

IZA DP No. 1832

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Discussion Paper No. 1832
November 2005

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ABSTRACT

The Impact of Parental Income and Education on the Health of their Children^{*}

This paper investigates the robustness of recent findings on the effect of parental background on child health. We are particularly concerned with the extent to which their finding that income effects on child health are the result of spurious correlation rather than some causal mechanism. A similar argument can be made for the effect of education - if parental education and child health are correlated with some common unobservable (say, low parental time preference) then least squares estimates of the effect of parental education will be biased upwards. Moreover, it is very common for parental income data to be grouped, in which case income is measured with error and the coefficient on income will be biased towards zero and there are good reasons why the extent of bias may vary with child age. Fixed effect estimation is undermined by measurement error and here we adopt the traditional solution to both spurious correlation and measurement error and use an instrumental variables approach. Our results suggest that the income effects observed in the data are spurious.

JEL Classification: I1

Keywords: child health, intergenerational transmission

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^{*} Financial support from the ESRC's Evidence Based Policy programme, and the award of a Nuffield Foundation New Career Development Fellowship to Harmon, is gratefully acknowledged for facilitating the early development of this paper. This paper forms part of the Geary Institute programme of research. The data used in this paper was made available by the UK Data Archive at the University of Essex and is used with permission.

1. Introduction

There is a vast literature documenting the relationship between socioeconomic status (SES) and health (see, for example, Wilkinson and Marmot, 1999). Specifically the relationship between the health of children and the income of their parents has been the focus of much research. This relationship is important because it has been shown that the effects are long-lasting - poor health in childhood is associated with lower educational attainment, inferior labour market outcomes and worse health in adulthood.¹

Case, Fertig and Paxson (2004) investigate how the relationship between parental SES and UK child health varies as children get older using the UK National Child Development Study (NCDS) 1958 birth cohort - they find that the relationship between parental SES and child health gets steeper as children get older – i.e. the health differences across SES gets larger as children age. However it is not clear in this, and other, work whether the direction of causality is clearly established. In the Case *et al.* (2004) work, for example, it is not clear whether this is due to low SES children having more adverse health shocks, or more serious ones, or whether such households do not cope as well with these shocks. Currie and Hyson (1999) partially succeed in addressing a similar issue using US data - for low birthweight. They find that low SES births were more likely to be lighter but, surprisingly, the *effect* of low birthweight on health does not vary much across SES.

Recent work by Currie, Shields and Wheatley-Price (2004) also investigates the relationship between the health of children and the incomes (and education levels) of their parents, using pooled data from the 1997-2002 Health Surveys of England (HSE, see Sprosten and Primatesta, 2003). In this data two generations are present in the household, therefore it is possible to match the health of children with the educational attainment and income of their parents. That study attempted to confirm the extent to which findings for the US, in earlier research by Case, Lubotsky and Paxson (2002), are more generally applicable.

Case *et al.* (2002) analysed the relationship between family income and child health using the US National Health Interview Survey (NHIS) which, like the HSE, is

¹ Marmot and Wadsworth (1997) identify several “pathways” whereby childhood health affects adult health. See also Case *et al.* (2002), Currie (2004), Currie and Hyson (1999), and Graham and Power (2004).

a cross-section dataset.² They showed the existence of a significant and positive effect of income, with children in poorer families having significantly worse health than children from richer families. They also showed that the income gradient in child health increased with child age in the US, with the protective effect of income accumulating over the childhood years.³ Unlike the US, where private health insurance is the norm, the UK has had, since 1948, a National Health Service (NHS) with health care being free at the point of delivery (see Culyer and Wagstaff, 1993). Currie *et al.* (2004) argue that the NHS is successful in insuring the health of the children of low income UK parents as they find no evidence that the income effect on child health increases with child age.⁴ They also extend the findings of US research in a number of important ways. For example, they find clear effects of vegetable consumption and physical exercise on child health, but controlling for these, they find that their income effect results are largely unchanged. They also show that an income effect exists for objective measures of child health, derived from anthropometrical measurements and blood samples, but not for a variety of subjective child health indicators.

The contribution of this paper is to further investigate the robustness of the main results presented in Case *et al.* (2002) and Currie *et al.* (2004), in several ways. First, we are concerned with the extent to which their finding that income effects on child health is the result of a spurious correlation rather than a causal mechanism. This can arise because of endogeneity (i.e. reverse causation arising from a sick child reducing parental income, or from low income parents and sick children having some common unobservable cause). In this case we would expect least squares estimates of the income effect to be biased upwards since income would capture the effect of income and the effect of other factors that are correlated with income but not included. Moreover, we might expect the size of the upward bias to vary with child

² In addition to the children in the 1986-1995 National Health Interview Survey (NHIS), this study also used the Panel Study of Income Dynamics (PSID), and the National Health and Nutrition Examination Survey from 1988 and 1994. The NHIS has large sample sizes and so permits the analysis of conditions that are relatively rare, while the PSID allows the effect of household income over time to be investigated.

³ Currie and Stabile (2003) replicated this result for Canada, such that they also found evidence of an increasing income effect that increased with child age, which they attributed to low income children experiencing more health shocks than high income children.

⁴ Currie *et al.* (2004) do not, however, argue that there is no income effect at all - although the logic of their argument should apply for pre-natal child health as well since NHS is a “cradle to grave” service that ought to ensure maternal health before and during pregnancy.

age if, as seems likely, the effect of a young sick child on parental income is different from that of an older sick child. The subjective nature of the health measure that has been used in some of this work may exacerbate this endogeneity problem.

Secondly, a similar argument can be made for the effect of education - if education and child health are correlated with some common unobservable (say, low time preference) then least squares estimates of the effect of parental education will be biased upwards. A number of studies have addressed this issue using instrumental variable techniques (see, for example, Berger and Leigh, 1989; Arkes, 2003; and Lleras-Muney, 2002).

Also, it is very common for parental income data to be grouped, in which case income is measured with error and the coefficient on income will be biased towards zero. It is difficult to construct a likely argument for why measurement error in parental incomes should vary by the age of the child, so for example, the result in Case *et al.* (2002) of a significantly positive interaction effect between child age and parental income is likely to be robust to any measurement error in income. However, the strength of any reverse causation may well vary with child age. For example, a sick child may require greater parental care when the child is young and this may imply a larger reduction in parental labour supply and income. In which case, the extent of downward bias in the income effect obtained from least squares estimation ought to be larger for households with young children relative to older children. This might account for the changing gradient by age. However, it may well be possible to construct arguments that go in the opposite direction and the question ultimately becomes an empirical one that can only be resolved through obtaining unbiased coefficients from some alternative to least squares.

Finally, there is a well developed literature, mostly in a development context, that maternal background is more important than paternal.⁵ We examine the impact of both paternal and maternal influences on child health outcomes. Moreover we disaggregate the data by the gender of the child to allow for the parental influences to differ for sons and daughters.

⁵ A number of studies have noted that maternal factors can affect a wide range of child outcomes including educational choices (Simpson, 2003; Chevalier *et al.*, 2005), cognitive and social development (Menaghan and Pacel, 1991), political orientations (McAdams *et al.* 1997) and religiosity (Kieren and Munro, 1987).

In contrast to the well determined income effects in cross-section regressions, recent studies that have used panel data tend to find little support for the idea that increased income leads to improved health.⁶ Of course, fixed effect estimation may have problems of its own and it is not at all clear that it necessarily produces more appropriate estimates than least squares. For example, measurement error and its associated bias is likely to be exacerbated using differences. Here we adopt the traditional solution to both spurious correlation and measurement error and use an instrumental variables approach to see if we can reconcile the cross-section results with the panel evidence.

Our analysis, based on the sample of over 7,000 children drawn from the Health Survey for England, finds that, in contrast to Case *et al.* (2002) and Currie *et al.* (2004), there is no significant income gradient and no significant interaction with child age. This paper is structured as follows. Section 2 outlines the existing literature. Section 3 describes the data. Section 4 presents and discusses results and Section 5 concludes and suggests further research directions.

2. Literature

The mechanisms by which income is related to health remain controversial and, as noted by Deaton and Paxson (1998), “there is a well-documented but poorly understood gradient linking socio-economic status to a wide range of health outcomes”. There are a variety of potential disadvantages for children from having low parental income and at least some of these may have longlasting, and even, permanent effects. Case *et al.* (2004) quantify the effects of childhood ill health on adult health, employment and socioeconomic status, using data from the UK NCDS birth cohort that has been followed from birth into middle age. They find that, controlling for parental income, education and social class, children who have poor health also have significantly lower educational attainment, poorer adult health, and lower subsequent socioeconomic status. They suggest that health is a potentially important transmission mechanism for the intergenerational correlation of income and education.

⁶ See, for example, Adams *et al.* (2003), Contoyannis *et al.* (2004), Frijters *et al.* (2003), and Meer *et al.* (2003).

Case *et al.* (2002) find that not only do children from poorer households suffer from poorer health, but also that these adverse health effects tend to compound over time so that the variation in health across income or social class increases with age, even across children with similar chronic conditions. This results in children of poorer households entering adulthood in worse health and with more serious chronic conditions. They refer to this income effect as a “gradient” in health status. The gradient applies not just to subjective health responses - they also find that poorer children spend more days in bed, are absent from school for more days due to illness, and suffer from more episodes of hospitalization. Indeed, doctors also reported poorer children to be in worse health, therefore on average it is not the case that poorer parents are simply more likely to report their children to be in poor health even if their health is actually not any worse. In addition, their results appear not to arise because higher income parents tend to have more education. They find that this income gradient remains even after controlling for parental education, and that education has an independent positive effect on health. Despite the common finding that income effects on child outcomes are larger at lower levels of income, they find that the gradient appears at all income levels; upper-income children do better than middle-income children, and middle-income children do better than lower-income children.

The authors also find that the disparities in child health by parental income become larger with child age. Even after controlling for parental education, doubling household income increases the probability that a child aged 0–3 (4–8, 9–12, 13–17) is in excellent or very good health by about 4% (5%, 6%, 7%). They go on to investigate chronic conditions, such as asthma, respiratory conditions in general, kidney disease, heart conditions, diabetes, digestive disorders, and mental retardation. Even though the incidences of some of these conditions are small, they find that some conditions, such as digestive disorders, hearing problems, heart conditions, and mental retardation, are more likely at low incomes, and only a few conditions (such as hay fever) are more likely amongst the rich. However, the effects of chronic conditions on health are consistently more severe for poorer children. Poor children with chronic conditions have poorer health, spend more days in bed, and have a greater incidence of hospitalization than do higher-income children with the same conditions. For example, they calculate that poor children with asthma (e.g., those at the 25th percentile of income) spend 5.6 more days in bed per year, while higher-income

children with asthma (75th percentile) spend 3.8 more days in bed compared with children in the same income brackets without asthma. Finally, Case *et al.* (2002) examine whether it is only permanent income that matters or, rather, whether the timing of income matters such that, for example, low income in early childhood has a more adverse effect on later health than low income later in childhood. The authors find no effect of the timing of income. It seems that it is not the inability of low current income parents to borrow to produce better long term health, rather it is the inability or unwillingness of low current income parents to understand that it is permanent income which matters for child health at later ages.

Like Case *et al.* (2002), Currie *et al.* (2004) find robust evidence of an income gradient using subjectively assessed general health status, both controlling for parental education and not. However, the size of this gradient is somewhat smaller than in Case *et al.* (2002). Moreover, they find no evidence that the income gradient increased with child age. They find statistically significant income effects on the probability of having some chronic health conditions - notably asthma, mental and other nervous system problems, and skin complaints, which have a higher incidence in poorer families. There is some evidence that income does 'protect' children from the adverse general health consequences of some conditions such as mental illness and other nervous system problems, metabolic problems such as diabetes, and blood pressure problems such as hypertension. Independent effects of parental education, especially the mother's, on the health of children were also found.⁷ However, they failed to find a significant interaction between child age and parental income – something which they attribute to the success of the NHS.

While both Case *et al.* (2002) and Currie *et al.* (2004) show that their income gradient results are robust to including other observable parental characteristics and lifestyle variables, there remains the possibility that unobservable factors might still account for the results. We attempt to address this using instrumental variable analysis.

⁷ Additionally, they found that a significant income gradient remains after controlling for family fixed effects, child diet and parental exercise.

3. Data and Sample Selection

This paper investigates the relationship between parental characteristics and child health using pooled data from the 1997-2002 Health Surveys of England (HSE), which include information on two generations - the health of children and the educational attainment and income of their parents.

The HSE was initiated by the UK's Department of Health in 1992 to monitor trends in the nation's health.⁸ Each survey uses the Postcode Address File as a sampling frame, and is collected by a combination of face-to-face interviews, self-completed questionnaires and medical examinations. Each year the survey over-samples particular groups – for example, the elderly, ethnic minorities, etc. and our analysis applies the sampling weights to produce correct standard errors. The HSE surveys are a unique source of information on household/individual characteristics and subjective/objective measures of health.

Although the HSE was initiated in 1992, the sample used in this paper only includes surveys from 1997-2002, as information on children aged 2-15 was only collected from 1995 onwards⁹ (the 2001 survey extended the analysis to children under the age of 2) and household income was only collected from 1997 onwards. As both children and parents from the same household are interviewed it allows us to match parental characteristics to the child's record.¹⁰ Pooling the six surveys resulted in a dataset containing 26,498 children; however as the parents of the over-sampled children included in 1997 and 2002 surveys were not interviewed, this substantially reduces our sample size. In addition, unlike Currie *et al.* (2004) we exclude children whose fathers or mothers are either missing from the survey or are missing from the household i.e. one-parent families, therefore we restrict our analysis to children whose both parents are included in the survey. This reduces our sample size to 9,958 children. We then drop any observation where data is missing on our variables of interest, for example household income is missing for approximately 10% of the

⁸ The HSE are carried out by the Joint Health Surveys Unit of the National Centre for Social Research and the Department of Epidemiology and Public Health, Royal Free and University College London.

⁹ Up to two randomly selected children per household are surveyed.

¹⁰ While the HSE data does distinguish between natural, adoptive, foster and step parents, we define a "parent" as any type of parent.

sample. Our final sample therefore includes 7,005 children aged between 0 and 15 (3,540 boys and 3,465 girls).¹¹

Table 1 describes the summary statistics for the sub-sample used in the analysis. It shows that there is little difference in terms of health status, age, household income, parental age and schooling between boys and girls in the sample. The average age that fathers left school (17.46) is slightly higher than mothers (17.41) and, as expected, the average age of fathers is approximately 2 years greater than that of mothers. 23.58 % of the mothers and 34.33% of fathers in the sample are affected by the raising of the school leaving age (RoSLA).

The primary variable of interest in this paper is a subjective measure of children's general health. It is a self-reported measure for children aged between 13 and 15 and is reported by parents for children less than 13 years of age. The variable is based on responses to the question "*How is your health in general?*". The possible answers range from *Very Good* to *Very Bad* on a 1 to 5 scale. Following Currie *et al.* (2004) the measure was recoded into a 4-category variable, whereby "*Bad*" and "*Very Bad*" were combined due to low sample sizes in these categories. Almost 95% of our sample is reported as having "*Very good*" or "*Good*" health. The surveys also include information on whether the child has a long-term chronic health condition (CHC). In our sample of 7,005 children 20.06% have a chronic health condition. The respondent can list up to 6 CHC which are then coded into 42 categories. A cross tabulation of the subjective health measure and the chronic health condition measure reveals that some children with a chronic health condition were reported as having "*Very good*" health. To correct for this apparent inconsistency, the subjective general health measure was recoded from "*Very good*" to "*Good*" if the child has a CHC. Therefore the distribution of our dependent variable is as follows: Very Good (53.70%), Good (40.79%), Fair (4.94%), Very Bad/Bad (0.57%).

While we include a number of explanatory variables in the analysis, we are essentially interested in the impact of parental income and education on child health outcomes. Following Currie *et al.* (2004) current total pre-tax annual family income is used as a measure of parental income. It is coded in 31 income bands ranging from less than £520 to more than £150,000. The midpoints of each band was taken and

¹¹ Full details of the original HSE data, and the (small) impact of our selection criteria, are available upon request.

deflated to 2000 prices using the UK average earnings index according to the month in which the interview was conducted. The average annual household real income is £34,869.¹² Our measure of parental schooling is derived from two sources. The HSE asks parents the age at which they finished full-time education. It is coded 1-8 (where 1=Not yet finished, 2=Never went to school, 3= aged 14 or under, 4=aged 15, 5= aged 16, 6= aged 17, 7=aged 18 and 9=aged 19 or over). As the variable is top coded at 19, we use an additional HSE variable which captures the parents highest educational qualification to distinguish parents who left at 19 from those who left after 19. We combine this with information from the UK Labour Force Survey to determine the average leaving age of individuals with a degree.¹³ This allows us to create a new schooling variable ranging from 14 to 21.

Indeed the Labour Force Survey provides an important point of comparison to gauge the reliability of the HSE data in regards the parental income and educational measures. Therefore we compare our HSE sample to a similar sample in the UK Labour Force Survey from 1997-2002. We attempt to replicate the HSE sample by analysing two-parent households who have children between the ages 0 and 15.¹⁴ Unlike the HSE, the household income measure in LFS is continuous and represents a combination of mothers and fathers income. The average real household income of £34,889 in LFS is almost the same as the HSE measure (£34,869). Figures 1a and 1b show that the distribution of income (as reported in the 31 income bands in the HSE and equivalent income bands imposed on LFS) is relatively similar across both samples.

As already noted, one particular concern with the HSE data is that the educational measure, which reports the age at which the parent left full-time education, has an upper bound at age 19; therefore we cannot distinguish different

¹² Note that this figure is greater than Currie *et al.* (2004) findings as we only include households with two parents, while Currie *et al.* also include single-parent households. We use the log of household income in the empirical analysis.

¹³ The HSE data contains two education measures – the age at which the respondent left school (which is top coded at 19) and the respondent’s highest qualification level. The LFS data also contains the same two measures, however it does not top code the age left school variable. To overcome the top-coding problem within HSE, we use the LFS data to generate the average age of a respondent with a degree (age 21), and the average age of a respondent with a teaching qualification (age 20). Then, for respondents within HSE who have a degree or a teaching qualification, we recode their age left education variable with the average age left education generated from the LFS data. Therefore the new age left education variable the HSE data ranges from 14 to 21.

¹⁴ In addition we restrict the sample to respondents from England only, in order to match the HSE sample.

levels of higher education. The LFS data, on the other hand, includes a continuous educational measure. Table A1 in the Appendix compares the age at which mothers and fathers left full-time education in both the LFS and HSE samples. It shows that the majority of mothers (43.21% in LFS and 43.51% in HSE) and fathers (46.98% in LFS and 43.717% in HSE) left education at 16. There are notable similarities between the two datasets. While a direct comparison of the upper age categories is not possible, Table A1 shows that 25.47% of fathers and 23.41% of mothers in the LFS left education at 19 or over, compared with 28.23% and 23.27% in the HSE. Appendix Figures A1a-A1d report the corresponding histograms.

Table 1 Descriptive Statistics HSE 1997-2002 - Estimation Sample

	All	Boys	Girls
Child's Subjective Ill Health	1.52 (0.62)	1.53 (0.62)	1.52 (0.62)
Household Log Income	10.24 (0.68)	10.23 (0.67)	10.24 (0.68)
Mother's Schooling	17.41 (1.85)	17.41 (1.84)	17.41 (1.85)
Father's Schooling	17.46 (2.06)	17.45 (2.04)	17.47 (2.08)
Birth Weight	3.01 (1.15)	3.06 (1.17)	2.96 (1.13)
Child's Age	7.97 (4.24)	7.95 (4.27)	8.0 (4.20)
Mother's Age	36.95 (6.31)	36.89 (6.42)	37.02 (6.19)
Father's Age	39.28 (6.95)	39.21 (7.00)	39.35 (6.90)
Mother Smokes	0.22 (0.41)	0.22 (0.41)	0.22 (0.42)
Father Smokes	0.23 (0.42)	0.24 (0.43)	0.23 (0.42)
Years exposed to Mother's Smoking	2.20 (4.23)	2.15 (4.19)	2.26 (4.27)
Years exposed to Father's Smoking	2.44 (4.29)	2.52 (4.35)	2.35 (4.23)
Mother Smoked when pregnant	0.01 (0.10)	0.01 (0.11)	0.01 (0.10)
Paternal Grandfather smoked	0.69 (0.46)	0.69 (0.46)	0.69 (0.46)
Paternal Grandmother smoked	0.46 (0.50)	0.46 (0.50)	0.46 (0.50)
Maternal Grandfather smoked	0.65 (0.48)	0.65 (0.48)	0.66 (0.48)
Maternal Grandmother smoked	0.44 (0.50)	0.44 (0.50)	0.45 (0.50)
Mother affected by RoSLA %	23.58	23.16	23.92
Father affected by RoSLA %	34.33	33.95	34.72
N	7005	3540	3465

Note: Means and standard deviations (in parentheses) reported.

Figure 1a: Household Income Bands- LFS 1997-2002 Data

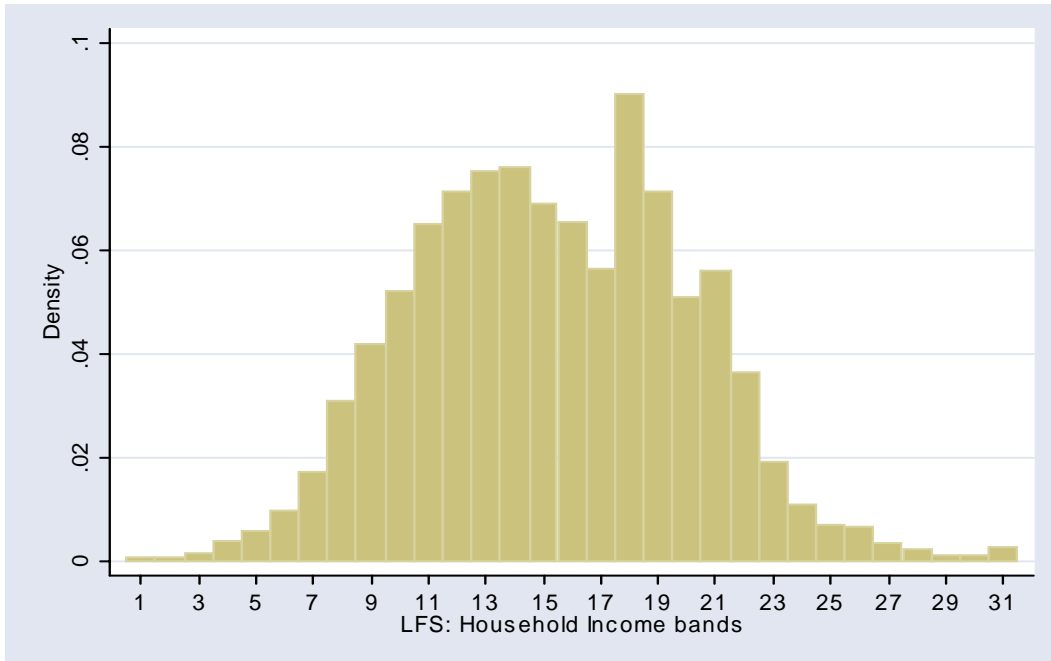
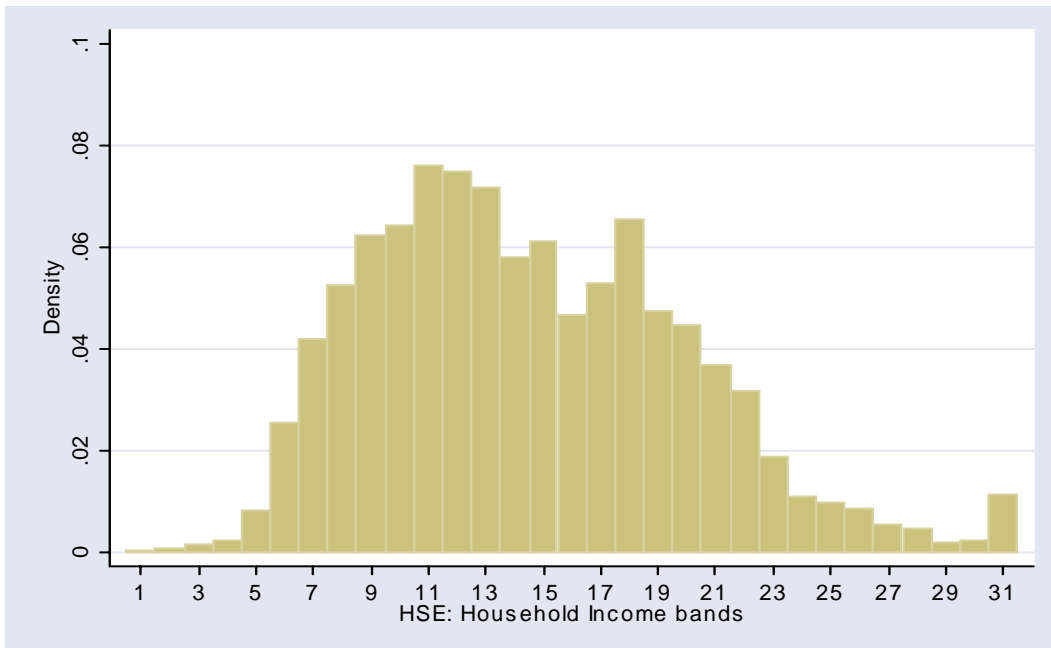


Figure 1b: Household Income Bands- HSE 1997-2002 Data



4. Estimation and Results

Our basic model of the impact of parental background on the child's health is:¹⁵

$$H_h^c = \mathbf{S}_h\boldsymbol{\beta} + \alpha Y_h + \mathbf{C}_h\boldsymbol{\delta} + \mathbf{X}_h\boldsymbol{\gamma} + \varepsilon_h^c \quad (1)$$

where h indicates household h . The dependent variable H^c is a four point ordinal variable defining child health status (very good, good, fair, bad/very bad) as discussed above. This model is estimated as an ordered probit with child health as a function of parental educations, \mathbf{S} , measured as the ages at which the mother and father left full-time education, and the (log of) household income (Y_h).¹⁶ We include controls for cigarette smoking, \mathbf{C} , specifically whether the father or mother is currently a smoker, whether the mother smoked during pregnancy and the number of years the child has been exposed to parental smoking. Finally, \mathbf{X} contains additional parental and child characteristics including the mother and fathers ages (entered as a cubic), the child's ethnicity, birthweight (and a dummy variable for missing birthweight), month of birth dummies, log of household size, year of survey dummies and region of residence at time of survey.

Table 2 presents our estimates from this model (replicating the structure of Table 1 in Currie *et al.* (2004)). The first column includes children of both genders and all age groups. The second and third columns divide the sample into boys and girls and examines four separate age cohorts, both to test for the presence of an income gradient and to control for the fact that the health of children up to the age of 13 were reported by their parents and self-reported thereafter. The final column then combines boys and girls and examines cohort effects.¹⁷ As with the Currie *et al.* (2004) results, there is little evidence of education effects (with the exception of both parent's education on the youngest age group of girls, and maternal education on the grouped age/gender sample and on the oldest age cohort of girls). The income effects are more significant across the samples. However it would appear that the impact of

¹⁵ While there are sibling pairs in the data the household is observed at only one point in time and so we cannot estimate sibling difference models. However, we do control for the clustering that occurs because households contain siblings.

¹⁶ The strong distributional assumptions of ordered probit models were relaxed in alternative specifications based on the semi-parametric estimator of Stewart (2004). While these estimates, available on request, seem statistically preferable to the ordered probit models (based on the likelihood tests in the Stewart model), the impact of the change in specification is slight.

¹⁷ Tables A2a and A2b in the Appendix replicate Table 2, however they exclude the parental smoking controls and birthweight respectively.

household income on child health outcomes is stronger for boys than girls – where it is only significant for girls aged 4-8. Moreover, we find that the income effect increases monotonically with child age only for boys and that even this effect is not statistically significant.

As already discussed, the impact of parental schooling and income on child health outcomes may suffer from endogeneity problems. In this paper we identify the effect of parental education on child health outcomes using the exogenous variation in schooling caused by the raising of the minimum school leaving age (RoSLA). Individuals born before September 1957 could leave school at 15 while those born after this date had to stay for an additional year. This policy change creates a discontinuity in the age at which parents left school. Figure 2a and 2b illustrates this by showing the mean schooling leaving age for males and females by birth year and month between January 1956 and December 1958. There is a marked jump in both graphs for respondents born in September 1957 which coincides with the introduction of the new school leaving age. We overcome this potential endogeneity problem by using RoSLA to instrument parental education. We also account for differences in attainment by month of birth by including controls for these in the specification (see Angrist and Krueger (1991, 1992). A recent report by HEFCE (2005) finds that the probability of entering higher education differs by birth month, such that children born in autumn are almost 20% more likely to enter higher education at age 18 than those born in the late summer.

We also account for the potential endogeneity of parental education by using grandparental smoking histories as instruments. We assume that having a grandparent who smokes creates an exogenous change in parental education which is independent of child's health outcomes. While adolescent smoking is often used as an instrument when examining educational choices (see Evans and Montgomery (1994) and a review in Harmon, Oosterbeek and Walker (2003)), no study to date has used grandparental smoking to instrument parental education in a child's health equation. To account for the potential endogeneity of parental income we use the predicted parental educational values from the first stage schooling equations as instruments. We therefore estimate

$$S_p = \eta_p RoSLA_p + g_p(G_p, MB_p, cohort_p) + \mathbf{Z}_p \boldsymbol{\pi}_p + \xi_p^{S_p} \quad (2)$$

$$S_m = \eta_m RoSLA_p + g_m(G_m, MB_m, cohort_m) + \mathbf{Z}_m \boldsymbol{\pi}_m + \xi_m^{S_m} \quad (3)$$

$$Y_h = \delta_m \hat{S}_m + \delta_p \hat{S}_p + f(cohort_p, cohort_p) + \mathbf{Z}_h \boldsymbol{\pi}_h + \xi_h^Y \quad (4)$$

where m and p indicate mother and father, $RoSLA$ is the dummy variable defined above, G_p and G_m are vectors containing *grandparental* smoking dummies (paternal and maternal) and a dummy variable accounting for whether the parent smoked before the age of 16, MB is a set of parental birth month dummies, $cohort$ is a (cubic) function of parental date of birth, and the \mathbf{Z} 's are relevant exogenous control variables. From the estimation of equation (2) through (4), using $RoSLA$, G and MB as instrumental variables, we are able to compute predicted values for maternal and paternal education, and for household income. We then re-estimate equation (1) as

$$H_h^c = \hat{\mathbf{S}}_h \boldsymbol{\beta} + \alpha \hat{Y}_h + \mathbf{C}_h \boldsymbol{\delta} + \mathbf{X}_h \boldsymbol{\gamma} + \varepsilon_h^c \quad (5)$$

Table 3 shows the results from the first stage regressions in (2) through (4). The $RoSLA$ variable shows a strong significant impact on the schooling level of the father, adding about one third of a year of schooling. This is consistent with the findings in Harmon and Walker (1995) and the survey in Harmon, Oosterbeek and Walker (2003), based on similar samples of males from a range of UK surveys. However the same variable does not have a significant effect on mothers. The teen smoking variable, for both the mothers and fathers, has a very strong and negative effect on schooling, reducing schooling by almost one year. The smoking status of grandparents have also strong, negative effects on both samples. Finally, in the parental education equations we find that month of birth has jointly significant effects, with more significance for fathers than for mothers.

Table 3 also presents the estimates of equation (4) for household income. The estimates based on predicted schooling levels are high – a return of approximately 11% per year of schooling. However these are consistent with instrumental variables estimates of the returns to schooling in the literature and indeed very similar to UK sourced estimates (such as reviewed in Harmon, Walker and Westergaard-Nielsen, 2001). Throughout all of the models in Table 4 the F-test for the significance of the instruments is passed with very low p – values.

Table 2: *HSE Ordered Probit Estimates of Parental Income and Education on Child Ill Health Status: Exogenous*

Subjective Health	All	Boys				Girls				Boys & Girls			
		0-3	4-8	9-12	13-15	0-3	4-8	9-12	13-15	0-3	4-8	9-12	13-15
Father Schooling	0.005 (0.009)	-0.024 (0.031)	0.018 (0.021)	-0.015 (0.027)	0.031 (0.028)	0.067** (0.033)	-0.025 (0.023)	-0.000 (0.025)	0.043 (0.031)	0.018 (0.023)	-0.004 (0.015)	-0.005 (0.018)	0.033 (0.020)
Mother Schooling	-0.020** (0.010)	0.001 (0.034)	-0.005 (0.024)	-0.040 (0.029)	0.026 (0.033)	-0.078** (0.035)	-0.024 (0.025)	-0.020 (0.029)	-0.078** (0.034)	-0.036 (0.024)	-0.012 (0.017)	-0.029 (0.020)	-0.016 (0.023)
Household Income	-0.145*** (0.027)	-0.181** (0.084)	-0.187*** (0.065)	-0.202*** (0.070)	-0.277*** (0.089)	-0.050 (0.086)	-0.125* (0.066)	0.011 (0.073)	-0.144 (0.096)	-0.116** (0.060)	-0.159*** (0.046)	-0.093* (0.051)	-0.227*** (0.064)
Observations	7005	678	1251	941	670	629	1233	946	657	1307	2484	1887	1327

Notes: Coefficients from ordered probit models of general health status (1= Very Good, 2=Good, 3=Fail, 4=Bad/Very Bad) are reported. Robust standard errors are in parenthesis. Thresholds are also estimated but not reported. All specifications include mother's and father's age in cubics, indicators of whether the mother or father is currently a smoker, indicator of whether the mother smoked during pregnancy, the number of years the child has been exposed to parental smoking, ethnicity (white base), log of household size, child's birth weight, a dummy variable for missing birth weight, month of survey dummies and year of survey dummies. Significant levels: *** 1%, ** 5% and * 10%.

Figure 2a HSE Age Left School by Birth Month: Males born Jan 1956-Dec 58

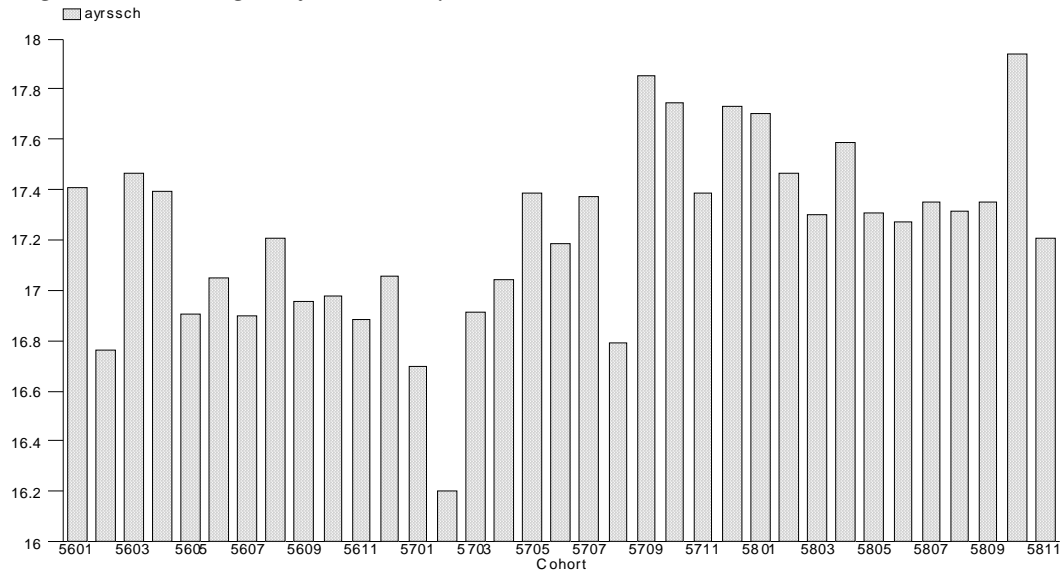


Figure 2b HSE Age Left School by Birth Month: Females born Jan 1956-Dec 58

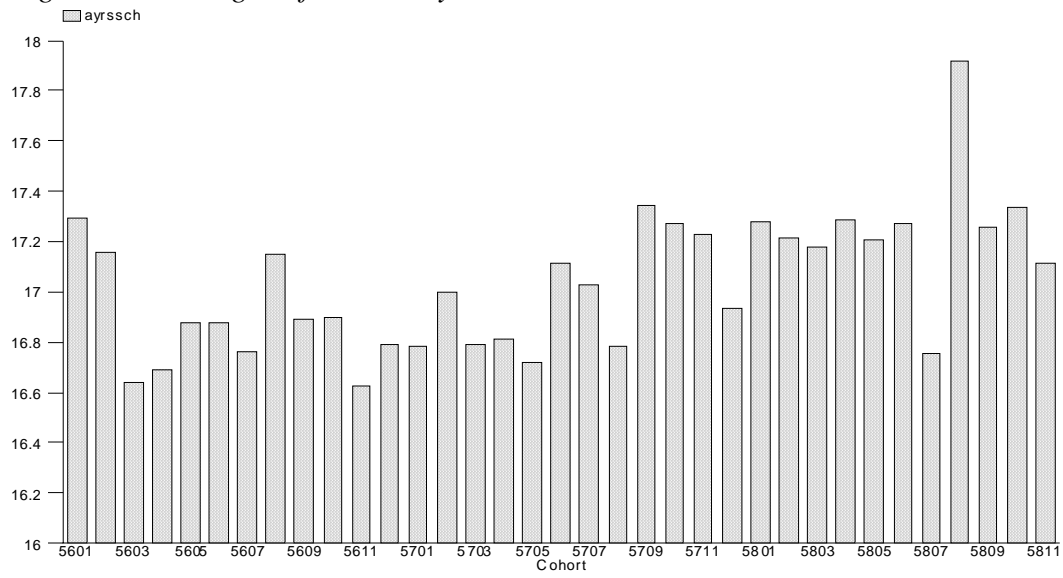


Table 3 HSE OLS First Stage Equations

Estimated as separate equations	Father's Schooling	Mother's Schooling	Household Income
RoSLA	0.383*** (0.100)	-0.026 (0.103)	-
Father's predicted schooling	-	-	0.114*** (0.013)
Mother's predicted schooling	-	-	0.112*** (0.016)
Teen Smoker	-0.986*** (0.048)	-0.905*** (0.045)	-
Paternal Grandfather smoked	-0.355*** (0.055)	-	-
Paternal Grandmother smoked	-0.467*** (0.049)	-	-
Maternal Grandfather smoked	-	-0.279*** (0.048)	-
Maternal Grandmother smoked	-	-0.351*** (0.046)	-
Birth Months:			
February	0.170 (0.123)	-0.112 (0.115)	-
March	0.325*** (0.123)	-0.045 (0.110)	-
April	0.279** (0.127)	-0.035 (0.115)	-
May	0.184 (0.121)	-0.125 (0.110)	-
June	0.157 (0.102)	-0.158* (0.094)	-
July	0.399*** (0.136)	-0.220** (0.110)	-
August	0.557*** (0.139)	0.243* (0.127)	-
September	0.546*** (0.123)	-0.171 (0.110)	-
October	0.207* (0.123)	0.165 (0.116)	-
November	0.356*** (0.128)	-0.005 (0.113)	-
December	0.148 (0.123)	0.048 (0.114)	-
F test of instruments (p-value)	174.99 (0.000)	164.32 (0.000)	79.32 (0.000)
Observations	7005	7005	7005

Notes: Robust standard errors are in parentheses. The model specification in the Father's Schooling equation includes father's date of birth in cubics (they are continuous variables with months divided by 100 being the unit of measurement with September 1934 being equal to zero), father's month of birth, whether father started smoking before 16, grandparental smoking histories and regional dummies. The mother's Schooling equation includes mother's date of birth in cubics (they are continuous variables with months divided by 100 being the unit of measurement with September 1934 being equal to zero), mother's month of birth, whether mother started smoking before 16, grandparental smoking histories and regional dummies. The Income equation includes predicted father's and mother's schooling from the above OLS equation, mother and father's age, mother and father's age squared, a categorical variable capturing the age of the youngest child, survey dummies, regional dummies and interactions between survey year and regions. Significant levels: *** 1%, ** 5% and * 10%.

Table 4 presents the child health model from equation (5). This replicates the structure of Table 2 but parental schooling and household income are now endogenous. The weak impact of education from Table 2 is repeated in this table. However, the strong impact of parental income on child health outcomes has been all but eliminated (with the sole exception of the oldest age cohort of boys, itself the strongest effect in Table 2). This implies that there is little, if any, causal relationship between parental characteristics such as income and education, and the child health outcome.

Table 4 HSE Estimates of Parental Income and Education on Child Ill Health Status: Endogenous

Subjective Health	Boys				Girls			
	0-3	4-8	9-12	13-15	0-3	4-8	9-12	13-15
Father Schooling	0.082 (0.162)	0.022 (0.111)	-0.024 (0.132)	-0.292** (0.145)	-0.081 (0.182)	0.016 (0.914)	0.134 (0.129)	-0.001 (0.138)
Mother Schooling	-0.206 (0.154)	-0.101 (0.130)	-0.180 (0.161)	-0.275 (0.183)	-0.150 (0.201)	-0.009 (0.118)	-0.070 (0.151)	-0.110 (0.157)
Household Income	-0.293 (0.940)	0.297 (0.591)	-0.084 (0.826)	1.640 (1.159)	0.694 (1.255)	0.225 (0.608)	-0.628 (0.876)	-0.328 (1.112)
Mother smokes	0.091 (0.258)	0.342 (0.209)	0.207 (0.243)	0.045 (0.293)	0.391 (0.259)	-0.216 (0.219)	0.054 (0.239)	0.536* (0.288)
Father smokes	-0.176 (0.186)	-0.051 (0.181)	0.320* (0.188)	0.448 (0.274)	-0.302 (0.242)	0.201 (0.183)	-0.05 (0.204)	-0.132 (0.228)
Years exposed to father's smoking	0.053 (0.100)	-0.021 (0.031)	-0.021 (0.022)	-0.001 (0.020)	-0.053 (0.092)	0.044 (0.032)	0.012 (0.020)	-0.036* (0.020)
Years exposed to mother's smoking	0.145** (0.070)	0.014 (0.025)	-0.026 (0.017)	-0.029 (0.018)	0.094 (0.091)	-0.015 (0.026)	0.010 (0.018)	0.020 (0.015)
Mother smoked when pregnant	-0.050 (0.272)	-0.325 (0.291)	0.014 (0.467)	-0.746 (0.592)	-0.552* (0.331)	0.953*** (0.219)	0.541 (0.399)	-0.147 (0.626)
Observations	678	1251	941	670	629	1233	946	657
Exogeneity Test	8.36	2.50	1.24	6.23	1.41	1.82	5.93	1.80
Significant of residuals	pr=0.039	pr=0.475	pr=0.744	pr=0.101	pr=7.04	pr=0.611	pr=0.115	pr=6.15

Notes: Coefficients from ordered probit models of general health status (1= Very Good, 2=Good, 3=Fail, 4=Bad/Very Bad) are reported. Bootstrapped standard errors are in parenthesis for Dad Schooling, Mom Schooling and Household Income. This used 100 replications in Stata 9's bootstrap routine with the force option to allow for weights. Thresholds are also estimated but not reported. All specifications include mother's and father's age in cubics, indicators of whether the mother or father is currently a smoker, indicator of whether the mother smoked during pregnancy, the number of years the child has been exposed to parental smoking ethnicity (white base), log of household size, child's birth weight, a dummy variable for missing birth weight, month of survey dummies and year of survey dummies. Exogeneity test is from Smith and Blundell (1986). The residuals from each first stage regression are included in the ordered probit model along with the variables that the first stage equations would have instrumented. Estimation of the model gives rise to a test for the hypothesis that each of the coefficients on the residual series are zero. Significant levels: *** 1%, ** 5% and * 10%.

5. Conclusion

In this paper we have investigated the relationship between key parental characteristics of education and income on child health using data from the Health Survey of England (HSE). This is motivated by a large literature, mainly from the US, which suggests a strong parental income gradient in child health which increases with the age of the child. This paper is further motivated by the work of Currie *et al.* (2004) who, based on the same HSE data, finds evidence of similar, although smaller, income effects.

In this paper we replicate the main finding of the Currie *et al.* (2004) results and confirm their main findings, although we find stronger evidence of the age cohort differences in line with the US literature (such as Case *et al.* 2002), suggestive of, as described in the literature, a ‘protective’ influence of parental income. However we extend the approach of both the UK and US literature by treating both parental education and income as endogenous. Despite the apparent strength of our instrument we find no effect of income – our conclusion is that the effect observed in earlier correlations seems likely to be spurious.

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APPENDIX

Table A1 Comparison of Age Left Full-Time Education in LFS and HSE Surveys

Age	Age FATHER left full-time education %		Age MOTHER left full-time education %	
	LFS	HSE	LFS	HSE
15	7.06	8.81	3.71	4.85
16	46.98	43.71	43.21	43.51
17	8.95	8.82	12.98	11.76
18	11.53	10.44	16.67	16.60
19	2.88	7.84	3.87	6.97
20	2.05	0.36	2.07	1.50
21	6.98	20.03	7.02	14.80
22	6.28		5.74	
23	3.0		2.36	
24	1.87		1.08	
25	2.41		1.27	
Total	46,572	7005	46,572	7005

Figure A1a: Age Dad Left Full-Time Education- LFS Data

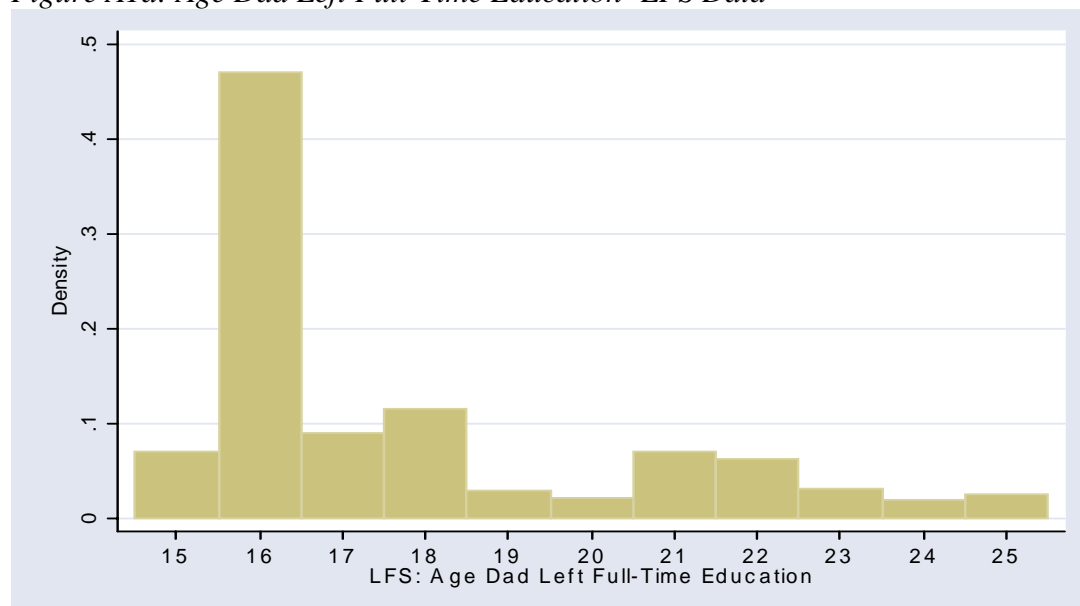


Figure A1b: Age Father Left Full-Time Education- HSE Data

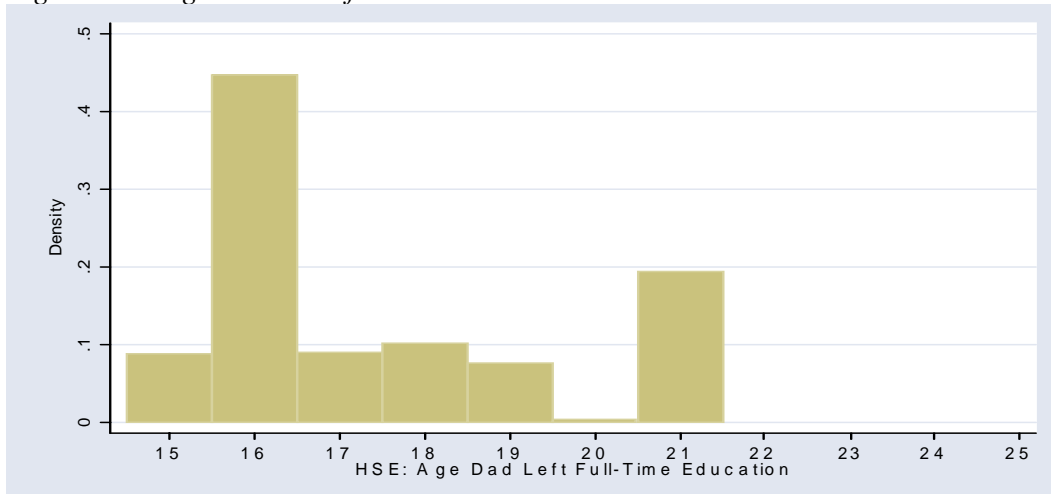


Figure A1c: Age Mother Left Full-Time Education- LFS 1997-2002 Data

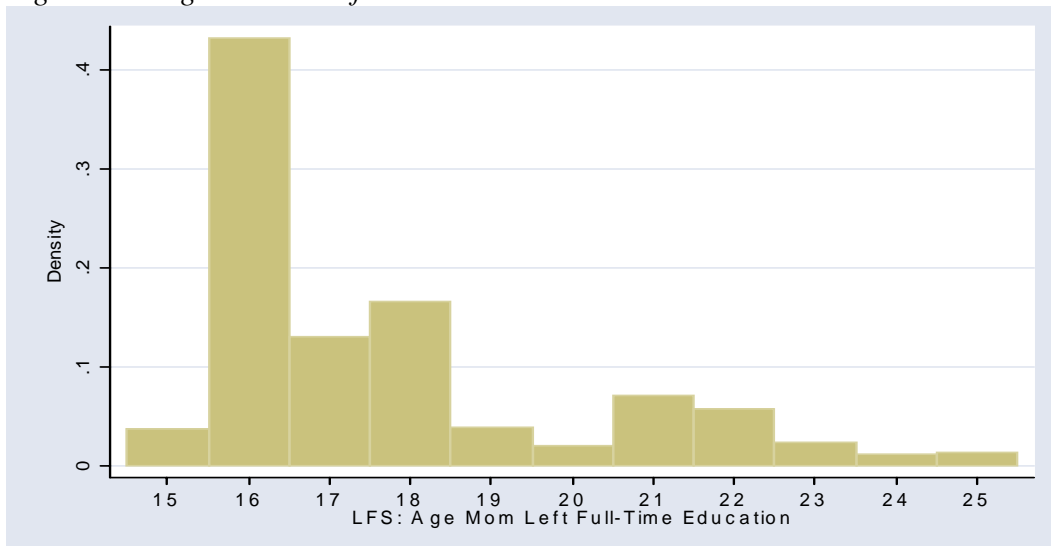
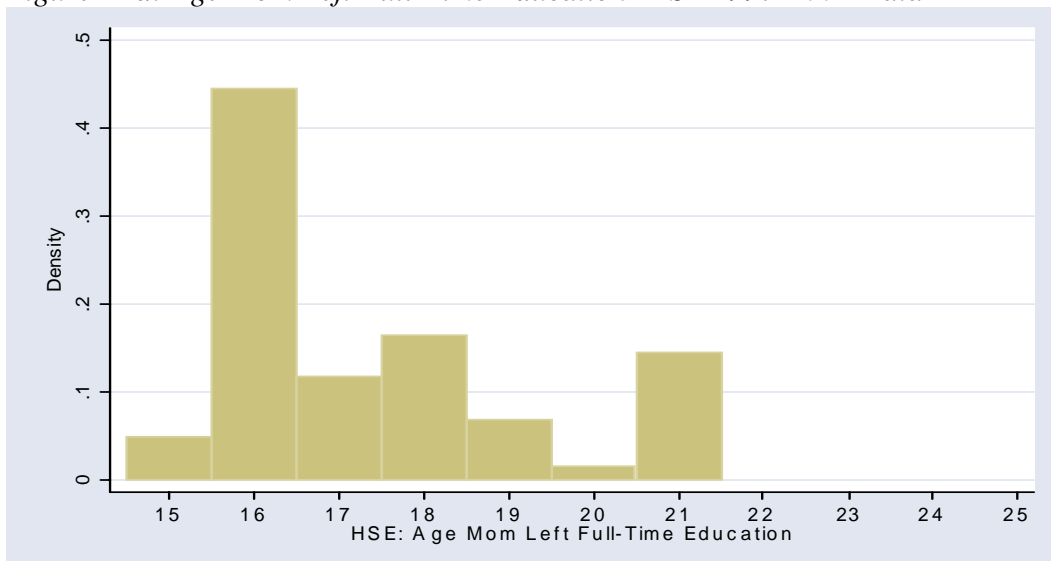


Figure A1d: Age Mom Left Full-Time Education- HSE 1997-2002 Data



*Table A2a: HSE Ordered Probit Estimates of Parental Income and Education on Child Health Status:
Exogenous (No Smoking Controls)*

Subjective Health	All	Boys				Girls				Boys & Girls			
		0-3	4-8	9-12	13-15	0-3	4-8	9-12	13-15	0-3	4-8	9-12	13-15
Dad Schooling	0.003 (0.009)	-0.030 (0.031)	0.015 (0.021)	-0.011 (0.027)	0.031 (0.029)	0.063* (0.034)	-0.025 (0.023)	-0.003 (0.025)	0.036 (0.030)	0.013 (0.023)	-0.006 (0.015)	-0.007 (0.018)	0.030 (0.020)
Mom Schooling	-0.023** (0.010)	-0.005 (0.034)	-0.009 (0.024)	-0.040 (0.029)	0.022 (0.033)	-0.081** (0.035)	-0.025 (0.025)	-0.031 (0.029)	-0.075** (0.033)	-0.041* (0.024)	-0.015 (0.017)	-0.033* (0.020)	-0.016 (0.023)
Household Income	-0.152*** (0.027)	-0.218** (0.084)	-0.191*** (0.065)	-0.206*** (0.069)	-0.280*** (0.090)	-0.047 (0.086)	-0.135** (0.066)	-0.001 (0.074)	-0.171* (0.098)	-0.127** (0.060)	-0.164*** (0.046)	-0.099** (0.051)	-0.239*** (0.064)
Observations	7005	678	1251	941	670	629	1233	946	657	1307	2484	1887	1327

Notes: Coefficients from ordered probit models of general health status (1= Very Good, 2=Good, 3=Fail, 4=Bad/Very Bad) are reported. Robust standard errors are in parenthesis. Thresholds are also estimated but not reported. All specifications include mother's and father's age in cubics, ethnicity (white base), log of household size, child's birth weight, a dummy variable for missing birth weight, month of survey dummies and year of survey dummies. Significance levels: *** 1%, ** 5% and * 10%.

*Table A2b: HSE Ordered Probit Estimates of Parental Income and Education on Child Health Status:
Exogenous (No Smoking Controls or Birthweight)*

Subjective Health	All	Boys				Girls				Boys & Girls			
		0-3	4-8	9-12	13-15	0-3	4-8	9-12	13-15	0-3	4-8	9-12	13-15
Father Schooling	0.003 (0.009)	-0.033 (0.031)	0.014 (0.021)	-0.012 (0.028)	0.032 (0.029)	0.063* (0.034)	-0.030 (0.023)	-0.004 (0.025)	0.039 (0.030)	0.011 (0.023)	-0.008 (0.015)	-0.007 (0.018)	0.031 (0.020)
Mother Schooling	-0.024** (0.010)	-0.006 (0.034)	-0.007 (0.024)	-0.039 (0.029)	0.021 (0.033)	-0.081** (0.035)	-0.025 (0.025)	-0.032 (0.028)	-0.077** (0.033)	-0.042* (0.024)	-0.014 (0.017)	-0.032 (0.020)	-0.016 (0.023)
Household Income	-0.155*** (0.027)	-0.223*** (0.084)	-0.201*** (0.064)	-0.208*** (0.069)	-0.287*** (0.089)	-0.051 (0.086)	-0.136** (0.065)	0.007 (0.073)	-0.174* (0.097)	-0.130** (0.060)	-0.171*** (0.046)	-0.097* (0.051)	-0.244*** (0.064)
Observations	7005	678	1251	941	670	629	1233	946	657	1307	2484	1887	1327

Notes: Coefficients from ordered probit models of general health status (1= Very Good, 2=Good, 3=Fail, 4=Bad/Very Bad) are reported. Robust standard errors are in parenthesis. Thresholds are also estimated but not reported. All specifications include mother's and father's age in cubics, ethnicity (white base), log of household size, month of survey dummies and year of survey dummies. Significance levels: *** 1%, ** 5% and * 10%.