

# Parental Income and Child Health in Germany\*

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## Abstract

Using newly available data from Germany we study the relationship between parental income and child health. We find a strong gradient between parental income and subjective child health as has been documented earlier in the US, Canada and the UK. The relationship in Germany is about as strong as in the US and stronger than in the UK. However, in contrast to US results, we do not find consistent evidence that the disadvantages associated with low parental income accumulate as the child ages, nor that children from low socioeconomic background are more likely to suffer from doctor-diagnosed conditions. There is some evidence, however, that high income children are better able to cope with the adverse consequences of chronic conditions. Investigating potential diagnosis bias, we find only weak evidence for health disadvantages for low-income children when using objective health measures, but some evidence for under-utilization of health services among low-income families.

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# 1 Introduction

Persons with high socioeconomic status (SES) are in better health and they live longer. Although this empirical finding of such an SES-health gradient is very robust, there is an ongoing debate about the underlying reasons for this relationship. The positive correlation could arise because (i) better health leads to better education and income (Currie and Madrian 1999), (ii) education, income or occupational status cause better health outcomes (Grossman 1972), or (iii) there are third factors as, for instance, time preference rates affecting both socioeconomic status and health (Fuchs 1982).

In order to uncover the “origins of the gradient”, Case, Lubotsky and Paxson (2002), henceforth denoted as CLP, investigate whether this association between socioeconomic status and health can also be found among children. They argue that – since children in industrialized countries do not work in the labor market – there is less of a problem of reverse causality running from poor health to lower family earnings. Using cross-sectional US data they find a strong positive relationship between parental income and children’s health. This relationship strengthens as children grow older, which points to an accumulation of health disadvantages for children of low-income parents.<sup>1</sup> CLP also decompose the gradient into what they call a prevalence and a severity effect. A prevalence effect is present if low- and high-income children have different probabilities of suffering from acute or chronic health conditions, whereas a severity effect is present if, conditional on having an acute or chronic condition, the impact of chronic conditions on subjective general health differs between children of low- and high-income parents. CLP find stronger evidence for a severity effect than for a prevalence effect.

The CLP study has been highly influential and it has been replicated with Canadian (Currie and Stabile 2003), British (Currie et al. 2007, Propper et al. 2007, and Case et al. 2008), Australian (Khanam, Nghiem and Connelly 2009), and Indonesian data (Cameron and Williams 2009). All of these studies find a positive relationship between family income and child health. Interestingly, the relationship between income and child health is of about

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<sup>1</sup>There is also an alternative interpretation of this steepening gradient, namely that the effect of income on health is stronger for older children because of developmental changes in children (Chen et al. 2006). Murasko (2008) finds some support for a growing role of a contemporaneous income effect using US data.

the same strength in the US and Canada but less pronounced in the UK. Thus, it seems unlikely that access to public health insurance or universal health care is an explanation for the more equitable outcomes in the UK.

Similar to the findings for the United States, Currie and Stabile (2003) and Khanam et al. (2009) find steeper gradients between parental income and children's health as children grow older in Canada and Australia.<sup>2</sup> However, there is some controversy whether this also applies in the UK. Propper et al. (2007) do not find that the association between parental income and child health becomes significantly stronger as children age, and Currie et al. (2007) find a moderately increasing gradient only up to age 8. However, Propper et al. (2007) only investigate younger children up to age 7, and the results of Currie et al. (2007) may depend on the period studied. When re-analyzing the HSE data used by Currie et al., Case et al. (2008) find moderately increasing gradients until age 12 when including more recent waves of the HSE. This points to the possibility that the effect of income on child health is not constant, for instance because public policies may shape the effect of income on health. Currie et al. (2008) show that the impact of income on child health decline when public health insurance was extended.

Furthermore, the UK results seem to be sensitive to the inclusion of additional covariates such as parental health. Propper et al. (2007) find that after controlling for parental health, in particular mother's mental health, there is no direct effect of income on child health. Similarly, Khanam et al. (2009) find a steepening gradient in Australian data when using similar controls as Case et al. (2002). But when including controls for parental health this income gradient disappears.<sup>3</sup> Similarly, Murasko (2008) reports that the income gradient for the US becomes flatter when controlling for baseline health. Another difference between countries is the relative importance of the prevalence and the severity effect. For instance, in Canada, the gradient between parental income and child health seems to be driven mainly by income-related differences in disease prevalence, while in the US there is empirical support mainly for income-related differences in the severity of diseases.

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<sup>2</sup>In less developed countries such as Indonesia, the impact of low income on health does not seem to increase for older children (Cameron and Williams 2009). This is explained by acute rather than chronic conditions being the main drivers of poor children's health.

<sup>3</sup>Note that it is not clear whether controls for parental health should be included as controls as they are potentially outcomes of higher income themselves.

The aim of our study is to add to the emerging literature on socio-economic status and child health by exploiting newly available data from Germany. We study the “origins of the gradient” using data from the German Interview and Examination Survey for Children and Adolescents (KiGGS). We study whether the gradient becomes steeper as the child ages in order to shed additional light on this controversy in an industrialized country with public health insurance coverage and a developed welfare state. Moreover, we follow CLP and decompose this correlation into a “prevalence effect” and a “severity effect”. We analyse whether low SES children have more chronic conditions and whether existing conditions have a stronger effect on overall health.

In addition to subjective health assessments by the parents we use information on objective health measurements such as blood pressure, obesity, height-for-age, blood haemoglobin, ferritin, and vitamin D levels. Parental reports of subjective health or doctor-diagnosed conditions may be biased if (i) there are systematic differences in reporting behavior between high-SES and low-SES parents or if (ii) acute or chronic conditions are underdiagnosed among poorer children, for instance because low-SES parents visit their physicians less often. Previous analyses for the UK find little evidence of a significant income gradient for some biomarkers (Currie et al. 2007). We use similar measures of child health available in our data to assess whether this finding translates to Germany as well. Furthermore, we use data on the utilization of recommended examination screenings to assess whether there are systematic differences in health care utilization between high- and low-income parents when health care is free at the point of access.

In further analyzes, we study the role of potential risk factors that are associated with parental income, such as low birth weight, adverse parental health behaviors (smoking, drinking, obesity), or nutrition. We interpret these variables as proxies for unobserved parental characteristics, as for instance the time preference rate, affecting both income and child health. By including these variables we probe whether the association between parental income and child health found in our data can be interpreted causally. However, there is also an alternative interpretation. These risk factors can themselves be seen as *results* of low income, in which case they should not be used as control variables in our estimates of the income-health gradient. Under this alternative interpretation, including them in our health

regressions allows us to identify possible channels through which low income parental income affects health.

## 2 Data and Measurements

We use data from the German Interview and Examination Survey for Children and Adolescents (KiGGS) public use file. KiGGS is a nationally representative sample of 17,641 children aged 0-17 residing in Germany, conducted over the years 2003-2006. Data were collected in self-completion questionnaires of parents and children older than 10, medical face-to-face interviews with parents, and in medical examinations undertaken by trained medical staff.<sup>4</sup>

Although part of the survey was also administered directly to children older than 10, we use in our study only information from the parent questionnaires and medical interviews. To avoid potential problems due to systematic between-parent differences in response behavior we include in our regression models dummies for answers from mothers, fathers, joint answers or answers by third persons such as grandparents. Following Case et al. (2002), we exclude children who live with their grand-parents or other relatives, with foster or adoptive parents, or in institutions.

To be comparable to earlier studies in the field, we use subjective child health assessed by the parents (or other proxy respondents) as our main outcome variable. This variable is derived from the self-completion questionnaire and originally coded in five categories: 1='very good', 2='good', 3='fair', 4='bad', 5='very bad'. Less than one percent of the respondent rated their child's health as 'bad' or 'very bad'. We have thus collapsed 'fair', 'bad' and 'very bad' into a single category. Depending on the analysis, we either use the recoded three-category variable as dependent variable in ordered response models or we use a binary indicator for 'very good' and 'good' versus 'fair' to 'very bad' subjective health.

In addition to self-assessments, we analyze the link between parental income and the prevalence of acute and chronic conditions. Parents were asked whether their child had ever been diagnosed with hayfever, neurodermatitis, chronic obstructive bronchitis, lung

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<sup>4</sup>For further details see the KiGGS website <http://www.KiGGS.de/service/english/index.html>

infection, asthma, heart problems, diabetes, migraines, scoliosis, thyroid problems, cramps or epileptic fits. Finally, we use blood ferritin, haemoglobin, and vitamin D levels, measured height and weight and blood pressure – all obtained in the course of medical examinations – as objective indicators of health. From measured height we construct height-for-age z-scores.<sup>5</sup> In addition, we use reports on the take-up of examination screenings for children as measures of health care utilization.

Table 1 contains summary statistics for the sample used in our study. Overall, the children in our sample appear to be very healthy. Around 40 percent of the parents described the health of their child as ‘very good’ and around 54 percent describe the health of their child as ‘good’. Only about 6 percent said their child is in fair or worse health. Based on this measure, older children are less healthy than younger children. While only around 4 percent of the youngest children are described to be in fair or worse health, this proportion rises to around 8 percent for the oldest age group. At the same time, the proportion of children in very good health drops from 53 percent to 32 percent.

We report summary statistics only for five common doctor-diagnosed conditions recorded in KiGGS: neurodermatitis (about 14 percent), bronchitis (about 13 percent), hay fever (about 10 percent), scoliosis (5 percent) and asthma (4 percent). The prevalence of some conditions such as hayfever and scoliosis clearly increases with age. Overall, the probability of suffering from any of the longer list of 13 conditions rises from 28 percent for the 0-3 age group to 53 percent for the 13-17 years group, and the average number of reported conditions rises from .35 to .88.

Among the health measurements, birth weight stands out as it is measured but parent-reported. Outcomes of all other health measures were recorded by trained medical personnel. Low birth weight (<2500g) is reported for around six percent of the children in our sample – with no discernable trend across age groups (i.e. cohorts). Six percent of the analytical sample suffered from high blood pressure (defined as having a diastolic blood pressure above the 95th age and sex adjusted percentile) – again with no obvious age trend. Further, six percent of the children (aged 3 or older) were obese – defined as having a BMI above the 97th percentile of the German reference population. Obesity rates increase with age. Three

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<sup>5</sup>We use the Stata function `zanthro` to calculate z-scores (Vidmar et al. 2004).

percent of infants but eight percent of teenagers were classified as obese. We constructed dummy variables for low haemoglobin and ferritin based on WHO (2001).<sup>6</sup> Low haemoglobin and ferritin levels were found for 5.7 and 7.9 percent of the children, respectively. Similarly, we constructed a dummy for low vitamin D status with a critical value of 25 nmol/l for all groups based on Prentice et al. (2006). Overall around 18 percent of children in our sample have low vitamin D status.

— about here Table 1 —

Our main explanatory variable is current net monthly parental income. In KiGGS, it is reported in 13 brackets: ‘below 500 Euro’, then eight intervals of 250 Euro each (up to 2,500 Euro), ‘2,500 to below 3,000 Euro’, ‘3,000 to below 4,000 Euro’, ‘4,000 to below 5,000 Euro’, and ‘5000 and above’. We use empirical within-interval averages – derived from the 2005 wave of the German Socio-economic Panel (SOEP) – as income measure.<sup>7</sup> These averages are usually very close to the interval midpoints, except for the lowest and the (open) highest category, for which we use 384 and 6,837 Euro, respectively.

## 3 Empirical Models and Results

### 3.1 Parental Income and Self-Assessed Health

We first present evidence for the relationship between parental income and self-rated child health, by age and group. Figure 1 shows average self-rated health by income bracket (brackets are represented by the log of the empirical within-bracket income average as described above). Larger values of subjective health mean worse health. Figure 1 shows that children in households with a higher net income are healthier than children in low income households. Consistent with earlier findings, the relationship can be described as a gradient throughout the income distribution, i.e. there is no apparent threshold value at which income becomes

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<sup>6</sup>The critical values for haemoglobin are 11 g/dl for children under 5 years, 11.5 g/dl for children aged 5 to 11, and 12 g/dl for children aged 12 and over. For ferritin the critical values are 12  $\mu$ g/l for children under 5 years and 15  $\mu$ g/l for children aged 5 and over.

<sup>7</sup>See [www.diw.de/en/soep](http://www.diw.de/en/soep) for a description of the German SOEP.

unimportant for health, and the positive association between income and health can be found also among the very high income households (except for the 9-to-12 age category).

— about here Figure 1 —

In US data, CLP find that the slope of the family income-health gradient increases as children become older. This is interpreted as support for the notion that the socioeconomic disadvantages in health accumulate over time. Our analysis for Germany does not confirm this finding. We find that older children are on average less healthy than younger children, i.e. average health gets worse as children age. However, the gradients for different age groups are essentially parallels. This holds in particular in the middle of the income distribution where we have most cases. There is thus no evidence for a differential accumulation of bad health between low- and high-income children.

We estimate ordered probit models in order to gauge the association between subjective health and log parental income using different sets of control variables. The choice of the covariates allows us to directly compare the results to those reported in CLP and other studies. One might be concerned about comparability between the “US”-version of the self-rated health question used in CLP – which has five categories ranging from “excellent” to “poor” – and the “European” version used in our study – ranging from “very good” to “very bad”. However, recent evidence suggests that although health levels are not directly comparable across the two response formats, both versions are in fact different categorizations of the same latent continuous variable (Jürges, Avendano and Mackenbach 2008). In particular, both scales were found to have the same properties with respect to demographics and health indicators. Thus, data from surveys using different versions of questions about self-rated health can still be used to compare associations of covariates with general health. This requires the use of appropriate statistical models (such as ordered probit models) that interpret self-rated health as different categorisations of an underlying (latent) continuous health variable.

The results for the ordered probit regressions for the relationship between parental income and subjective health are presented in Table 2. Following CLP, we present specifications with and without controls for parental education and unemployment. CLP find that including



additional controls for parental education and unemployment reduces the coefficients on parental income by around a third. There are several interpretations of why this might happen. First, there could be measurement error in income, and parental education would absorb some of the effect of income because it serves as a good proxy variable for it. Second, there could be unobserved factors, as for instance patience, which are correlated with income, education, and child health. In this case, including parental education would also reduce the coefficient on parental income because it captures some of the joint variation of the unobserved variable and health. Finally, education itself could cause better child health outcomes. If one does not control for parental education the coefficient on parental income would absorb some of this effect resulting in an upward bias. While we do not further investigate these hypotheses, it seems plausible that both parental education and income play an important role in determining child health. Thus, in specifications without controls for parental education and unemployment, we prefer to interpret the coefficient on parental income as the effect of overall socioeconomic status. The results describe the *socio-economic* gradient in child health. On the other hand, when controlling for parental education and unemployment as important determinants of parental income and, potentially, child health, we prefer to interpret our coefficient estimate as a description of an *income* gradient in child health.

— about here Table 2 —

In the upper panel of Table 2 we present the baseline specification including as covariates a full set of age dummies (in years), sex of child, log of household size, parity of birth, a dummy for being a twin, age of parents, dummies for family background and respondent, migrant status, dummies for East Germany and rural areas. In the lower panel we present results from a specification that includes additional control variables for parental education and unemployment.

In our baseline specification, family income is strongly associated with child health. One log point increase in income is associated with an 0.289 improvement in latent health. We also report the marginal effects (evaluated at the means of the explanatory variables) of

increasing family income by one log-unit.<sup>8</sup> In the baseline specification, one log-unit decreases the probability of the child being in good health by 8.0 percentage points and the probability of the child being in fair or worse health by 3.2 percentage points. Thus, the probability of being in the top health category increases by 11.2 percent. Controlling for parental education reduces the absolute value of the point estimate of the ordered probit coefficient of income to 0.254. Marginal effects are also only slightly reduced. Thus, we find that parents with higher income have children who are in better health also if parental education is controlled for. This holds true in all age groups.<sup>9</sup>

We do not find strong evidence for an age-related increase in the income-health gradient. Without controlling for education, the slope of the gradient is about the same in the first three age groups and somewhat larger in the oldest age group. The difference in slopes is not significant across age groups (e.g. compare the confidence intervals in Figure 2. Controlling for education, we find a clear U-shaped pattern with largest gradient in health for infants and teenagers. Some weak evidence for a gradient monotonically increasing in age can be found at the margins of being in fair or worse health.

Another difference between our results and those found for the US is that the coefficient on parental income is less affected by the inclusion of control variables for parental education and unemployment. This hold in particular in the 0-3 and 9-12 age groups. Hence compared to the US, less of the *socioeconomic* gradient in health is due to differences in parental education and unemployment. Thus the association of self-reported health and parental income is not just due to the fact that parents with higher income are better educated. Rather, we find evidence that parental income has a strong independent effect. Furthermore, controlling for parental education and unemployment brings us further away from the US result of a gradient that becomes stronger as children age.<sup>10</sup>

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<sup>8</sup>To make sure that we estimate marginal effects at the same margin for each age group, we evaluate marginal effects at full-sample means.

<sup>9</sup>We also tried a specification where we did not collapse the 3 lowest categories of self-rated child. These results are very similar to the results reported in the table 2. In the baseline category the point estimates are: age 0-3: -0.271, age 4-8: -0.277, age 9-12: -0.253, age 13-17: -0.355. Similarly, when controlling for education and parental employment the point estimates were for age 0-3: -0.271, age 4-8: -0.213, age 9-12: -0.234, age 13-17: -0.310.

<sup>10</sup>At this point it should be noted that when we regress health on income and education at the same time, we sometimes find an unexpected sign for the coefficient on parental education – indicating that conditional on family income children of better educated parents are in worse health. These strange result disappear when we drop either income or child’s age – which is negatively correlated with both mother’s education and

In Figure 2, we summarize the comparison of our results for Germany with those found for the US, Canada, and England (baseline specification without controls for parental education and unemployment). Overall, we find that – in three of the four age groups – the gradient is larger in Germany than in the US, Canada, and the UK, but point estimates are not significantly different from those in Canada or the US. Yet in contrast to Canada and the US, we do not find that the effect of parental income increases monotonically with child age. The gradient in Germany is steeper than in the US already for children aged 0 to 3 (-0.268 versus -0.183) and remains fairly stable at least up to age 12. Part of the US and Canadian increase in the gradient with child age can thus be explained (at least statistically) by smaller *initial* health inequalities.

— about here Figure 2 —

### 3.2 Prevalence and Severity Effects of Income

In this subsection, we use information on the presence of doctor-diagnosed (chronic) health problems to decompose the effect of parental income into two components. First, children from poorer families may suffer more often from chronic conditions (prevalence effect). Second, children from poorer families may be less able to cope with the consequences of acute or chronic conditions (severity effect).

To assess the importance of the *prevalence* effect we estimate a series of linear probability models:

$$C = \alpha_0 + \alpha_1 (\ln y - \overline{\ln y}) + X\delta^C + \varepsilon^C \quad (1)$$

where  $C$  is either a dummy for one of the conditions such hay fever or asthma, a dummy for having any condition, or the number of conditions,  $y$  is net family income, and  $X$  are additional control variables.  $\alpha_1$  is the coefficient on family income. Negative values of  $\alpha_1$  mean that children from richer households are less likely to have some specific condition, any condition, or have a lower number of conditions.

The quantitative importance of the *severity* effect is assessed in another equation. We

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health – from the regression.

estimate the following linear probability model separately for each health problem:

$$H = \beta_0 + \beta_1 (\ln y - \overline{\ln y}) + \beta_2 C + \beta_3 (\ln y - \overline{\ln y}) \times C + X\delta^H + \varepsilon^H \quad (2)$$

where  $H$  equals one if the child is in parent-reported fair or worse health.  $\beta_1$  reflects the effect of log income on the probability of reporting fair or worse health,  $\beta_2$  captures the ‘main’ effect of a chronic health problem on subjective health and answers the question just how much a condition affects general health on average. The interaction between the logarithm of parental income and the chronic condition reflects the severity effect of income, i.e. the effect of income on how much a chronic health problems affects general health. For instance, if children from richer families are better able to cope with the consequences of chronic conditions, the coefficient  $\beta_3$  should be negative. Overall, the prevalence effect is calculated as  $\alpha_1 \times \beta_2$  and the severity effect is calculated as  $\beta_3 \times \bar{C}$ .

One potential problem in estimating equation (2) is that when including only individual chronic or acute conditions there may be omitted variable bias if there is co-morbidity. In this case, omitted health conditions are correlated with the included health conditions and with self-reported health. For this reason, we also adopted three different specifications summarizing all available information on doctor-diagnosed conditions. As discussed above, we use a dummy for having any condition and the number of reported conditions. In addition, we also estimated an equation where we simultaneously include 13 conditions and their interactions with family income (thus  $C$  becomes a vector of conditions). All three specifications should suffer less from omitted variables bias than using single conditions.

Estimation results for selected conditions are shown in Table 3. Our selection is primarily based on prevalence, i.e., we have chosen to report regressions for single conditions that are fairly common in the sample (hay fever, neurodermatitis, bronchitis, asthma, and scoliosis). In contrast to our earlier results regarding health self-ratings, we do not find that parental income is negatively correlated with health when measured by the prevalence of doctor-diagnosed conditions. Rather, we find significant *positive* associations with hay fever, neurodermatitis, reporting any condition, and the number of reported conditions.

— about here Table 3 —

Table 3 also shows estimation results for equation (2). First, we find a strong protective effect of income on children’s subjective health, which reiterates our results from Table 2. Second, each of the reported chronic conditions has a highly significant negative impact on subjective health ( $\beta_2$ ). In particular, parents of children suffering from asthma are more likely to report fair or worse general child health. Third, the coefficient of the interaction between chronic conditions and parental income ( $\beta_3$ ), is significantly negative for all conditions listed in Table 3 (except for neurodermatitis) as well as for having any condition or for the number of conditions. This means that high-income children with acute or chronic conditions are less likely to be in fair or worse general health than low-income children with the same conditions.

One explanation for this finding is that the symptoms of these conditions are less severe for children from richer parents. This is consistent with the notion that conditions of low-income children are under-diagnosed. When the symptomatic threshold at which low-income parents take their children to the doctor is higher, *diagnosed* conditions will be more severe on average. In the next section, we investigate these hypotheses further by looking at objective measures of health and self-reports of health care utilization.

— about here Table 4 —

The actual decomposition of the income gradient in subjective health into prevalence and severity effects is shown in Table 4. When considering all conditions together we find that the presence and severity of conditions statistically explains around two thirds of the gradient. Individual conditions explain between 11 and 26 percent of the income gradient in subjective health. Almost all of this explanation is due to the severity effect, whereas the prevalence effect even goes in the ‘wrong’ direction. Considering the positive association between income and the prevalence of diagnosed conditions, this was to be expected. Because of potential problems with diagnosis bias (see next section) our estimates of the severity effect are probably an upper bound of the true effect while our estimates of the prevalence effect are a lower bound. Note, however, that our results for the severity effect are quite similar to those reported in CLP.

## 4 Checking for under-diagnosis among low income children

The finding that children of high income children have a higher prevalence of several acute and chronic illnesses calls for an explanation. One such explanation is ‘diagnosis bias’, i.e. the possibility that children of high income parents are more likely to be diagnosed with some acute or chronic condition even if they are on average healthier. Diagnosis bias can arise for at least four reasons. First, high income parents might indeed be more likely to identify ill health among their children and thus take them to their doctor. Second, conditional on perceived health, they might be more likely to visit a doctor. Third, conditional on visiting, physicians might be more likely to diagnose a condition if the parents have higher SES/income. Fourth, low income parents might be less able to report correctly any diagnosis their child’s doctor has made.

Our data offer two separate ways to test for possible diagnosis bias. One is to look at ‘objective’ health measures (so-called biomarkers), such as BMI (obesity), blood pressure, and markers derived from blood samples. Diagnosis bias would imply that we find a gradient in measured health despite the absence of a gradient in doctor diagnosed conditions. A large number of objective health measures was collected for all KiGGS children above a certain age. To compare our results with previous studies such as Currie et al. (2007), we have chosen for our analysis blood pressure, BMI (obesity), blood haemoglobin, and blood ferritin levels. In addition, we study income gradients in height-for-age and vitamin D levels. Height-for-age is an overall measure of physical development and adequate growth, and there is evidence that adult height is associated with higher earnings, at least for male workers (see Heineck, 2005, for German evidence). We chose vitamin D levels as another marker because of its role in the growth and development of the human skeleton. Furthermore, vitamin D status can be improved through diet supplementation and sufficient sun exposure (Prentice et al. 2006). The role of nutrition and leisure activities in explaining the gradient is studied directly in a later section.

Another possibility to identify diagnosis bias is to look at health care utilization. Usually differences in health care utilization are not independent of health differences and it is thus

difficult to identify whether high income parents are more likely to visit a doctor conditional on true health. However, the German health care system offers a way to overcome this identification problem. From birth to age six, nine free screening examinations (abbreviated U1 to U9) are offered to all children in Germany.<sup>11</sup> The goal of these examinations is to detect any developmental problems as early as possible so that appropriate measures can be taken. Since the screening examinations are free, there is no obvious reason why low income parents should take their children less often to these screenings. On the one hand, one could argue that high income/high wage parents have higher opportunity costs and might thus be less likely to have their children examined. On the other hand, low income parents may have higher opportunity costs despite lower wages because of differential penalties for missing work in lower skilled jobs compared to a professional position. Which argument predominates is essentially an empirical question. Whatever the answer to that question, finding that compliance to screening examinations is lower among low income parents would provide indirect evidence of diagnosis bias because it implies that illnesses are more likely to be underdiagnosed.

#### **4.1 Is there a gradient in objective health?**

In Table 5 we report results for the relationship between our set of biomarkers and parental income, controlling for the same covariates as in the previous sections. In UK data, Currie et al. (2007, Table 6) found no significant relationship between parental income and any of their objective measures of health. This stands in contrast to the strongly significant link between parental income and subjective health. A similar picture emerges for Germany with respect to high blood pressure and low haemoglobin. There is, however, evidence for a gradient in vitamin D levels and weak evidence for a gradient in ferritin levels. One log point increase in income is associated with a 3.5 percentage point decrease in the probability of low vitamin D levels. Relative to the overall percentage of 17.6 this is a 20 percent decrease. The proportion of children with low ferritin levels decreases by 1 percentage point with each

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<sup>11</sup>Since 2007, the examinations are mandatory in some German states and enforced by local authorities. However this is after our observation period. Moreover, an additional examination has been introduced for three year old children in 2008 (U7a).

log point increase in income. Relative to the overall percentage of 7.9, this is 13 percent decrease.

Further, we find no link between family income and obesity and height-for-age once we control for parental obesity and parents' height, respectively. Only in models not controlling for parental obesity family income is strongly related to child obesity. Only if parental income is itself a cause for parental obesity this finding can be interpreted as evidence for a socioeconomic gradient in childhood obesity. Inadequate nutrition may be an important mediating factor for the impact of income on child health as our results for obesity suggest. Our finding of a significant income gradient in vitamin D blood levels supports this interpretation. Overall, however, we find differences in objective health measures by income levels only for some of the objective health markers, and there is no strong indication of a diagnosis bias.

— about here Table 5 —

## 4.2 Is there a gradient in health care utilization?

We study the link between income and health care utilization in Germany using the uptake of screening examinations as an example – concentrating on three of the screening examinations (U3, U6, and U9), scheduled for one month, one year and six year old children, respectively. Figure 3 shows the participation rates by parental income (represented by empirical within-bracket averages, similar to Figure 1). Apparently, participation rates decline across the entire income range as children become older. Overall rates decrease from about 95% (U3) to 72% (U9). Figure 3 also reveals a substantial income gradient. Children in the lowest family income category are about 20 percentage points less likely to participate in any screening examination than children in the highest income category. Moreover, the gap appears to become wider as children grow older. Our results have some political significance, because there have been discussions recently on whether welfare payments should be made conditional on compliance to screenings, and as noted previously some federal states in Germany have already made participation mandatory. Potentially, this is a way of improving compliance with the program and possibly improve diagnosis of conditions among low income children.



Bivariate results are confirmed in regression analyses using the uptake of U3, U6, and U9 as dependent variables. Low income parents use U-examinations significantly less often, especially when children become older. Using the same set of covariates as above (including parental education and unemployment), the marginal effects of increasing family income by one log point on utilization are 0.019, 0.036, and 0.040, respectively. This means that developmental problems and certain health conditions are probably less likely to be diagnosed among low income children. Hence our measures of chronic health conditions could indeed suffer from diagnosis bias.

—about here Figure 3

## 5 Robustness Checks and Extensions

In the previous sections, we somewhat permissively interpreted our coefficient on parental income as a causal effect. Of course, this interpretation is only valid if there are no omitted variables which are correlated with the error term and parental income. The rate of time preference of parents is an example of such an unobserved omitted variable. More patient parents may have higher income because of their past investments in their own human capital, and at the same time they will also invest more in their children's human capital (both education *and* health). A standard approach of dealing with the omitted variable bias are either instrumental variable techniques or the use of panel data. Unfortunately, we do not have the required data to implement these methods.

Therefore, we examine the robustness of our results by including proxy variables for possibly omitted variables. We consider low birth weight as an important correlate of later outcomes. If a large portion of the gradient in child health outcomes was driven by low birth weight this would suggest that interventions aimed at preventing low birth weight may be effective in both improving child outcomes and reducing inequalities in health. But low birth weight is also a proxy for parental risk attitudes because it may be the result of parental health behaviours such smoking during pregnancy.<sup>12</sup> We also use direct (i.e. respondent)

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<sup>12</sup>See Voigt et al. (2007) for evidence on preterm births due to smoking for Germany.

information on parental risk behaviors, and other factors such as child nutrition and child leisure activities as important correlates of child health.<sup>13</sup>

## 5.1 Long-term Impact of Low Birth Weight on Subjective Health

We now investigate whether low birth weight (<2,500g) has a long lasting impact on subjective health, and whether possible disadvantages of low birth weight dissipate over time or are affected by parental income. To this end, we include a dummy variable for low birth weight as an explanatory variable in our initial ordered probit specification. We add interactions between low birth weight and age to assess whether the impact of low birth weight dissipates over time, and interactions between family income and low birth weight to assess whether parents with higher incomes are better able to compensate possible problems due to low birth weight.<sup>14</sup> Specifications that include low birth weight have the advantage that we can exclude one source of reverse causality between parental income and child health, namely parents reducing their labor supply as a response to their children's initial bad health.

— about here Table 6 —

In the first column of Table 6, we show a basic specification similar to Table 2 but which excludes observations with missing information on birth weight. In column 2, we include a dummy variable indicating low birth weight. Children born with low birth weight are in worse subjective health than children born with normal birth weight. Including this additional variable does not much affect the coefficients on parental income. In column 3 we include an interaction term of low birth weight with age. If the disadvantages of low birth weight dissipated over time, we would expect a negative coefficient. This is indeed what we find. The point estimate indicates a reduction of the low birth weight effect of about a third (from 0.130 at birth to 0.096 at age 17), but the interaction effect is very imprecisely estimated and hence statistically insignificant.

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<sup>13</sup>Another interpretation of the results in this section is that these measures are themselves intermediate outcomes of parental income. For instance, we find that low income parents are more likely to smoke. But this could also be one consequence of low income (albeit not directly). If this was the case, we could not interpret the coefficient on income in the following section as the *total* effect of income.

<sup>14</sup>We are aware that the interpretation of interaction effects in non-linear regression models is more complicated than in OLS (Ai and Norton 2003). We have checked our results with linear models and found them to be similar in magnitude, sign and statistical significance.

In column 4, we add an interaction term between low birth weight and parental income. We find a positive, though insignificant, coefficient on this interaction term indicating that higher income parents are not better able to compensate the adverse affects of low birth weight. Again, note that in all specifications so far, the coefficient on parental income itself is not much affected, which indicates that the positive effect of parental income on health cannot be explained by parental income being related to problematic birth weight. Even if there is an association between current income and birth weight, there is an additional effect of parental income which cannot be explained by low income parents having more problematic births. This conclusion is also robust to the inclusion of more interactions as in columns 5 and 6, where the coefficient on parental income does not change much in comparison to the basic specification.

## 5.2 Risk behaviors

Both parents' and children's risk behavior and environmental factors may be other important determinants of child health outcomes. There are two interpretations of why risk behaviors are correlates of adverse child health outcomes. First, it could be the case that certain behaviors are causal factors for child health. For instance, the dangers of second hand smoke are now widely discussed, and so parental smoking may impair children's health. If parental smoking is itself caused by low income, then by including controls for parental smoking we would know how much of the effect of income is mediated through smoking behavior. A second interpretation of risk behaviors is that they are themselves proxies for unobserved taste differences. For example, a smoker could have a stronger preference for the present, and therefore invest less in her own and her child's health. We consider parental smoking, drinking and overweight at least partly as proxies for unobserved taste differences. If our results on the effect of parental income are robust to the inclusion of these proxy variables, we can be more assured that we are actually measuring the causal effect of parental income. In addition, we consider the child's junk food and media consumption as further potential determinants of child health correlated with parental income. Our interpretation of these results is that these variables are partly proxy variables for the extent that parents care

about their children’s health and education.

— about here Table 7 —

Results are presented in Table 7. We have constructed indicator variables for whether the parents are current smokers, and whether they smoke inside the house. Furthermore, we use dummy variables for smoking and drinking during the pregnancy. Based on self-reported weight and height we use further indicators for parental overweight ( $BMI > 25$ ). We find a significant association between smoking fathers and overweight mothers and worse child health. However, the coefficient on parental income is not much affected by accounting for parental health behavior. Thus, we cannot conclude that the strong relationship between parental income and children’s health is mainly driven by a more healthy behavior of high income parents.

In column 2, we include a variable summarizing the child’s consumption of junkfood.<sup>15</sup> In contrast to maternal overweight, this variable does not have a strong influence on subjective health assessments. In column 3, we consider the child’s leisure activities by considering dummy variables for excessive media consumption. We define excessive TV consumption as watching more than three hours of television on a weekday. In our sample, around 8% of the children fall into this category. Similarly, we define a dummy for playing video or computer games for more than one hour on weekdays. Around 11% of all children fall into this category. Excessive media consumption could affect health by crowding out exercise and playing outside. Hancox et al. (2004) use longitudinal data and show that the effects of watching TV as a child persist into early adulthood. We find some support for negative contemporaneous health effects, especially for TV consumption. However, it could also be the case that sickly children watch more television because they are more restricted in their choice of activities. While excessive media consumption is associated with worse child health outcomes, including these additional covariates does not affect the coefficient on income substantially.

By and large, in all our robustness checks, including additional variables does not affect the estimated coefficient on parental income. If these are good proxies for unobserved fac-

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<sup>15</sup>We constructed an index of junkfood consumption based on a series of questions about nutritional habits, such as “How often do you eat French fries?” or “How often do you eat sweets?” (Cronbach’s alpha=0.68).

tors affecting income and child health then we can be assured that we are indeed measuring a causal effect of parental income. Of course, the additional analyses do not exclude the possibility that there are still other unobserved factors driving or mediating the correlation between parental income and subjective child health, nor do they exclude the possibility that because of genetic ties both ‘ability’, income and health are positively correlated across generations. Since the sample contains only few children living with non-biological parents only, we cannot investigate the issue of genetic versus environmental determinants of childhood health any further.

## 6 Summary and Discussion

In this paper, we have used newly available data from Germany to study the relationship between parental income and child health. In our empirical analysis we found a strong gradient between parental income and subjective child health as has been documented in the US, Canada and to a somewhat lesser extent in the UK. The relationship in Germany is about as strong as in the US and stronger than in the UK. In contrast to the US and Canada, but consistent with some UK findings, we did not find that the disadvantages associated with low parental income accumulate as the child ages. When one does not control for education, the slope of the gradient remains about constant until age 12 and slightly increases for teenagers. Controlling for education, we even found a U-shaped pattern, with the largest gradients for infants and teenagers. We also did not find that children from low socioeconomic background are more likely to suffer from doctor-diagnosed chronic health problems. There is some evidence, however, that high income children are better able to cope with the adverse consequences of chronic conditions, in particular hay fever, bronchitis, scoliosis, and asthma. In other words, we found evidence for a severity effect of income but not for a prevalence effect.

In further analyses, we studied risk factors for child health outcomes. We found that parental smoking, overweight and other risk factors have an appreciable effect on child health. However, the effect of income on child health does not seem to be mediated through these risk factors, nor are these factors important confounders. The effect of income on health

mainly works through the severity effect which explains roughly two thirds of the gradient. This points to two policy conclusions: First, public policy should direct interventions to low-income parents with chronically ill children to better deal with these conditions. Second, interventions at the behavioral level (for example, encouraging parents to stop smoking) may improve overall health outcomes of children but will do little to address the problem of health inequalities in children.

The fact that we find conflicting results for the effect of parental income on parent-assessed subjective health on the one hand and most doctor diagnosed conditions and measured health indicators is disquieting. Self-reports of health are subject to considerable over-, under-, or misreporting, depending on the circumstances and dimensions at hand (Jürges 2007, Jürges 2008, Bago d’Uva, O’Donnell and van Doorslaer 2008). This becomes problematic if the reporting bias is correlated with important potential determinants of health such as income. However, we do not believe that the literature on a socioeconomic reporting bias has so far provided convincing evidence. Moreover, self-reports of health have their own distinct scientific value. For instance, it has been shown that they contain information on health status even after conditioning on objective measures of health (Idler and Benyamini 1997). Thus, results from ‘objective’ measures including biomarkers should be seen as complementary evidence rather than some higher order of evidence. Unfortunately, our evidence on objective biomarkers were mixed and not very conclusive except for the impact of income on vitamin D levels. This leaves researchers to further rely on the use of subjective health assessments. However, the value of those self-assessments alone as policy outcome measures is less clear. It would be hard to evaluate the benefits of a health care reform or massive income redistribution, say, that improves subjective health but leaves more objective measures of health unchanged.

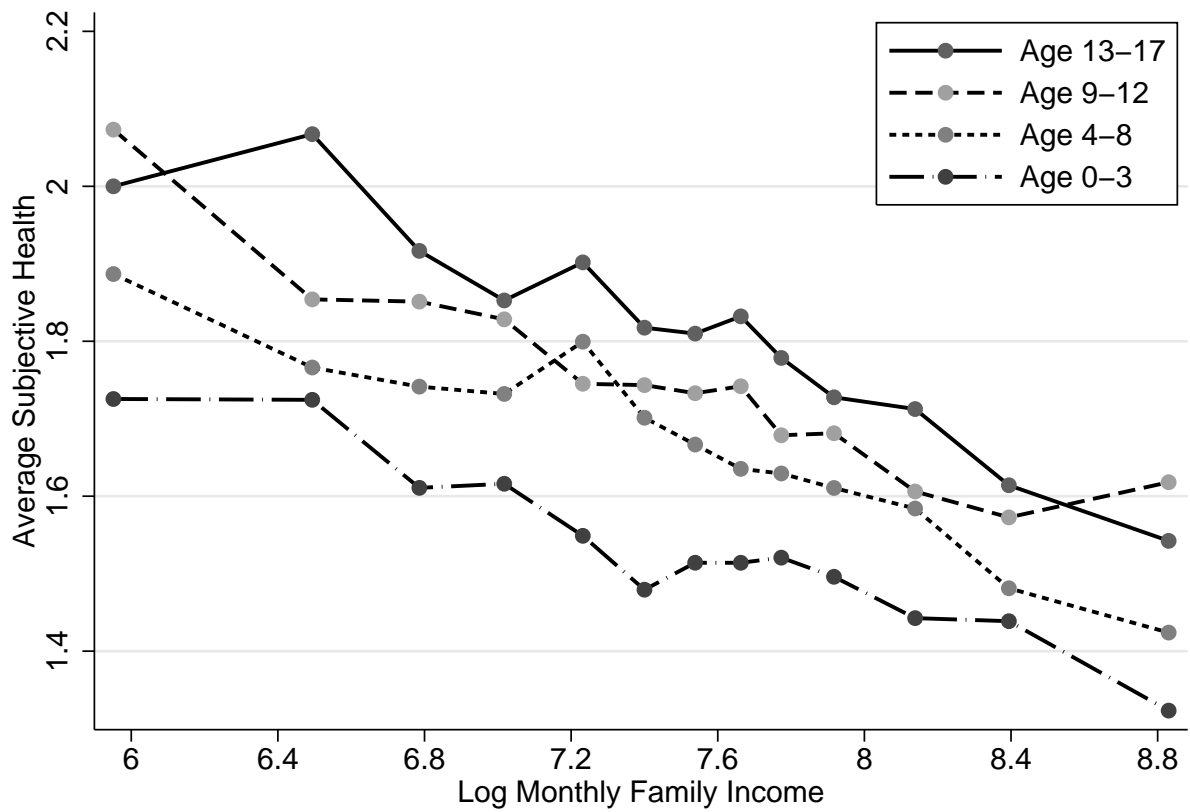
## References

- Ai, Chunrong and Edward C. Norton**, “Interaction terms in logit and probit models,” *Economics Letters*, 2003, 80 (1), 123–129.
- Bago d’Uva, Theresa, Owen O’Donnell, and Eddy van Doorslaer**, “Differential health reporting by education level and its impact on the measurement of health inequalities among older Europeans,” *International Journal of Epidemiology*, 2008, 37 (6), 1375–1383.
- Cameron, Lisa and Jenny Williams**, “Is the Relationship Between Socioeconomic Status and Health Stronger for Older Children in Developing Countries?,” *Demography*, 2009, 46 (2), 303–324.
- Case, Anne, Darren Lubotsky, and Christina Paxson**, “Economic Status and Health in Childhood: The Origins of the Gradient,” *American Economic Review*, December 2002, 92 (5), 1308–1334.
- , **Diana Lee, and Christina Paxson**, “The Income Gradient in Children’s Health: A Comment on Currie, Shields and Wheatley Price,” *Journal of Health Economics*, 2008, 27, 801–807.
- Chen, Edith, Andrew D. Martin, and Karen A. Matthews**, “Socioeconomic status and health: Do gradients differ within childhood and adolescence?,” *Social Science & Medicine*, 2006, 62, 2161–2170.
- Currie, Alison, Michael A. Shields, and Stephen Wheatley Price**, “The Child Health/Family Income Gradient: Evidence from England,” *Journal of Health Economics*, 2007, 26, 213–232.
- Currie, Janet and Brigitte C. Madrian**, “Health, Health Insurance, and the Labor Market,” in O. Ashenfelter and D. Card, eds., *Handbook of Labor Economics*, Vol. 3, Amsterdam: Elsevier Science, 1999, pp. 3309–3414.
- **and Mark Stabile**, “Socioeconomic Status and Child Health: Why is the Relationship Stronger for Older Children,” *American Economic Review*, 2003, 93, 1813–1823.
- , **Sandra Decker, and Wanchuan Lin**, “Has public health insurance for older children reduced disparities in access to care and health outcomes?,” *Journal of Health Economics*, 2008, 27, 1567–1581.
- Fuchs, Victor R.**, “Time Preference and Health: An Exploratory Study,” in V.R. Fuchs, ed., *Economic Aspects of Health*, University of Chicago Press, 1982, pp. 93–120.
- Grossman, Michael**, “On the Concept of Health Capital and the Demand for Health,” *Journal of Political Economy*, 1972, 80, 223–255.
- Hancox, Robert J., Barry J. Milne, and Richie Poulton**, “Association between child and adolescent television viewing and adult health: a longitudinal birth cohort study,” *The Lancet*, 2004, 364, 257–262.
- Heineck, Guido**, “Up in the Skies? The Relationship between Body Height and Earnings in Germany,” *Labour*, 2005, 19 (3), 469–489.

- Idler, E.L. and Y. Benyamini**, “Self-rated health and mortality: A review of twenty-seven community studies,” *Journal of Health and Social Behavior*, 1997, 38, 21–37.
- Jürges, Hendrik**, “True health vs. response styles: Exploring cross-country differences in self-reported health,” *Health Economics*, 2007, 16 (2), 163–178.
- , “Self-assessed health, reference levels, and mortality,” *Applied Economics*, 2008, 40 (5), 569–582.
- , **Mauricio Avendano, and Johan Mackenbach**, “Are different measures of self-rated health comparable? An assessment in five European countries,” *European Journal of Epidemiology*, 2008, 23 (12), 773–781.
- Khanam, Rasheda, Hong Son Nghiem, and Luke B. Connelly**, “Child Health and the Income Gradient: Evidence from Australia,” *Journal of Health Economics*, 2009, 28 (4), 805–817.
- Murasko, Jason E.**, “An evaluation of the age-profile in the relationship between household income and the health of children in the United States,” *Journal of Health Economics*, 2008, 27, 1489–1502.
- Prentice, Ann, Inez Schoenmakers, M. Ann Laskey, Stephanie de Bono, Fiona Ginty, and Gail R. Goldberg**, “Symposium on ‘Nutrition and health in children and adolescents’ Session 1: Nutrition in growth and development,” *Proceedings of the Nutrition Society*, 2006, 65 (4), 348–360.
- Propper, Carol, John Rigg, and Simon Burgess**, “Child Health: Evidence on the Roles of Family Income and Maternal Mental Health From a UK Birth Cohort,” *Health Economics*, 2007, 16, 1245–1269.
- Vidmar, Suzanna, John Carlin, and Kylie Hesketh**, “Standardizing anthropometric measures in children and adolescents with new functions for egen,” *The Stata Journal*, 2004, 4 (1), 50–55.
- Voigt, M., S. Straube, C. Fusch, G. Heineck, D. Olbertz, and K.T.M. Schneider**, “The Shortening of the Duration of Pregnancy due to Smoking and Associated Costs for Perinatal Health Care in Germany,” *Zeitschrift für Geburtshilfe und Neonatologie*, 2007, 211, 204–210.
- World Health Organization**, “Iron Deficiency Anaemia, Assessment, Prevention, and Control,” Technical Report, World Health Organization 2001.

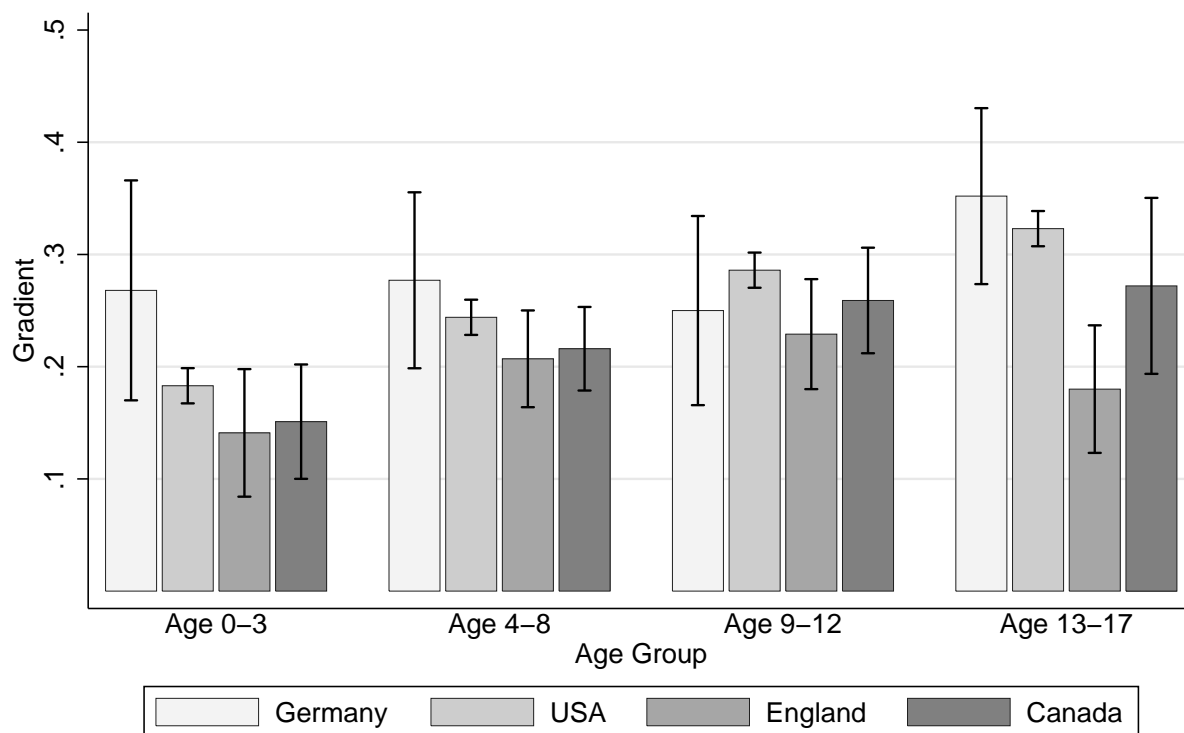


Figure 1: Relationship between log family income and subjective health; different age groups



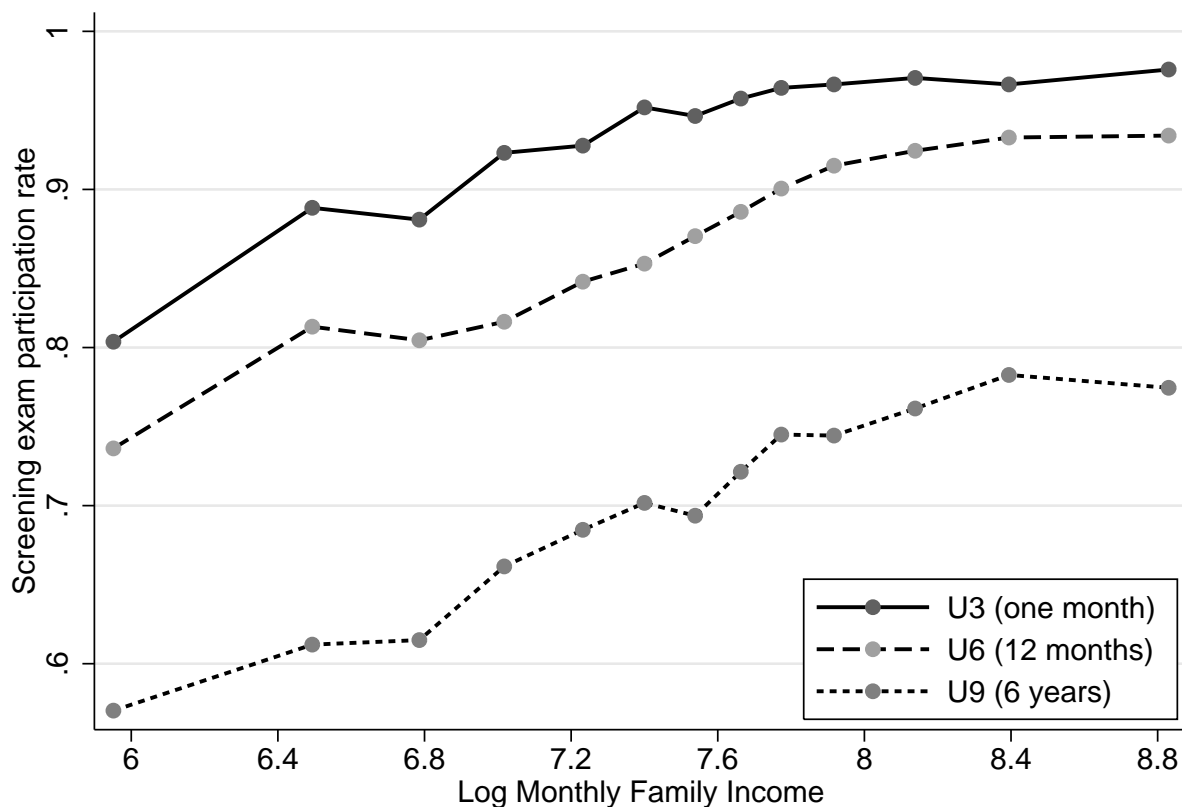
Note: The figure shows average subjective health by within-bracket income averages. Within-bracket income averages are based on calculations using 2005 German Socio-economic panel data.

Figure 2: International comparison of the parental income-child health gradient (controlling for education)



Note: Figures are based on own calculations using the KiGGS data, Case et al. (2002), Currie and Stabile (2003), and Case et al. (2008). Coefficients from baseline model without controls for parental education were used for all countries. The bars represent ordered probit regression coefficients of subjective health on log parental income. Error bars show 95% confidence intervals.

Figure 3: Relationship between log family income and screening examinations take up



Note: The figure shows screening participation rates by within-bracket income averages for selected examinations (at the age of one month, one year and six years). Within-bracket income averages are based on calculations using 2005 German Socio-economic panel data.

Table 1: Sample description (means and proportions)

	0-3 years	4-8 years	9-12 years	13-17 years	Total
Net household income	2296.4	2535.5	2486.1	2596.2	2488.8
<b>Subjective health</b>					
Subjective health (mean)	1.509	1.633	1.702	1.766	1.658
SRH very good	0.530	0.421	0.364	0.318	0.403
SRH good	0.431	0.526	0.571	0.598	0.535
SRH fair or worse	0.039	0.053	0.066	0.084	0.061
<b>Diagnoses</b>					
Hay fever	0.007	0.068	0.131	0.178	0.099
Neurodermatitis	0.100	0.142	0.157	0.140	0.136
Bronchitis	0.124	0.149	0.125	0.111	0.128
Asthma	0.007	0.034	0.063	0.070	0.044
Scoliosis	0.007	0.021	0.053	0.106	0.048
Any condition	0.284	0.394	0.460	0.526	0.420
Number of conditions	0.354	0.585	0.750	0.878	0.650
<b>Health measurements</b>					
Low birth weight	0.060	0.067	0.055	0.060	0.061
High blood pressure	0.064	0.060	0.057	0.060	0.059
Obese	0.026	0.046	0.063	0.079	0.060
Height-for-age (mean)	0.416	0.482	0.539	0.452	0.474
Low haemoglobin	0.119	0.070	0.029	0.045	0.057
Low ferritin	0.078	0.062	0.052	0.120	0.079
Low vitamin D	0.100	0.155	0.186	0.220	0.176
N	3342	4474	3724	4143	15683

Notes: Number of observations refer to analytical sample for main specifications.

Table 2: Subjective Child Health and Log Family Income, Ordered Probit Regression Results

For ages	0-3	4-8	9-12	13-17	0-17
Baseline specification					
Ordered probit	-0.268*** (0.050)	-0.277*** (0.040)	-0.250*** (0.043)	-0.352*** (0.040)	-0.289*** (0.021)
ME good health	-0.083*** (0.016)	-0.080*** (0.012)	-0.062*** (0.011)	-0.059*** (0.010)	-0.080*** (0.006)
ME fair or worse health	-0.024*** (0.005)	-0.028*** (0.004)	-0.031*** (0.006)	-0.059*** (0.008)	-0.032*** (0.002)
With additional controls for parental education and unemployment					
Ordered probit	-0.268*** (0.055)	-0.213*** (0.046)	-0.233*** (0.051)	-0.308*** (0.049)	-0.254*** (0.025)
ME good health	-0.083*** (0.017)	-0.062*** (0.014)	-0.057*** (0.013)	-0.055*** (0.010)	-0.070*** (0.007)
ME fair or worse health	-0.024*** (0.005)	-0.021*** (0.005)	-0.029*** (0.007)	-0.050*** (0.009)	-0.028*** (0.003)
N	3342	4474	3724	4143	15683

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Control variables for the base line specification include a full set of age dummies (in years), sex of child, log of household size, parity of birth, dummy for being a twin, age of parents, dummies for family background and respondent, migrant status, dummies for East Germany and rural areas. The specification with additional controls include all of the above and dummies for parental education including a dummy for missing information (Basic education of 9 years is omitted category) and unemployment status. Marginal effect of ln family income on the probability on being in "good" health (category 2) and "fair" and worse (category 3) health.

Table 3: Linear Probability Models: The Prevalence and Severity Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Hay fever	Neurodermatitis	Bronchitis	Asthma	Scoliosis	Any condition	Number of conditions
$C$	0.099	0.136	0.128	0.044	0.048	0.420	0.650
$\alpha_1$	0.017** (0.006)	0.020** (0.007)	0.010 (0.007)	0.003 (0.004)	0.002 (0.004)	0.029** (0.010)	0.059** (0.020)
$\beta_1$	-0.023*** (0.005)	-0.025*** (0.005)	-0.020*** (0.005)	-0.023*** (0.005)	-0.023*** (0.005)	-0.013* (0.005)	-0.011 (0.005)
$\beta_2$	0.083*** (0.010)	0.038*** (0.007)	0.089*** (0.008)	0.154*** (0.016)	0.075*** (0.013)	0.061*** (0.004)	0.049*** (0.003)
$\beta_3$	-0.045* (0.018)	-0.024 (0.014)	-0.054** (0.017)	-0.070* (0.030)	-0.093*** (0.027)	-0.033*** (0.009)	-0.027*** (0.006)
N	15482	15353	15388	15453	15391	14532	14532

Standard errors in parentheses; \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ ; Regression models contain a full set of age dummies (in years), sex of child, log of household size, parity of birth, dummy for being a twin, age of parents, dummies for family background and respondent, migrant status, dummies for East Germany and rural areas, dummies for parental education including a dummy for missing information (Basic education of 9 years is omitted category) and unemployment status. Regressions are based on equations:  $C = \alpha_0 + \alpha_1 (\ln y - \overline{\ln y}) + X\delta^C + \varepsilon^C$  and  $H = \beta_0 + \beta_1 (\ln y - \overline{\ln y}) + \beta_2 C + \beta_3 (\ln y - \overline{\ln y}) \times C + X\delta^H + \varepsilon^H$

Table 4: Decomposition of Gradient into Prevalence and Severity Effect

Condition	Total effect $\beta$	Percent of total effect			
		Unexplained gradient $\frac{\beta_1}{\beta}$	Severity effect $\frac{\beta_3 \bar{C}}{\beta}$	Prevalence effect $\frac{\alpha_1 \beta_2}{\beta}$	Residual $\frac{\beta - \beta_1 - \beta_3 \bar{C} - \alpha_1 \beta_2}{\beta}$
Hay fever	-0.026	0.882	0.169	-0.056	0.004
Neurodermatitis	-0.027	0.909	0.119	-0.029	0.000
Bronchitis	-0.026	0.778	0.263	-0.035	-0.006
Asthma	-0.026	0.891	0.122	-0.018	0.005
Scoliosis	-0.027	0.854	0.164	-0.005	-0.013
Any condition	-0.025	0.516	0.565	-0.072	-0.010
Number of conditions	-0.025	0.424	0.701	-0.115	-0.011
All conditions	-0.025	0.453	0.658	-0.046	-0.065

Note: Total effect  $\beta$  equal to OLS coefficient of poor self-rated health regressed on log family income *not* controlling for  $C$ . Unexplained gradient, severity effect, prevalence effect, and residual are expressed relative to this total effect. Parameters  $\bar{C}$ ,  $\alpha_1$ ,  $\beta_1$ ,  $\beta_2$ ,  $\beta_3$  are taken from Table 3.

Table 5: The Relationship between Parental Income and Objective Health Measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	high blood pressure	obese	height-for-age	low haemoglobin	low ferritin	low Vitamin D
Ln family income	-0.001 (0.005)	-0.002 (0.005)	-0.018 (0.020)	0.002 (0.005)	-0.010 <sup>+</sup> (0.006)	-0.035 <sup>**</sup> (0.011)
Sample means	0.059	0.060	0.474	0.057	0.079	0.176
<i>N</i>	13042	11210	13768	12594	11696	9034

Standard errors in parentheses

<sup>+</sup>  $p < 0.1$  \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Probit models are estimated for the outcomes high blood pressure, obesity, low haemoglobin, ferritin levels and vitamin D levels in blood. Marginal effects are reported. OLS models are estimated for height-for-age. Additional controls for the base line specification include age of child (quadratic for blood pressure, full set of age dummies for other outcomes), sex of child, log of household size, parity of birth, age of parents, dummies for family background and respondent, a set of dummies for parental education (some college and more is omitted category) and employment status, migrant status, dummies for East Germany and rural areas. The model for obesity also includes parents' BMI, the model for height-for-age also includes parents' height.



Table 6: The Long-term Impact of Low Birth Weight on Subjective Health. Ordered Probit Regression Results.

	(1)	(2)	(3)	(4)	(5)	(6)
Ln family income (lny)	-0.263*** (0.025)	-0.262*** (0.025)	-0.262*** (0.025)	-0.265*** (0.025)	-0.265*** (0.025)	-0.265*** (0.025)
Low birth weight (lbw)		0.110** (0.042)	0.130 (0.080)	-0.260 (0.592)	0.131 (0.080)	0.101 (1.078)
lbw × age			-0.002 (0.008)		-0.050 (0.067)	-0.047 (0.121)
lbw × lny				0.049 (0.077)		0.004 (0.142)
lbw × age × lny					0.006 (0.009)	0.006 (0.016)
<i>N</i>	15357	15357	15357	15357	15357	15357

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Control variables include a full set of age dummies (in years), sex of child, log of household size, parity of birth, a dummy for being a twin, age of parents, dummies for family background and respondent, a set of dummies for parental education (some college and more is omitted category) and employment status, migrant status, dummies for East Germany and rural areas.

Table 7: Robustness check: The Role of Health Behavior. Ordered Probit Models.

	(1)	(2)	(3)	(4)
Ln family income	-0.242*** (0.025)	-0.264*** (0.026)	-0.250*** (0.025)	-0.250*** (0.026)
Father smokes	0.046* (0.022)			0.043 (0.023)
Mother smokes	-0.013 (0.026)			-0.021 (0.027)
Smoke in apartment	0.011 (0.025)			0.011 (0.026)
Smoke during pregnancy	0.066* (0.031)			0.080* (0.032)
Drink during pregnancy	-0.001 (0.027)			0.005 (0.028)
Father overweight	0.037 (0.021)			0.040 (0.021)
Mother overweight	0.081*** (0.020)			0.079*** (0.021)
Junkfood		0.013 (0.015)		0.011 (0.015)
TV			0.106* (0.046)	0.081 (0.048)
Games			0.044 (0.037)	0.037 (0.038)
<i>N</i>	15683	14247	15683	14247

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Additional controls for the base line specification include a full set of age dummies (in years), sex of child, log of household size, parity of birth, a dummy for being a twin, age of parents, dummies for family background and respondent, a set of dummies for parental education (some college and more is omitted category) and employment status, migrant status, dummies for East Germany and rural areas.