Education Panel Survey" (NEPS), the "German Health Interview and Examination Survey for Children and Adolescents" (KiGGS), and the "Panel Analysis of Intimate Relationships and Family Dynamics" (pairfarm). However, the NEPS is a panel that is designed to survey respondents about their educational biography and associated outcomes, which could also include health. In the NEPS, parental information for adult panel members is only available retrospectively, as it can be inferred only by the adult children's reports (Hans-Peter, Roßbach, and Maurice 2011). KiGGs provides the best available data on children's and adolescents' health. However, the parental information is very scarce and we would observe children only at very young ages (Hölling et al. 2012). Since we argue that differences in health due to different socio-economic environments during childhood stay latent until mid-age, the KiGGs data would not allow for our analysis. pairfam is primarily designed to study relationship dynamics. It also includes information on child development. However, the data is limited to 14 waves and only covers the parental birth cohorts 1971-73, 1981-83, 1991-93, and 2001-03 (Huinink et al. 2011). Thus, there is no alternative data set covering Germany that provides information on parents and their adult children. Importantly, in none of these alternative data sets, are we able to see children at age 30 or older. As a result, the SOEP is the German benchmark when it comes to the study of intergenerational relationships in Germany. Examples for intergenerational analyses include Dohmen et al. (2012) and Zumbuehl, Dohmen, and Pfann (2021), who study the formation and transmission of economic preferences, as well as Bratberg et al. (2017) and Schnitzlein (2016), who study intergenerational income mobility using the SOEP.

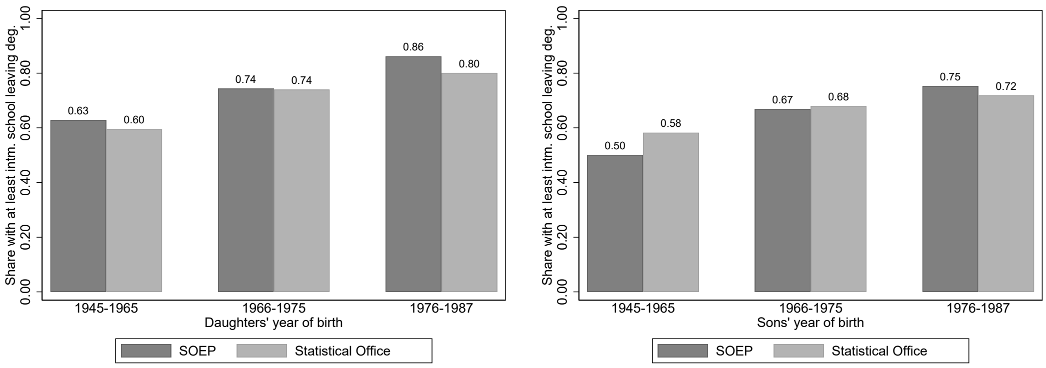
However, when we compare our sample to some known marginal distributions of known population characteristics, we conclude that our sample is representative of the underlying population. The relevant population of interest are all parent-child pairs in the age range of 30 to 65. In order to analyze the representativity of our sample, we focus on the children. The reason is that the selection into parenthood could cause unknown deviations of the characteristics of our population from the overall population, e.g., all persons living in the Federal Republic of Germany. However, we would not expect such deviations for the children. Specifically, every person has some parents, but not every person is a parent to a child. In order to facilitate the discussion, we focus on the time invariant characteristic of education. In addition, we adopt the cohort notation from Section V. Thus, we distinguish between the cohorts born from 1945-1965, 1966-1975, and 1976-1987. We perform this analysis separately for men and for women.

Panel A6 displays the results for education. Figure A6A displays the share of daughters who have at least an intermediary school leaving degree for the SOEP across the three birth cohorts in dark grey. The same figures using the official data from the German Federal Statistical Office is displayed in light grey. This data stems from the 2010 German census (Statistisches Bundesamt 2022). Clearly, the comparison suggests that our sample is very comparable to the underlying population. For the two first birth cohorts, the shares coincide. For the last cohort, the share of women with at least an intermediate school leaving degree is about 7.5% higher in the SOEP than in the official statistics. Overall, the comparison suggests that our sample of adult daughters is comparable to the population of interest.

Similarly, Figure A6B compares the share of sons with at least an intermediate school leaving degree to the corresponding figure from the statistical office over cohorts. Clearly, the shares are very similar across data sources for all three cohorts. For sons who were born between 1945-1965, the share of sons with at least an intermediate school leaving degree is about 14% smaller than the share provided by the statistical office. However, the comparison of the educational background of our population to what represents our population at best suggests that our sample indeed reflects the population of interest well.

We also conclude that our sample is also representative when it comes to the mothers' number of children. Figure A7 compares the share of mothers that have up to two children for the SOEP and the German census from 2008 (Statistisches Bundesamt 2019). Figure A7 displays these figures for different birth cohorts. We focus on birth cohorts that ended their fertility phase or are close to the end of it. We have to group the birth cohorts as depicted in Statistisches Bundesamt (2019). We focus on mothers since the SOEP did not consistently track the birth biography of men. Typically, within households, women were asked to fill out their birth biography. For all but one cohort, we track the

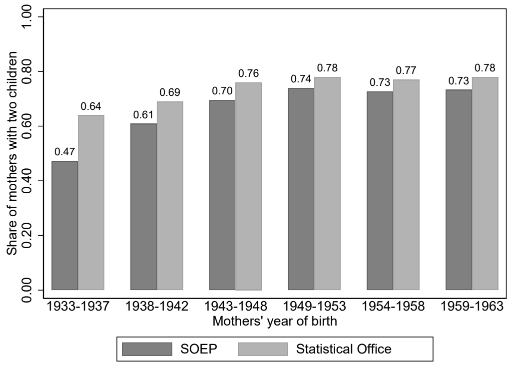
FIGURE A6. Comparison of our sample to the population of interest - Education



A. Daughters

B. Sons

FIGURE A7. Comparison of our sample to the population of interest - Number of children

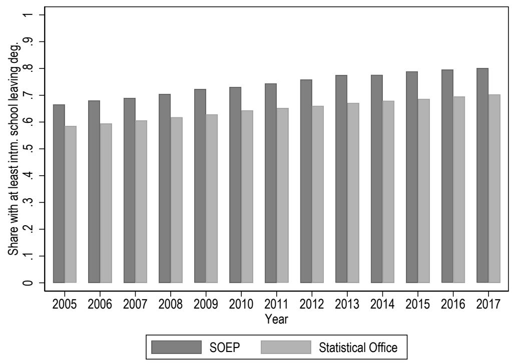


final fertility of mothers very well. However, for the first cohort, we underestimate the fertility somewhat. Regardless, for this cohort, the number of mothers in our data also decreases considerably, making point estimates prone to small sample variation. In addition, for all cohorts, we would also have to take into consideration the statistical uncertainty associated with the point estimates for the SOEP and the census.[13]

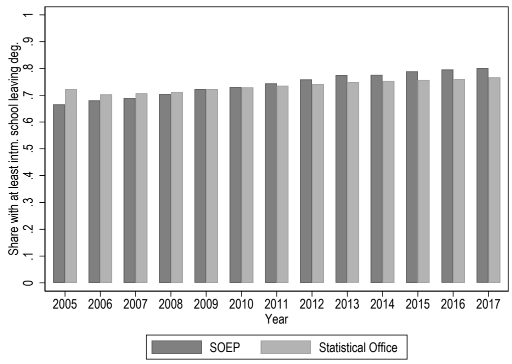
Finally, we also conclude that our sample is representative over the relevant survey years. To gauge the representativeness of our sample with respect to the overall population of child-parent pairs in the relevant survey years, we compare the education of the children in our sample to the overall population for various survey years (Statistisches Bundesamt 2022). For this, we rely on data from the census from the German Federal Statistic Office. Based on this data, we calculate the share of individuals who have at least an intermediate school leaving degree for every year. Unfortunately, this time series from the German Federal Statistical Office is restricted to the years 2005 to 2019. Our sample ranges from 1992 to 2017. Thus, we focus on the years 2005 to 2017. Figure A8A compares the share of individuals with at least an intermediate school leaving degree for both the children in our sample and the population of 30 to 65 year old individuals living in Germany over the survey years 2005 to 2017. Clearly, the figure suggests that for most of the years, the children in our sample are somewhat better educated than the population of all persons that are in the age range 30 to 65. Three possible explanations can cause this difference. First, the German census is a survey and, hence, results based on this survey are also associated with unknown measurement errors that could possibly affect the results. Second, in the last two decades, the net migration

[13]We do not display point estimates since we only have aggregated data from the German census in 2008. However, since the census is also a survey, non-response and misreporting are possible in the census as well.

Figure A8. Comparison of our sample to the population of interest - Education over survey years



A. Age 30 - 65



B. Age 30 - 40

Note: Figures A8A and A8B compares the share of individuals with at least an intermediate school leaving degree in our analysis sample and for the Federal Statistical Office over the survey years 2005 to 2017 for individuals in the age range 30 to 65 and 30 to 40, respectively. The data from the Federal Statistical Office is based on the censuses from 2005 to 2017.

was positive for Germany. Many of these migrants do not yet have children that could be part of our sample, nor are they themselves part of our sample. This could be one reason why our sample appears to be slightly better educated than the population of all individuals living in Germany. A third reason could be the age distribution within our sample. In each year, our population draws more strongly from the age groups 30 to 40 than the older cohorts. If these younger individuals are better educated than the older persons, then this would be reflected by a higher share of individuals with intermediate school leaving degrees in our sample compared to the overall population of individuals in the age range 30 to 65.

We find that the third reason indeed explains a large part of the difference we observe in Figure A8A. Figure A8B displays the analysis as in Figure A8A, but we restrict the age range to 30 to 40 years in both our sample and the data from the German census. Clearly, the difference of the fractions of individuals with at least an intermediate school leaving degree between the SOEP and the German census is smaller for the comparison in which we restrict the age to between 30 and 40 years compared to the analysis in Figure A8A. Overall, the analysis suggests that our sample is comparable to the population of interest for all survey years.

Overall the representativeness of our sample suggests that attrition is not a problem for our analysis. Our estimates can be interpreted as reflecting the underlying population parameters.

Appendix F. Short literature overview about parental SES and children's health

An influential literature investigates the gradient in the association between parental income or earnings and children's health (e.g. Blau 1999; Case, Lubotsky, and Paxson 2002; Reinhold and Jürges 2012; Khanam, Nghiem, and Connelly 2009; Currie, Shields, and Price 2007; Currie and Stabile 2003; Apouey and Geoffard 2013; Kuehnle 2014). Typically, parents with higher earnings are hypothesized as being able to provide a more favorable environment for their children, e.g., they can buy healthier food, medical services, or are better able to adhere to medical instructions (Case, Lubotsky, and Paxson 2002). Three stylized facts emerge from this literature: First, the gradient between parental income and children's health increases with the children's age. Second, the association between parental income and children's health is mainly attributed to differences in the severity of health conditions in contrast to the prevalence of health conditions. Third, it is permanent income rather than contemporaneous income that matters. In what follows, we compare intergenerational mobility in health for children of parents with permanent earnings above and below the median.

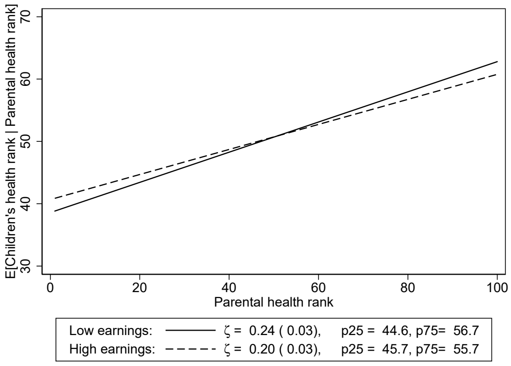
A large literature investigates the effect of parental education on children's health (Thomas, Strauss, and Henriques 1991; Lindeboom, Llena-Nozal, and van der Klaauw 2009; Lundborg, Nilsson, and Rooth 2014; Silles 2015; Kemptner and Marcus 2013; Huebener 2022). In this literature, parental education is hypothesized to affect the children's health via improved parental behavior or increased financial resources (e.g. Lindeboom, Llena-Nozal, and van der Klaauw 2009). While still inconclusive, the majority of studies in this literature points toward a positive effect of parental education on children's health.

A low occupational status is often associated with physical and mental strain as well as low job control (Ravesteijn, Kippersluis, and Doorslaer 2018). In particular, the stress associated with low occupational status can negatively affect the interaction between parents and their children. Moreover, the literature shows that stress on the parents' side limits the attention parents can give to parenting (e.g. Cobb-Clark, Salamanca, and Zhu 2019). Consequently, we expect health mobility to differ by parental occupational prestige.

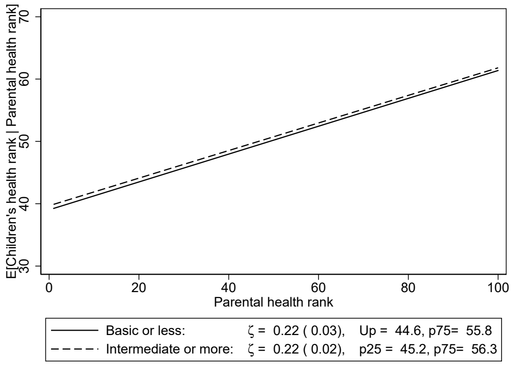
In social sciences, the literature documents a "healthy immigrant effect" (e.g. Antecol and Bedard 2006; Domnich et al. 2012; Jasso et al. 2004; zur Nieden and Sommer 2016; Palloni and Arias 2004; Razum et al. 1998; Ullmann, Goldman, and Massey 2011; Giuntella and Mazzonna 2015; Kennedy, McDonald, and Biddle 2006; Antman, Duncan, and Trejo 2020). The "healthy immigrant effect" describes the empirical phenomenon that immigrants are healthier than the native population. Typical explanations for this are selection, health behaviors, and return migration (e.g. Giuntella and Mazzonna 2015). In addition, a scarce literature focuses on health differences between children of immigrant and native born parents (e.g. García-Pérez 2016; Kotwal 2010; Razum et al. 1998). In the U.S., evidence points toward a convergence, if not reversal, of the initial health advantage of immigrants across generations (García-Pérez 2016). For Germany, epidemiological studies suggest a persistence of the "healthy immigrant effect" into the second generation (Kotwal 2010; Razum et al. 1998).

Appendix G. Additional figures

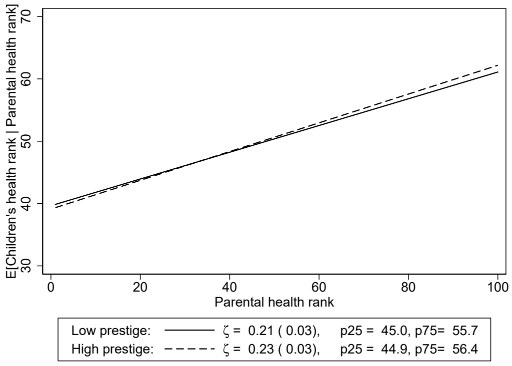
FIGURE A9. Parental socioeconomic characteristics and health mobility



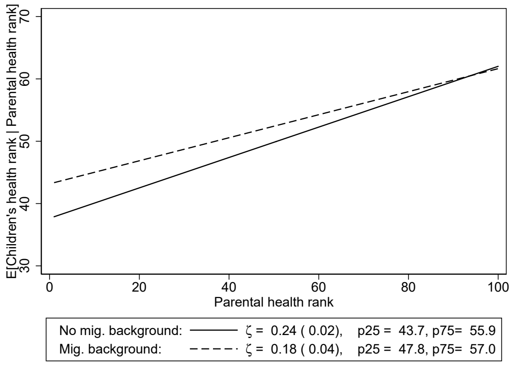
A. Permanent earnings



B. Education



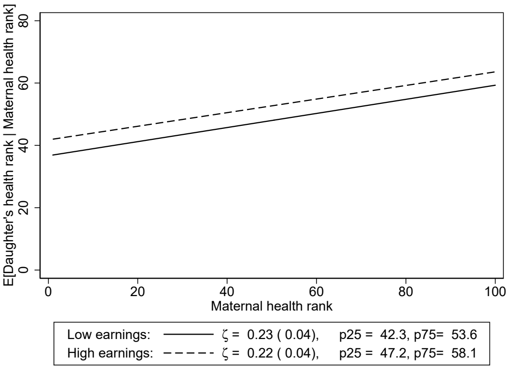
C. Occupational prestige



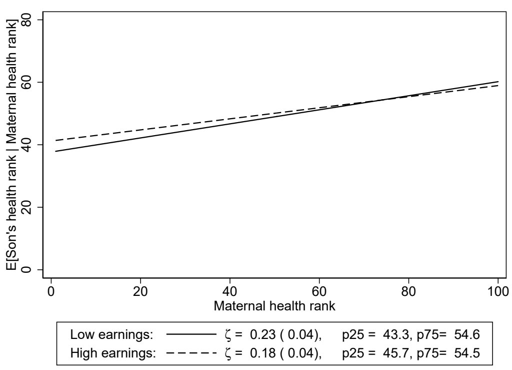
D. Migration background

Note: Figures A9A to A9D display the variation in intergenerational mobility in health with parental socioeconomic characteristics. Each figure displays a linear fit of a regression of the children's percentile rank on the parents' percentile rank for subgroups. The respective estimates of up- and downward mobility are denoted p25 and p75, respectively. Robust standard errors are clustered on the family level.

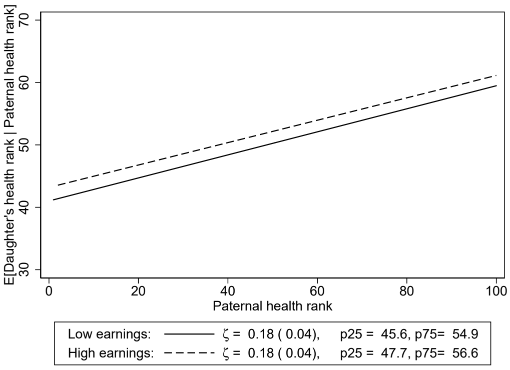
FIGURE A10. Parental permanent earnings and health mobility



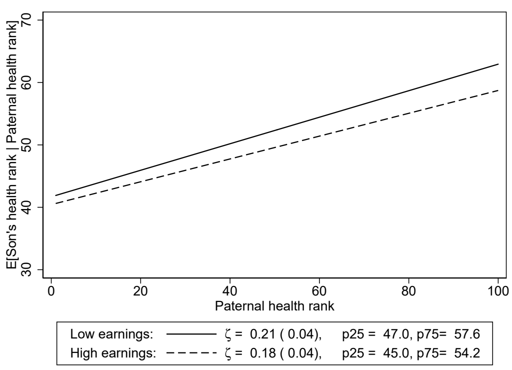
A. Mothers and daughters



B. Mothers and sons



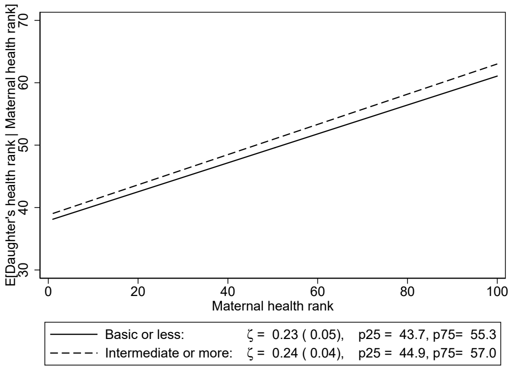
C. Fathers and daughters



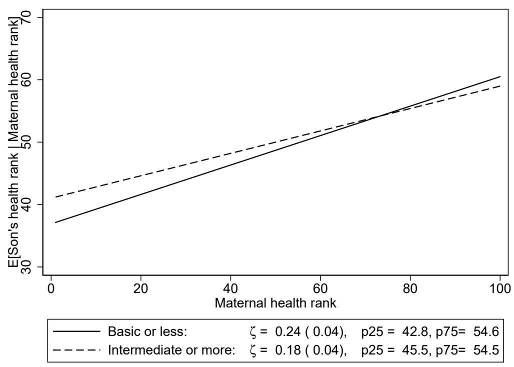
D. Fathers and sons

Note: Figures A10A to A10D display the variation in intergenerational mobility in health with respect to parental permanent earnings for different parent-child relations. Each figure displays a linear fit of a regression of the children's percentile rank on the parents' percentile for parents with high and low permanent earnings. The respective estimates of up- and downward mobility are denoted p25 and p75. Robust standard errors are clustered on the family level.

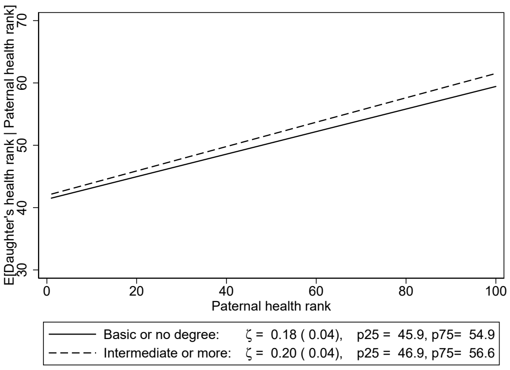
FIGURE A11. Parental education and health mobility



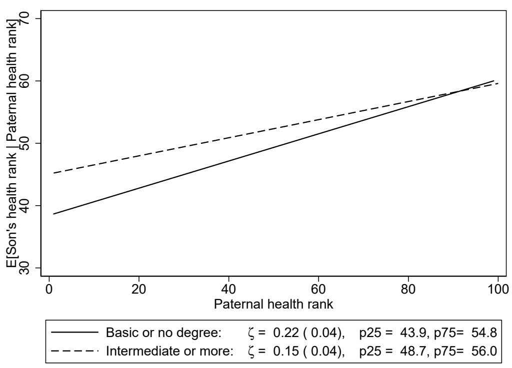
A. Mothers and daughters



B. Mothers and sons



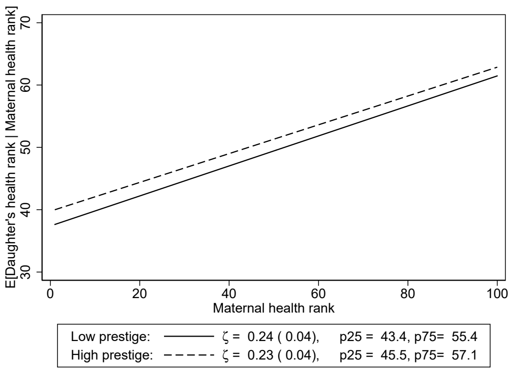
C. Fathers and daughters



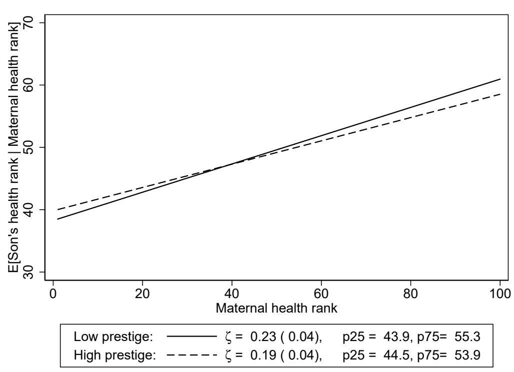
D. Fathers and sons

Note: Figures A11A to A11D display the variation in intergenerational mobility in health with respect to the parental education for different parent-child relations. Each figure displays a linear fit of a regression of the children's percentile rank on the parents' percentile rank for parents with low and high education. The respective estimates of up- and downward mobility are denoted p25 and p75. Robust standard errors are clustered on the family level.

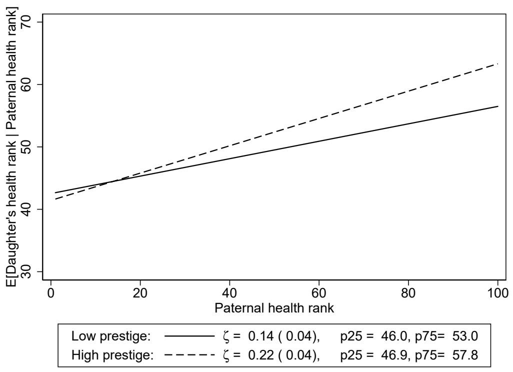
Figure A12. Parental occupational prestige and health mobility



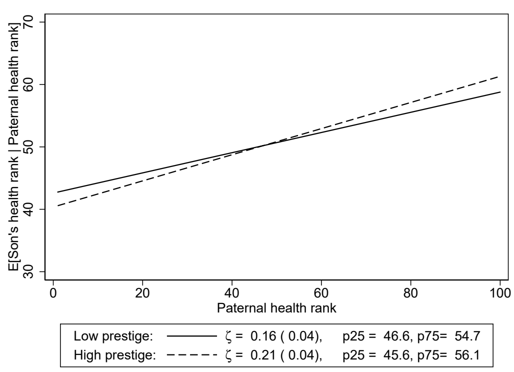
A. Mothers and daughters



B. Mothers and sons



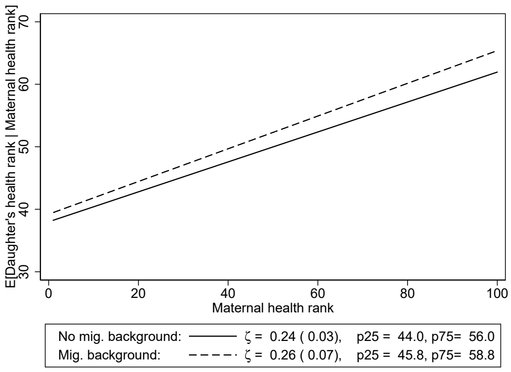
C. Fathers and daughters



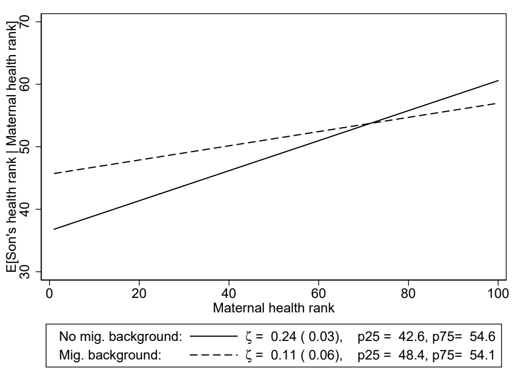
D. Fathers and sons

Note: Figures A12A to A12D display the variation in intergenerational mobility in health with respect to the occupational prestige for different parent-child relations. Each figure displays a linear fit of a regression of the children's percentile rank on the parents' percentile rank for parents with high and low occupational prestige. The respective estimates of up- and downward mobility are denoted p25 and p75. Robust standard errors are clustered on the family level.

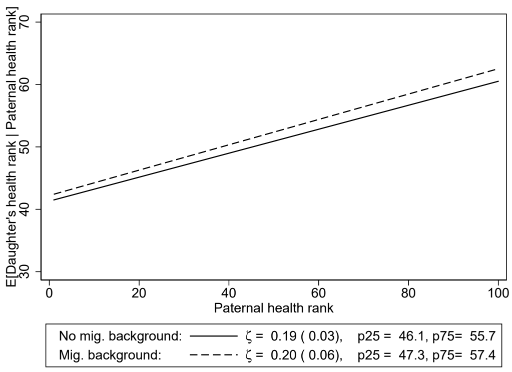
FIGURE A13. Parental migration background and health mobility



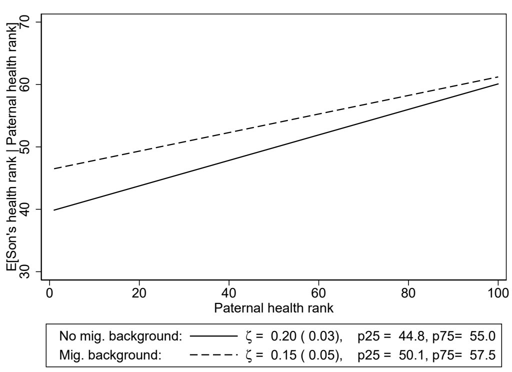
A. Mothers and daughters



B. Mothers and sons



C. Fathers and daughters



D. Fathers and sons

Note: Figures A13A to A13D display the variation in intergenerational mobility in health with respect to the parental migration background for different parent-child relations. Each figure displays a linear fit of a regression of the children's percentile rank on the parents' percentile rank for parents with and without migration background. The respective estimates of up- and downward mobility are denoted p25 and p75, respectively. Robust standard errors are clustered on the family level.

Appendix H. Additional estimates of absolute health mobility

Table A2 displays the results of a regression of an indicator that is equal to one if the child has a higher health rank than the respective parent, and zero otherwise, on the parental health rank. These terms are fully interacted with an indicator that is equal to one if the child is a daughter and zero otherwise. The inclusion of the parental health rank ensures that, in these regressions, the estimates for upward mobility are not confounded by the regression to the mean, which would otherwise confound our estimates of absolute upward mobility. For this regression, the estimate of the intercept corresponds to the estimated share of children who are healthier than their parent at percentile rank zero. Thus, the share of children who have a higher health rank than their parent, who are located at the bottom of the permanent health distribution, is the sum of estimate of the intercept term and the coefficient estimate on the parental health rank. The estimate of the coefficient on the gender indicator reflects permanent shifts of the mobility curve that is associated with the children's gender. The coefficient estimate on the interaction of the gender indicator with the parental health rank captures gender differences of the slope of the absolute health mobility curve. Column (1) of Table A2 displays the estimates for the sample of mothers and their children, column (2) for the sample of fathers and their children, and column (3) displays the results for the parents' joint parental health rank and their children.

The estimates for mothers and their children show that about 89.8 percent of the sons are healthier than their mothers who are located at the bottom of the permanent health distribution. For the daughters, this figure equals 91.6. However, the standard errors associated with the estimates do not suggest that significant gender differences exist. Turning to the estimates for fathers and their children, displayed in column (2) of Table A2, we find that the son's probability of having a higher health rank than their father is 93.8 percent, if the father is located at the bottom of the paternal permanent health distribution. For the corresponding daughters, the estimates suggest that this figure is 1.7 percentage points smaller. However, the associated standard error suggests that this difference is not statistically significant. Lastly, turning to the parents' joint health, depicted in column (3) of Table A2, we see that 90.6 percent of the sons are located at a higher health rank than their parents, if the parents are located at the bottom of the health distribution. The corresponding figure is one percentage point smaller for the daughters, although, the associated standard error suggests that those differences are not statistically significant.

TABLE A2. Child's probability of having a higher health rank than their parents

	Mothers	Fathers	All
	(1)	(2)	(3)
Constant	0.906	0.947	0.916
	(0.018)	(0.019)	(0.018)
Parental health rank	-0.008	-0.009	-0.008
	(0.000)	(0.000)	(0.000)
I(Female)	0.018	-0.017	-0.010
	(0.027)	(0.028)	(0.027)
Parental health rank x I(Female)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Observations	3536	3090	3655

Note: Table A2 displays association between the child's probability of having a higher health rank than their parent and the parental health rank. The estimates are from a regression of an indicator that is equal to one if the child is located at a higher health rank than their parent on the parental health rank, an indicator that is equal to one if the child is female and an interaction of the parental health rank and the the indicator for the child's gender. Column (1) and (2) displays the results for mothers and fathers and their children, respectively. Column (3) displays the results for the health rank of both parents jointly and their children. Throughout, robust standard errors, in parentheses, are clustered on the family level.

Next, we show that the alternative measure of upward mobility also suggests that individuals with parents who have a more advantageous SES, are more upwardly mobile than those children who do not have parents with a more advantageous SES. Table A3 shows the results for the OLS regression of an indicator that is equal to one if the children have a health rank that is higher than the parent's health rank, and zero otherwise, on the parental joint health rank, an indicator that is equal to one if the proxy of the parent's SES has a high realization and an interaction of the two latter terms. This analysis confirms the previous conclusion that children whose parents have a migration background are considerably more upwardly mobile than children whose parents do not have a migration background. Children whose parents have a migration background are 6.9 percentage points more likely to have a higher health rank than their parents, compared to children who have parents that do not have a migration background.

In the following, we also present the aforementioned measure for upward mobility for different parent-child-lineages and interact them with different background characteristics of the respective parents. The results are displayed in Tables A4 to A7. For the estimations in the mother-daughter sample, we find suggestive evidence that daughters with a mother who has permanent earnings that is above the median are 7.5 percentage points more likely to have a higher health rank than their mothers, compared to children whose mother does not have earnings above the median. However, the estimate is too imprecise to reject the null hypothesis that this estimate is equal to zero.[14] Turning to the results for sons and their mothers, displayed in Table A5, we find that sons with a mother who has a migration background are about 7.8 percentage points more likely to have a higher health rank than their mother, compared to sons who have a mother without a migration background. Turning to the estimates for the daughter-father sample, depicted in Table A4, we find weak evidence that daughters with a father who has permanent earnings above the median are 5.5 percentage points more likely to have a higher health rank than their father than sons with a father who does not have a permanent earnings above the median. However, we fail to reject the null hypothesis that this difference is equal to zero. Lastly, turning to sons and their fathers, we find that sons who have a father with a migration background are 11.3 percentage points more likely to have a higher health rank than their fathers compared to sons that do not have a father with a migration background.

[14] The associated p-value is 0.101.

TABLE A3. Child's probability of having a higher health rank than their parents, for differential parental SES

	Education	Prestige	Permanent earnings	Migration background
	(1)	(2)	(3)	(4)
Constant	0.955	0.937	0.920	0.913
	(0.020)	(0.017)	(0.017)	(0.017)
Parental rank	-0.009	-0.009	-0.008	-0.008
	(0.000)	(0.000)	(0.000)	(0.000)
Education:				
I(Intm. or high degree)	-0.034			
	(0.028)			
Parental rank x I(Intm. or high degree)	0.001			
	(0.000)			
Occupational prestige:				
I(Prestige > median)		-0.006		
		(0.029)		
Parental rank x I(Prestige > median)		0.000		
		(0.000)		
Permanent earnings:				
I(Perm. earn. > median)			0.037	
			(0.030)	
Parental rank x I(Perm. earn. > median)			-0.001	
			(0.000)	
Migration background:				
I(Mig. background)				0.069
				(0.028)
Parental rank x I(Mig. background)				-0.001
				(0.001)
Observations	3367	3367	3367	3367

Note: Table A3 displays associations between the child's probability of having a higher health rank than their parent and their parent's health rank. The estimates are from a regression of an indicator that is equal to one if the child is located at a higher health rank than their parents on the parental health rank, an indicator that is equal to one if the parent has an advantageous SES and the interaction between the parental health rank and the indicator that is equal to one if the parent has an advantageous SES. Column (1) displays the results for parents with different educational backgrounds. Column (2) displays the results for parents with different levels of occupational prestige. Column (3) displays the results for different levels of permanent parental earnings. Column (4) displays the results for parents with and without migration background. Throughout, robust standard errors, in parentheses, are clustered on the family level.

TABLE A4. Daughter's probability of having a higher health rank than their mother, for differential maternal SES

	Education	Prestige	Permanent earnings	Migration background
	(1)	(2)	(3)	(4)
Constant	0.948	0.907	0.898	0.930
	(0.035)	(0.031)	(0.029)	(0.026)
Maternal rank	-0.009	-0.009	-0.009	-0.009
	(0.001)	(0.001)	(0.001)	(0.000)
Education:				
I(Intm. or high degree)	-0.041			
	(0.046)			
Maternal rank x I(Intm. or high degree)	0.001			
	(0.001)			
Occupational prestige:				
I(Prestige > median)		0.040		
		(0.046)		
Maternal rank x I(Prestige > median)		0.000		
		(0.001)		
Permanent earnings:				
I(Perm. earn. > median)			0.075	
			(0.046)	
Maternal rank x I(Perm. earn. > median)			0.000	
			(0.001)	
Migration background:				
I(Mig. background)				-0.026
				(0.051)
Maternal rank x I(Mig. background)				0.000
				(0.001)
Observations	1259	1259	1259	1259

Note: Table A3 displays associations between the daughter's probability of having a higher health rank than their mother and their mother's health rank. The estimates are from a regression of an indicator that is equal to one if the daughter is located at a higher health rank than their mother on the maternal health rank, an indicator that is equal to one if the mother has an advantageous SES and the interaction between the maternal health rank and the indicator that is equal to one if the mother has an advantageous SES. Column (1) displays the results for mothers with different educational backgrounds. Column (2) displays the results for mothers with different levels of occupational prestige. Column (3) displays the results for different levels of permanent maternal earnings. Column (4) displays the results for mothers with and without migration background. Throughout, robust standard errors, in parentheses, are clustered on the family level.

TABLE A5. Son's probability of having a higher health rank than their mother, for differential maternal SES

	Education	Prestige	Permanent earnings	Migration background
	(1)	(2)	(3)	(4)
Constant	0.900	0.918	0.908	0.902
	(0.029)	(0.027)	(0.025)	(0.024)
Maternal rank	-0.008	-0.009	-0.008	-0.009
	(0.001)	(0.000)	(0.000)	(0.000)
Education:				
I(Intm. or high degree)	0.046			
	(0.041)			
Maternal rank x I(Intm. or high degree)	-0.001			
	(0.001)			
Occupational prestige:				
I(Prestige > median)		0.011		
		(0.041)		
Maternal rank x I(Prestige > median)		0.000		
		(0.001)		
Permanent earnings:				
I(Perm. earn. > median)			0.037	
			(0.043)	
Maternal rank x I(Perm. earn. > median)			-0.001	
			(0.001)	
Migration background:				
I(Mig. background)				0.078
				(0.043)
Maternal rank x I(Mig. background)				-0.001
				(0.001)
Observations	1444	1444	1444	1444

Note: Table A5 displays associations between the son's probability of having a higher health rank than their mother and their mother's health rank. The estimates are from a regression of an indicator that is equal to one if the son is located at a higher health rank than their mother on the maternal health rank, an indicator that is equal to one if the mother has an advantageous SES and the interaction between the maternal health rank and the indicator that is equal to one if the mother has an advantageous SES. Column (1) displays the results for mothers with different educational backgrounds. Column (2) displays the results for mothers with different levels of occupational prestige. Column (3) displays the results for different levels of permanent maternal earnings. Column (4) displays the results for mothers with and without migration background. Throughout, robust standard errors, in parentheses, are clustered on the family level.

TABLE A6. Daughter's probability of having a higher health rank than their father, for differential paternal SES

	Education	Prestige	Permanent income	Migration background
	(1)	(2)	(3)	(4)
Constant	0.950	0.944	0.920	0.930
	(0.030)	(0.027)	(0.026)	(0.025)
Paternal rank	-0.009	-0.009	-0.008	-0.009
	(0.001)	(0.001)	(0.001)	(0.000)
Education:				
I(Intm. or high degree)	-0.020			
	(0.043)			
Paternal rank x I(Intm. or high degree)	0.001			
	(0.001)			
Occupational prestige:				
I(Prestige > median)		0.000		
		(0.045)		
Paternal rank x I(Prestige > median)		0.001		
		(0.001)		
Permanent earnings:				
I(Perm. earn. > median)			0.055	
			(0.046)	
Paternal rank x I(Perm. earn. > median)			-0.001	
			(0.001)	
Migration background:				
I(Mig. background)				0.025
				(0.047)
Paternal rank x I(Mig. background)				0.000
				(0.001)
Observations	1307	1307	1307	1307

Note: Table A6 displays associations between the daughter's probability of having a higher health rank than their father and their father's health rank. The estimates are from a regression of an indicator that is equal to one if the daughter is located at a higher health rank than their father on the paternal health rank, an indicator that is equal to one if the father has an advantageous SES and the interaction between the paternal health rank and the indicator that is equal to one if the father has an advantageous SES. Column (1) displays the results for fathers with different educational backgrounds. Column (2) displays the results for fathers with different levels of occupational prestige. Column (3) displays the results for different levels of permanent paternal earnings. Column (4) displays the results for fathers with and without migration background. Throughout, robust standard errors, in parentheses, are clustered on the family level.

TABLE A7. Son's probability of having a higher health rank than their father, for differential paternal SES

	Education	Prestige	Permanent earnings	Migration background
	(1)	(2)	(3)	(4)
Constant	0.935	0.982	0.966	0.928
	(0.028)	(0.024)	(0.023)	(0.024)
Paternal rank	-0.009	-0.009	-0.009	-0.009
	(0.001)	(0.000)	(0.000)	(0.000)
Education:				
I(Intm. or high degree)	0.055			
	(0.039)			
Paternal rank x I(Intm. or high degree)	-0.001			
	(0.001)			
Occupational prestige:				
I(Prestige > median)		-0.049		
		(0.040)		
Paternal rank x I(Prestige > median)		0.001		
		(0.001)		
Permanent earnings:				
I(Perm. earn. > median)			-0.022	
			(0.043)	
Paternal rank x I(Perm. earn. > median)			0.000	
			(0.001)	
Migration background:				
I(Mig. background)				0.113
				(0.039)
Paternal rank x I(Mig. background)				-0.001
				(0.001)
Observations	1546	1546	1546	1546

Note: Table A7 displays associations between the son's probability of having a higher health rank than their father and their father's health rank. The estimates are from a regression of an indicator that is equal to one if the son is located at a higher health rank than their father on the paternal health rank, an indicator that is equal to one if the father has an advantageous SES and the interaction between the paternal health rank and the indicator that is equal to one if the father has an advantageous SES. Column (1) displays the results for fathers with different educational backgrounds. Column (2) displays the results for fathers with different levels of occupational prestige. Column (3) displays the results for different levels of permanent maternal earnings. Column (4) displays the results for fathers with and without migration background. Throughout, robust standard errors, in parentheses, are clustered on the family level.

Appendix I. Accounting for educational downgrading among migrants

Educational downgrading is known to attenuate or mute the returns to education for migrants. For instance, uncertainty about the content and quality of the education in other countries causes employers to downgrade the migrants' education, leading to smaller returns to educational degrees for migrants than in their home countries. For instance, Chiswick (1978), Borjas (1985), and Dustmann (1993) find that the earnings-profile of migrants is basically flat with respect to education for migrants. At a minimum, this points toward a less pronounced income channel between education and health for migrants. To account for potential downgrading or misclassification of migrants' educational degrees, we repeat our analysis for parents with different educational backgrounds for a subsample of parents without any migration background. The results are displayed in Table A8 and A9. Clearly, the results in Table A8 indicate that the results are robust to the exclusion of parents with a migration background. Additionally, the results in Table A8 indicate that, for different child-parent combinations, the results are qualitatively robust to the exclusion of parents with migration background. However, while the difference in our estimates for upward mobility are economically significant, we cannot reject the hypothesis that the difference of the two estimates of upward mobility is different from zero (p-value = 0.113) when we compare upward mobility in health for sons from father with a basic or no degree and fathers who have at least an intermediate school leaving degree.

Table A8. Health mobility and parental educational background, excluding parents with migration background

	Rank-rank slope	Upward mobility	Downward mobility	N
	(1)	(2)	(3)	(4)
Educational degree of parents:				
Basic or less	0.224	44.471	55.650	996
	(0.034)	(1.212)	(1.358)	
Intermediate or more	0.260	43.059	56.052	1547
	(0.027)	(1.089)	(0.902)	
P-value test of equality	0.402	0.386	0.805	

Note: Each row of Table A8 displays the estimate of rank-rank slope, up- and downward mobility, stratified according to the educational background of the respective parent. Throughout, we exclude parents with any migration background. The estimates are based on a regression of the percentile rank of the child's permanent health distribution on the percentile rank of the parent in the parent's permanent health distribution. Column (1) displays the rank-rank slope, column (2) displays the expected percentile rank of children whose parents are at the 25th percentile rank, column (3) displays the expected percentile rank of children whose parents are at the 75th percentile rank and column (4) displays the associated number of observations. The p-values are based on a Wald Chi-square test of equality of the rank slopes or predicted ranks across groups after a seemingly unrelated regression model, in which each subgroup corresponds to a separate equation in the seemingly unrelated regression model. Robust standard errors, in parentheses, are clustered on the family level.

TABLE A9. Health mobility and parental educational background for different parent child combinations and excluding parents with migration background

	Daughter				Son			
	Rank-rank slope	Upward mobility	Downward mobility	N	Rank-rank slope	Upward mobility	Downward mobility	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Educational degree of mother:								
Basic or less	0.208	43.848	54.246	416	0.257	42.027	54.857	546
	(0.051)	(1.831)	(2.016)		(0.044)	(1.638)	(1.625)	
Intermediate or more	0.257	44.093	56.959	613	0.224	43.185	54.397	608
	(0.040)	(1.620)	(1.474)		(0.039)	(1.703)	(1.334)	
P-value test of equality	0.450	0.920	0.277		0.582	0.624	0.827	
Educational degree of father:								
Basic or less	0.185	45.847	55.081	483	0.229	43.242	54.670	587
	(0.047)	(1.740)	(1.860)		(0.043)	(1.483)	(1.714)	
Intermediate or more	0.194	46.408	56.132	548	0.164	47.037	55.244	591
	(0.045)	(1.806)	(1.547)		(0.045)	(1.887)	(1.408)	
P-value test of equality	0.881	0.823	0.664		0.295	0.113	0.795	

Note: Each row of Table A9 displays the estimate of rank-rank slope, up- and downward mobility for different subsamples, stratified according to the educational background of the respective parent. Throughout, we exclude parents with any migration background. Column (1) to column (4) display the results for the daughters. Column (5) to column (8) display the results for the sons. The estimates are based on a regression of the percentile rank of the child's permanent health distribution on the percentile rank of the parent in the parent's permanent health distribution. The p-values are based on a Wald Chi-square test of equality of the rank slopes or predicted ranks across groups after a seemingly unrelated regression model, in which each subgroup corresponds to a separate equation in the seemingly unrelated regression model. Robust standard errors, in parentheses, are clustered on the family level.

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