Re-examining the Relationship between Income and Child Health on Both Sides of the Atlantic*

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Abstract

There has been a significant amount of literature on the relationship between household income and children's health, and in particular, whether this relationship is constant as a child ages. That is, are there breaks in the income-health profile according to the age of the child? In this paper we re-examine this relationship but hypothesize that the use of 'standard' age ranges (as in the existing literature) may mask 'true' changing gradients and breakpoints: there is no reason to suppose that the 'standard' age bands used to date reflect the actual ages at which breakpoints occur. Indeed, we allow the data to determine if, and where, breaks occur. We find positive gradients in both US and English data sets, and breakpoints which coincide with school changeover ages. Our results have significant policy implications in terms of allocation of resources.

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1 Introduction

In recent years, the relationship between income and health has generated a great deal of interest from both academic researchers and policy makers (see for example Adler, Boyce, Chesney, Cohen, Folkman, Kahn, and Syme (1994); Deaton and Paxson (1998); Van Doorslaer (1997); Wilkinson and Marmot (2003)). While the relationship between adult health and income is now fairly well established, that between child health and family income is less well proven. The relationship between family income and child health is important because it has been shown that poor health in childhood is associated with lower lifetime human capital accumulation (low educational attainment and poor lifetime health outcomes) and consequently poor labour market outcomes as adults (see for example Currie and Hyson (1999); Case, Lubotsky, and Paxson (2002); Currie (2004). Chen, Matthews, and Boyce (2002) provide an extensive survey of the literature dealing with the relationship between socioeconomic status and the prevalence of different childhood chronic and acute conditions such as asthma and cardiac conditions, as well as injuries. The evidence supports the notion of a monotonic relationship between increased health problems and low-socioeconomic status, but the authors go on to emphasize that much less is known about the socioeconomic status-health relationship for people at more extreme ages, including children.

Using US data Case, Lubotsky, and Paxson (2002), in a heavily cited paper, found a positive relationship between family income and child health (the income gradient of child health), with the beneficial effects of income accumulating over the child's lifetime: that is, the income gradient increases with the age of the child. For example, they found that a doubling of family income was associated with a 4 percentage point (p.p.) increase in the probability of a child aged $0-3$ being rated as being in excellent or very good health; this increased to 4.9 p.p. for children aged $4-8$, 5.9 p.p. for $9-12$ year olds and 7.2 p.p. for those aged $13-17$. Currie and Stabile (2003) using data from Canada also obtained evidence of an increasing income gradient with child age, which they attributed to children from low SES households experiencing more health shocks compared to children from higher SES households.

Murasko (2008) using a different data set from the US finds that poor health is more persistent in older children, and that the income gradient is substantially flattened over age groups when controlling for baseline health. However, even when controlling for baseline health, there remains a stronger effect from income on the health of adolescents. He argues that these results may reflect a cumulative effect from income that explains much of the strengthening association between income and health before adolescence, with a remaining stronger contemporaneous association in that age group. Condliffe and Link (2008) also using panel data from the US find that low-socioeconomic status children in the US are subject to the arrival of more new health conditions compared to children from high socioeconomic status households.

On the other hand Currie, Shields, and Price (2007), using the pooled data across the $1997-2002$ Health Surveys for England (HSE), found only a small income gradient of child health, and no evidence that this increases with the age of the child. The authors conclude that (at least in the context of England) family income is not an important determinant of child health. Similar results are obtained by West (1997), using data from the 1991 British census and Propper, Rigg, and Burgess (2007), using a regional cohort of children drawn from the Avon longitudinal study of parents and children. More recently however Case, Lee, and Paxson (2008) have re-examined the US and English data, comparing similar data (in terms of time periods). They find using similar years and methods reduces differences between the two countries, especially when re-analysing data on chronic conditions.[1]

Turning to developing countries (where one might expect the effect of income on health to be greater and a more pronounced steepening of the health-income gradient with age), Cameron and Williams (2008), using data from Indonesia find that while

[1]Chen, Martin, and Matthews (2006) is the only other paper using data from the US (to the best of our knowledge) that does not find an increasing income gradient of health as children grow older (they do find a positive association between income and child health). They use the National Health Interview Survey (NHIS) data from 1994. Case, Paxson, and Vogl (2007) argue that the divergence of the Chen, Martin, and Matthews (2006) results to those obtained by Case, Lubotsky, and Paxson (2002) arises from the fact that Chen, Martin, and Matthews (2006) inappropriately include 17 and 18 year olds in the sample, who tend to live independently and they use current income of these individuals rather than incomes of the households in which they were raised.

low income does adversely effect child health, the impact remains constant over the ages $0-14$. Park (2006) however, using the same data, finds that the gradient is strong for children under 7 but is insignificant for older children. To summarize, there appears to be no consensus as to even whether household income has any effect on child health; and if it does, no consensus as to whether the effect varies with a child's age or not.

One point that is common across all of the existing literature, is that the age bands are pre-determined. The literature typically uses the following age groupings $0-3$, $4-8$, $9-12$ and 13 and higher. We hypothesize that use of these pre-determined age groupings could be hiding information and that if we allow the data to determine where any breakpoints (across ages) occur we might get a more complete picture of the relationship between income and child health. Indeed, the breakpoints themselves may also be of interest in determining when these changes take place. To test this hypothesis, we start by analysing the relationship between income and child health for the US and England using the pre-determined age breaks used by Case, Lubotsky, and Paxson (2002) and Currie, Shields, and Price (2007). This analysis serves as a reference point for the rest of the paper. We then proceed to re-estimate the relationship between family income and child health across different age groups but allow the data to determine the age groups.

Our results show that allowing the age groupings to be data determined can make quite a difference. In the case of the US, with the pre-determined age groupings, there is only weak evidence of an increasing gradient between ages 8 and 9. With data determined groups, the gradient increase occurs at a different point (after age 5), is quite substantial, and clearly statistically significant. For the UK, only the pre-determined increase in gradient after age 4 is significant, and there is weak evidence of improvement in the gradient after age 12. In contrast, the data determined analysis highlights a significant worsening of the gradient after the first year of a child's life, and then a significant reduction in the gradient at age 14.

The contrast in findings using this data-driven approach could have real policy implications. For example, the UK results suggest that the health care system is quite effective in providing for infant health in an equitable manner, but that the situation changes quite substantially after that first year. This difference is otherwise undetectable.

2 Data

The US data are from the annual National Health Interview Survey (NHIS) for 2005, an annual representative cross sectional survey. Our estimating sample consists of 26,767 individuals aged $0-17$. Selected descriptive statistics are presented in Table 1. We can see that the average age of the children in the sample is 8.61 years and average health status is 1.72 (on a scale of 1 - excellent, to 4 - fair or poor); two percent are in fair or poor health; 51 percent are male; 77 percent are white; and the average age of the fathers (mothers) is 39 (36) years. Income is banded into 11 categories (see Table A-1) and the household income is defined as the mid-point of the category in which it belongs.

The English data are from the Health Surveys for England (HSE) pooled over the period $1999-2005$.[2] These are annual nationally representative surveys, and we have 20,644 observations for children aged $0-15$, pooled over 7 years of data. Summary statistics are presented in Table 2. The survey interviews adults and a maximum of two randomly selected children from each household. For children below the age of 13 the parents are questioned with the child present. Less than one percent are in bad or very bad health. Average age of the children in the sample is 7.91, and average health status 1.48 (again on a scale of 1 - very good, to 4 - poor or very poor). 52 percent are male; 87 percent white; and the average age of fathers and mothers is 38. Income is banded into 31 categories (see Table A-1). To get a measure of income that is consistent with the literature and because the data that we use are pooled over 6 years, we took the mid-point of these bands and then deflated them (2000 = 100) using the UK Average Earnings Index. Unlike the US case, in the case of England we therefore have a *pseudo*-continuous measure of

[2]These are pooled to yield sufficiently large sample sizes.

family income.

2.1 Measuring Child Health

In line with the existing literature, our main child health variable is a subjective measure resulting from the question asked to parents about the general health of their child (or to the children themselves in the case of older children). The possible responses are on an ordinal scale. In the US data, these categories were: (1) Excellent; (2) Very Good; (3) Good; (4) Fair; and (5) Poor, while in the UK data the categories were: (1) Very Good; (2) Good; (3) Fair; (4) Bad; and (5) Very Bad. Due to a very small percentage of children in the US being classified as of Poor health and similarly a very small percentage of children in England being classified as being of Very Bad health, in the case of US we collapse the responses Poor and Fair into one category (4 = Fair/Poor), while for UK we collapse the responses Bad and Very Bad into one category (4 = Bad/Very Bad). Our analysis is therefore based on a four-point ordinal indicator of self-assessed general health status (H). The percentage of children in the different health categories are as follows (parentheses denote the English sample):

1. Excellent (Very Good): 50.63 (59.06)
2. Very Good (Good): 28.44 (34.58)
3. Good (Fair): 18.85 (5.54)
4. Fair or Poor (Bad or Very Bad): 2.08 (0.82).

Figure 1 presents the average level of general health by family income and child age where the categories are in line with the categories used by Case, Lubotsky, and Paxson (2002) and Currie, Shields, and Price (2007). Thus we initially consider four age categories for children: $0-3$, $4-8$, $9-12$ and $13-17$ ($13-15$ in the case of England). It is clear that for both the US and England, an income gradient is present for both younger and older children, but there is no suggestion that the income gradient increases with age as was found by Case, Lubotsky, and Paxson (2002). This is also evident from the raw correlation coefficients, which do not increase systematically with the age of the child (see Table 3). In Figure 2 we present the non-parametric locally weighted regressions of health status by family income and child age. Again while, in general, we witness evidence of a gradient, there is no suggestion that this increases with the child's age.

3 Empirical Analysis: Using Pre-Determined Breaks in Age

We start by estimating ordered probit (OP) models of health status on income and a range of standard control variables. In light of the techniques we wish to use in due course, we differ from previous research by not simply splitting the sample by the child's age, but by interacting the coefficients by the relevant set of age dummies (numerically, these yield identical parameter estimates). Thus we define three dummies: $AGE[4,8] = 1$ if the child belongs to the age group $4-8$; $AGE[9,12] = 1$ if the child belongs to the age group $9-12$ and $AGE[13,17] = 1$ if the child belongs to the age group $13-17$.[3] The reference category in both cases is that the child belongs to the age group $0-3$. As noted, each of the age dummies are then interacted with the log of family income $LogIncome$. Specification 1 (model with no controls) is therefore specified as:

$$\begin{aligned} H^* &= \gamma_0 + \beta_0(LogIncome) + \beta_1(LogIncome \times AGE[4,8]) \\ &\quad + \beta_2(LogIncome \times AGE[9,12]) + \beta_3(LogIncome \times AGE[13,17]) + \\ &\quad + \gamma_1(AGE[4,8]) + \gamma_2(AGE[9,12]) + \gamma_3(AGE[13,17]) + \varepsilon. \qquad (1) \end{aligned}$$

H^* is the latent variable representing "true" health status, which is unobserved. However, as in the standard OP set-up, the observable health categories H are determined by the relationship between H^* and certain boundary parameters (μ) in

[3] In the case of England, the relevant dummy is $AGE[13,15] = 1$ if the child belongs to the age group $13-15$.

the following manner

$$H = \begin{cases} 1 & \text{if } H^* \le \mu_1 \\ 2 & \text{if } \mu_1 < H^* \le \mu_2 \\ 3 & \text{if } \mu_2 < H^* \le \mu_3 \\ 4 & \text{if } \mu_3 < H^* \end{cases} \tag{2}$$

Note that in equation (1) the estimated coefficients $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ give the 'difference' estimates. For example $\hat{\beta}_1$ is the differential effect of the log of household income on the child health status for children aged $4-8$ relative to that for children aged $0-3$. By the same logic, $\widehat{\gamma}_1, \widehat{\gamma}_2$ and $\widehat{\gamma}_3$ yield the differential effects for the regression intercepts. To obtain the complete effect of income on the health status of children aged $4-8$ we need to add the coefficient estimates $\hat{\beta}_0$ and $\hat{\beta}_1$. Estimated values of β_2 and β_3 are interpreted similarly.

In specifications 2 and 3 we progressively add additional controls following Case, Lubotsky, and Paxson (2002). Specification 2 includes dummies for the age and the presence of the father and mother in the household, for gender and race of the child, for mother or father as family respondent (only in the case of US); and an interaction term between presence of mother or father and age of mother or father. Finally specification 3 also includes dummies to characterize the educational attainment of the father and mother.

The estimates of the child health-income gradient are presented in Tables 4 and 5, for the US and England, respectively. The primary variables of interest are the *LogIncome* variable and this interacted with the relevant child-age dummies. The point estimates corresponding to Specification 1 indicate that a one-log point increase in family income is associated with a 0.2609 increase in latent health for children aged $0-3$ in the US sample and a 0.1696 increase in latent health for children aged $0-3$ in the English sample. These results are remarkably similar to those of Case, Lee, and Paxson (2008), who find an overall gradient of 0.262 for the US sample (using $1998-2005$ data, we use only 2005 data), and 0.19 for the English data (using $1997-2005$ data, we use $1999-2005$ data). In terms of probability, we find that a one-log point increase in family income is associated with a 10.4 p.p. (6.5 p.p.) increase in the probability of being in excellent (very good) health for children aged $0-3$ in the US (England).

Note that in the case of US, there is a jump in the income gradient for those aged $9-12$ while in the case of England there is a jump in the income gradient for those aged $4-8$. What we do not find therefore, is a persistent increase in the income gradient as children become older. These results hold for both the US and the English data. It appears therefore that the data exhibits some breaks, but not corresponding to the age categories that the existing literature has typically used. In the case of US the income gradient of health is not different for the $4-8$ year olds compared to the $0-3$ year olds (the difference estimate $LogIncome \times AGE[4,8]$ is never statistically significant). Similarly for older children there is no break: the null hypothesis that the estimated income gradient of health of the $9-12$ year olds is not different to that of the $13-17$ year olds cannot be rejected. There is however, a statistically significant break between those aged $4-8$ and those aged $9-12$: the null hypothesis that the estimated income gradient of health for the $9-12$ year olds is not different to that for the $4-8$ year olds is rejected (at the 10% level) for all three specifications. Additionally the coefficient estimates indicate that the income gradient of health is steeper for the older children ($9-17$ year olds).

Turning to the English data, we find some interesting differences compared to the US data. First, the difference estimate $LogIncome \times AGE[4,8]$ is statistically significant and the signs indicate that the income gradient of health is steeper for the $4-8$ year olds relative to the $0-3$ year olds. However, there is no evidence of a monotonically increasing income gradient of health for older children: indeed the estimated income gradient of health is the highest for the $4-8$ year olds and then falls monotonically as we move to higher age groups. The null hypothesis that the estimated income gradient of health for the $9-12$ year olds is different to that for the $4-8$ year olds can never be rejected, but the null hypothesis that the estimated income gradient of health for the $13-15$ year olds is not different to that for the $9-12$ year olds is rejected in Specifications 2 and 3 (at the 10% level, and even in the case of Specification 1, the associated $p-value$ is 0.108).

Figure 3 presents the predicted probability of excellent (very good) health for children in the different age groups as we increase (log of) family income. These predicted probabilities correspond to those for Specification 1 (see Table 4). In general, the probability that a child is of excellent (very good) health is consistently higher for younger children and this holds for both countries. There is a clear income gradient of health which is not constant across the different age groups. However, it is very difficult to argue that the income gradient of health changes monotonically across the different, pre-determined, age groups.

For both the US and the English data, adding parental educational attainment (Specification 3) significantly reduces the point estimate of $LogIncome$ for the $0-3$ year olds, but they continue to remain highly significant. Interestingly the difference estimates are not particularly different across the different age categories. However given that the point estimate of $LogIncome$ is significantly higher in Specification 3, the total effect is much higher in every age category for Specification 3. Controlling for parental education therefore reduces the effect of income on child health at every age category in both the US and England. This may have several explanations, including that explored by Case, Lubotsky, and Paxson (2002) where 'true' household income is highly correlated with parental education levels, so the coefficient on education is picking up part of the 'true' income effect. They test for this using instruments, but still find the coefficients on parental education to be large and significant. Case, Lee, and Paxson (2008) go on to examine differences related to income and chronic illness, and while not discounting the importance of this, we suggest here the relevance of a more fundamental question, relating to the pre-determined nature of the age breaks.

4 Breakpoint Analysis

From this point, we diverge from the earlier analyses. We hypothesize that using 'standard' age ranges in the earlier papers may mask 'true' gradients and breakpoints, and that allowing the data to find breaks - to define new age bands - may give us valuable new insights. Indeed, there is no reason to suppose that the 'standard' age bands previously used reflect the actual ages at which breakpoints occur. There may be other factors which impact upon where these breaks really occur and this is what we now investigate. We begin with no further hypotheses than this and the technique we propose allows the data to determine where breaks (if any) occur, after which we determine possible causal effects. Initially we have no reason to speculate as to where the actual breaks will occur.

We start with the simplest specification: the possibility of one break in the relevant age group. Define $AGE[i, 17]; i = 1, ..., 17$ as a dummy variable that takes the value of 1 if the age of the child is in the range i to 17 and 0 otherwise. We start by estimating the following model

$$H^* = \gamma_0 + \beta_0(LogIncome) + \beta_1(LogIncome \times AGE[i, 17]) + \gamma_1(AGE[i, 17]) + \varepsilon \quad (3)$$

where $i \in [1, 17]$. As before, β_1 and γ_1 represent the differential effects with respect to the age band $[i, 17]$ relative to the omitted age group $[0, i-1]$. We estimate equation (3) for each value of i in the specified range and choose the value of i which yields the greatest maximized likelihood function across this range. The maximum likelihood estimate (MLE) of i is labeled i^*; this is the value of i that maximizes the various maximized conditional likelihoods.

When $i = i^*$ is substituted into equation (3), this gives

$$H^* = \gamma_0 + \beta_0(LogIncome) + \beta_1(LogIncome \times AGE[i^*, 17]) + \gamma_1(AGE[i^*, 17]) + \varepsilon \quad (4)$$

A test for whether the gradient changes with age is performed by testing the hypothesis that $\beta_1 = 0$.

Note that the specification of equation (3) allows both the effect of income *and* the constant term to vary by the age of the child (where the differential effects are respectively given by β_2 and γ_1). Thus this approach exactly replicates those obtained in the literature by splitting the overall sample by the child's age, except we let the data determine where these age-breaks occur.

Once we have obtained the first (and 'strongest') break and ascertained that the differential effect (β_1) is statistically significant, we examine whether there are any further breaks. Suppose the maximum likelihood estimator of i, as obtained above, is given by i_1^*. We then search over all values of i again, with $i \in [1, 17]$ and $i \neq i_1^*$, and estimate models of the form

$$\begin{aligned} H^* &= \gamma_0 + \beta_0(LogIncome) + \\ &\quad +\beta_1(LogIncome \times AGE[i, i_1^* - 1]) + \beta_2(LogIncome \times AGE[i_1^*, 17]) + \\ &\quad +\gamma_1(AGE[i, i_1^* - 1]) + \gamma_2(AGE[i_1^*, 17]) + \varepsilon \end{aligned} \tag{5}$$

for $i < i_1^*$; and

$$\begin{aligned} H^* &= \gamma_0 + \beta_0(LogIncome) + \\ &\quad +\beta_1(LogIncome \times AGE[i_1^*, i]) + \beta_2(LogIncome \times AGE[i + 1, 17]) + \\ &\quad +\gamma_1(AGE[i_1^*, i]) + \gamma_2(AGE[i + 1, 17]) + \varepsilon \end{aligned} \tag{6}$$

for $i > i_1^*$. We estimate equations (5) and (6) for the relevant values of i in the specified range (defined over both equations (5) or (6)) and again choose the value of i ($i \neq i_1^*$) that yields the maximized likelihood function over all model estimations. Note that this maximum likelihood estimate of i_2 (call this i_2^*) is chosen over the entire range of $i \in [1, ..., i_1^* - 1, i_1^* + 1, ..., 17]$. Thus i_2^* gives us the second break point.

A test for whether the second break in the income gradient is justified can be performed as an appropriate restriction on equation (5) or (6). If $i_2^* < i_1^*$, then the second break model is based on equation (5), and if $\beta_2 = 0$, this model simplifies to the model with only one change in gradient. If $i_2^* > i_1^*$, then the restricted model is found by testing if $\beta_1 = \beta_2$ in equation (6).

Conditional on i_1^* and i_2^* we can estimate further breaks in the effect of income on child health using a similar approach. One can then decide on an appropriate model specification by performing a range of tests of restrictions on the more general models to see whether the restricted models are valid or not.

A critical part of the analysis is deciding how many breaks in gradient to allow for. A data-driven approach to this question would be based on tests of restrictions:

for example, if we reject $H_0 : \beta_1 = 0$ in equation (4), this is evidence of at least one break. However, there is a complication with undertaking these tests: because the test is performed at each possible break point (each value of i) in the range $[1, 17]$, the overall test procedure effectively involves a sequence of individual tests and the size of the test will be distorted. The problem is similar to that found in the time series literature when testing for structural breaks with unknown break points. Asymptotic results for the distribution of the $Wald$ statistic in this case were obtained by Andrews (1993). The distributions are not standard χ^2 because of this unidentified nuisance parameter and Andrews (1993) tabulates critical values based on the asymptotic distribution results presented in that paper.

Unfortunately we are not able to use the critical values presented in Andrews (1993), as asymptotic results there are specific to the assumed properties of the regressors and the nature of the structural change and they do not apply to the type of models we are analyzing. That is, here we are dealing with models with discrete dependent variables and regressors whose asymptotic moments would not satisfy the required properties. However, we can draw on the general approach developed by Andrews (1993) to devise a procedure for simulating critical values for our situation. We illustrate the methodology with reference to testing for the presence of at least one break. For each value of i, a standard $Wald$ statistic for testing the linear restriction that $\beta_1 = 0$ in equation (3) can be calculated. We refer to this test as $Wald(i)$. This can be repeated for each value of $i \in [1, 17]$. We define the test statistic as the maximum (sup) of these statistics:

$$\sup W = \sup Wald(i). \tag{7}$$

While the distribution of each individual $Wald(i)$ statistic is a standard χ^2 under the null hypothesis, the distribution of $\sup W$, given by the sup of all these asymptotic χ^2 distributions, will be very complex, as it will be dependent on the specific dependence structure between the separate $Wald(i)$ tests, which in turn will depend on the asymptotic behavior of standardized moments of the explanatory variables in the model. In other words, the asymptotic distribution depends on the specific asymptotic properties of the explanatory variables in the model. We will outline the theoretical issue in a more general context here, before moving to a practical solution to performing the required tests in the above cases.

First, consider the more general model

$$y = \beta(i)Q'(i) + x'\alpha + \varepsilon \tag{8}$$

where y is a dependent variable of interest, x is a vector of explanatory variables, and $Q(i)$ is a vector of explanatory variables where the exact composition of the $Q(i)$ vector can vary across I different cases (J being a finite constant). That is, there are I possible sets of $Q(i)$ vectors, each with coefficient vector $\beta(i)$. Equation (8) encompasses the various models described above, plus other cases where one might wish to consider a range of possible explanatory variables. For example, $Q(i)$ may represent a set of possible standardized indices acting as a proxy for some unobserved latent variable presumed to influence y.[4]

The maximum likelihood estimator for i, denoted i^*, and for $\beta(i)$, can be obtained by estimating equation (8) using maximum likelihood for each value of $i = 1, ..., I$ and choosing the value of i which maximizes the likelihood function. We are interested in testing hypotheses about $\beta(i)$: consider the general linear restriction $R\beta(i) - r = 0$. In general, the $Wald$ statistic for this testing problem for a given i can be written as

$$Wald(i) = (R\beta(i) - r)'[R'V(i)R'^{-1}](R\beta(i) - r) \tag{9}$$

$\beta(i)$ is the estimate of β obtained when $Q(i)$ is included in the estimated model, and $V(i)$ is the estimated variance-covariance matrix of $\beta(i)$. The optimal test is the i^{th} order statistic of this vector of $Wald$ statistics $\sup W = \sup Wald(i)$. The distribution function of $\sup W$ is given by David and Nagaraja (2003)

$$Pr(\sup W < w) = Pr(Wald(1) < w, Wald(2) < w, ..., Wald(I) < w). \tag{10}$$

Importantly, this distribution depends on the joint distribution of the $Wald$ statistics. It is clear from equation (9) that the $Wald$ statistics will be correlated with

[4]We should point out that this framework is similar, but conceptually different to that considered in threshold regression models. With threshold models, the set of explanatory variables is fixed, and the coefficient vector varies, depending on whether a chosen indicator variable crosses some threshold value, which might be estimated from the data. So while there are analogies here, the specific context is quite different.

each other, so there is no obvious or general means of simplifying their joint distribution to obtain a closed form for the desired distribution function. This leaves no practical choice but to obtain critical values by simulation for any given case.

In the present context, we proceed in this direction by generating repeated samples under the null hypothesis, using the estimated parameter values from the null model and the actual data corresponding to the explanatory variables, to generate the artificial data. For each sample, we construct the $Wald(i)$ statistics and the $\sup W$ statistic. After repeated sampling, we have an empirical null distribution for $\sup W$. This can be used to calculate an appropriate test critical value or to obtain the empirical $p-$value for the actual test statistic.

5 Breakpoint Results

We now turn to the regression results where the breaks are data determined. The results are presented in Tables $6-11$. To recap, the initial OP regression results with pre-determined breaks for the US (Table 4) shows that the effect of income on the health of $0-8$ year olds is different to that on the $9-17$ year olds. The corresponding regressions for England (Table 5) show that the income gradient for the $0-3$ year olds is different to that of the $4-12$ year olds, which in turn is different to that for the $13-15$ year olds.

5.1 Results with No Additional Control Variables (Specification 1)

We start by analyzing the results for the US data. Table 6 presents the relevant regression results. We start by maximizing the likelihood function for each value of $i \in [1, \ldots, 17]$ and then choosing the value of i that yields the maximum of these likelihoods. As a result of this analysis, the first and the strongest break is obtained at $i_1^* = 5$ (*i.e.* at age 5).

The regression results presented in column (1) show that the income gradient for the $0-5$ year olds is significantly different to that for the $6-17$ year olds ($\sup W = 9.00$; $simulated\ p-value = 0.002$). In terms of probabilities, a one log point increase in household income is associated with a 10 p.p. increase in the probability of being in excellent health for the $0-5$ year olds but a 12 p.p. increase in the corresponding probability for the $6-17$ year olds. There is a strong income gradient within each category and more importantly the gradient worsens as children grow older: the health of poorer children is relatively worse to begin with (poorer children are more likely to be of fair or poor health to begin with, in the age category $0-5$) and they are even more likely to be worse off when in the age group $6-17$.

Such a strong break at this age is especially interesting, as most children start school at around this age (5 years old). The results presented in column (1) show that the income gradient becomes stronger as children start attending school. Given the long term implications of poor health, this worsening of the health gradient for school age children has potentially severe implications for aggregate human capital accumulation. The results suggest the need for direct and specific age and education related policy interventions. We discuss the potential policy implications of our results in greater detail later (Section 6).

Once we have estimated the location of the first break, we hold this break as given and search for a possible second break. Maximizing the likelihood function for each value of $j \in [1, \ldots, 4, 6, \ldots 17]$ and then choosing the value of i that produces the maximum of these likelihoods gives us $i_2^* = 10$. So we now allow for (log) income to have different effects on child health in the age groups $6-10$ and $11-17$ (again, relative to the omitted category here of 5 and below). However, the null hypothesis that the estimated income gradient in the age group $6-10$ is the same as that in the age group $11-17$ cannot be rejected ($\sup W = 0.25$; $simulated\ p-value = 0.622$). The test results therefore suggest that the additional complexity of allowing for a second break is not rewarded in terms of a significant improvement in model fit and the preferred model has one break at age 5 (column (1)).

Turning to the results using the English data (see Table 7), and proceeding exactly the same way, yields $i_1^* = 13$; ($\sup W = 3.98$; $simulated\ p-value = 0.035$), *i.e.*, the first and the strongest break is obtained at age 13. Again, this is clearly potentially related to schooling as it represents the year after which most children start high school. The results are however, rather interesting. A one log point increase in family income reduces the latent health of the $0-13$ year olds by 0.237 and that for the $14-15$ year olds by 0.178. In terms of probabilities, a one log point increase in family income increases the probability that a child aged $0-13$ is of very good health by 9.2 p.p., but is associated with a 7.0 p.p. increase that a child aged $14-15$ is of very good health. It appears therefore, we do not find a worsening of the income gradient for older children. Richer children aged $0-13$ are more likely to be of very good health compared to richer children aged $14-15$.

Conditional on the first break, we again proceed to search for a second (Table 7, column (2)). The second break turns out to be at age 0; ($\sup W = 4.64; \textit{simulated } p-value = 0.046$): this implies that the income gradient for children less than 1 year old is different to that for children aged $1-13$, which in turn is different to that for children aged $14-15$. The coefficient estimates show that a one log point increase in family income is associated with a 0.103 increase in latent health for children aged less than 1, a 0.241 increase in the latent health of children aged $1-13$ and a 0.1785 increase in the latent health of children aged $14-15$. In terms of probabilities, a log point increase in family income is associated with a 4 p.p. increase in the probability that a child less than 1 is of very good health, a 9.3 p.p. increase in the probability that a child aged $1-13$ is of very good health and finally a 7 p.p. increase in the probability that a child aged $14-15$ is of very good health.

Conditional on the first and the second break, we now search for a third break (Table 7, column (3)) and find that $i_3^* = 10$. However, the null hypothesis that the income gradient for children aged $1-10$ is the same as that for children aged $11-13$ cannot be rejected ($\sup W = 1.57; \textit{simulated } p-value = 0.213$). The test results suggest that the additional complexity of having a third break is not rewarded by a significant improvement in model fit. Our preferred specification is one with two breaks at 0 and 13. In summary of our preferred model here, we find that, for the English data, while there is some evidence of a worsening income gradient for older children (the income gradient is steeper for the $1-13$ year olds relative to those below 1, for the eldest group of children (aged $14-15$) if anything there is an improvement in the income gradient of health.

Figure 4 presents the non-parametric locally weighted regressions of health status by family income and child age, where the age categories are data determined. There is some evidence of a gradient but again there is no systematic variation in this gradient across the different age categories, as implied by our regression results and the prediction probabilities. Figure 5 presents the predicted probability of excellent (very good) health for children in the different age groups as we increase log family income. These predicted probabilities correspond to those for Specification 1 and the age breaks are data determined. Notice that, in general, the probability that a child is of excellent (very good) health is consistently higher for younger children and this holds for both countries. More importantly there is a clear income gradient of health which is not constant across the different age groups. Additionally note that the difference in the probability of being in excellent (very good) health for the rich and poor households is always greater for older children compared to the youngest set (though in the case of England the effect is not monotonic).

5.2 Results with Additional Control Variables (Specifications 2 and 3)

Tables $8-11$ present the results corresponding to Specifications 2 and 3 for the US (Tables 8 and 10) and England (Tables 9 and 11). Qualitatively the results are very similar to those for Specification 1: in the case of the US, the first and the strongest break is always attained at age 5; whereas in the case of England, the first and the strongest break is always attained at age 13. In the case of England the preferred model (irrespective of the specification) always has 2 breaks at age 0 and age 13, where as in the case of US, the preferred model is always one with 1 break at age 5. It is worth noting that as in the case with pre-determined breaks (Tables 4 and 5), adding parental educational attainment to the set of controls significantly reduces the magnitude of the effect of $LogIncome$; however, the estimated coefficients continue to remain statistically significant.

Figure 7 illustrates how the results differ when the age groupings are data determined (as opposed to the breaks being pre-determined). These figures (which essentially summarize some of the results presented in the tables above) show how the income gradient varies with age (using Specification 3) for the US and English data. What is apparent from the US results, is how the standard approach (pre-determined breaks) allows for too many possible age breaks, and also misses the timing of the age break. While only some of the age breaks are strongly statistically significant using pre-determined breaks, the data determined break after age 5 is clearly significant. Similar problems are apparent for the English data. The dramatic change in gradient at age 1 (in the case of England) is completely missed in the analysis using pre-determined breaks, with potentially very important policy implications. Likewise, the improvement in the gradient after age 12 is strongly significant in the data-determined models, but not so with the specifications with pre-determined breaks.

These results correspond to specifications where the only differential effects, by age, are on the income and constant terms. If *all* effects are allowed to vary by age (that is, we interact all variables with the relevant age dummies, not just the income and constant ones) the results are essentially unchanged, though the difference estimates are not as strong. This latter approach could be considered more akin in spirit to the previous research of Case, Lubotsky, and Paxson (2002) and Currie, Shields, and Price (2007). However as the remaining coefficients appeared relatively stable across age-cohorts, the restriction that they were held constant is justified on parsimonious grounds.

5.3 Comparisons with a Fully Flexible Approach

The analyses considered above (*i.e.* of pre-determined and data-driven breakpoints), can both be considered as restricted versions of a fully-flexible approach where the household income effect is allowed to vary across *all* observed child ages. This can be undertaken by estimating separate models on sub-samples corresponding to the age of the child; or equivalently by using a pooled sample and allowing all coefficients to vary by age along with a complete set of age dummies. The latter would be obtained by estimating a simple regression of the form:

$$H^{*} = \gamma_0 + \beta_0(LogIncome) + \sum_{i=1}^{17} \beta_i(LogIncome \times AGE\,[i]) + \sum_{i=1}^{17} \gamma_i AGE\,[i] + \varepsilon \quad (11)$$

where $AGE\,[i]$ is a dummy variable that takes the value 1 if age $= i; i = 1, ...17$, 0 otherwise. In the case of England $i \in [1, 15]$. For ease of computation and exposition, we consider only the simple specification with no additional controls (Specification 1).

The results, in terms of estimated coefficients on income by age, for the U.S. and English data, are presented in Figure 6. Superimposed on the figures are those coefficients, for the same model specification, obtained from the data-determined procedure described above. Taking the fully flexible results from the U.S. sample first, two quite distinct 'regimes' appear apparent: a *high* coefficient value for ages $0-5$, and a *low* coefficient range for ages 6 onwards. The data-determined approach for this data, did indeed identify a single breakpoint at exactly the age that the fully flexible approach also suggests. Moreover, the magnitude of the two coefficients identified by the data-driven approach, appear to be very close to the mean values of the coefficients within each regime. Thus here one might conclude that the data-driven approach yields substantively very similar results to a fully flexible approach, although the former is a much more parsimonious representation of the data.

For the English cohort, the fully flexible approach estimates a quite clear $u-$shape in the magnitude of the effect of household income across a child's age. Indeed here, unlike the U.S. case, there are no clearly discernible regimes. The data-determined approach however, found two breakpoints: at ages 0 and 13. Thus here, one would draw quite differing conclusions as to the 'true' shape of the household income-child health gradient across children's ages. However, the approach advocated in the current study, explicitly searches for *statistically significant* breaks. That is, the fully flexible approach, in this case, would erroneously estimate a quite volatile profile across ages: both a non-parsimonious representation of the data and one that represents many statistically insignificant breaks.

6 Policy Implications and Concluding Comments

We set out to test the hypothesis that the standard age breaks used in previous analyses of the links between child health and income gradients may be hiding information, and that data-determined breaks may in fact be more useful in eliciting information as to this relationship. We do find a relationship between income and child health, it is clearly the case that increased income is related, overall, to increased levels of health. As Case, Lubotsky, and Paxson (2002) observe, income is indeed a powerful determinant of children's health status and may in part protect them from chronic conditions, those from lower income households enter adulthood with poorer health status. Although we find a gradient in the US sample, our initial results using the same pre-determined age breaks as Case, Lubotsky, and Paxson (2002) (albeit on a more recent year of data) do not confirm that this gradient increases across-the-board with the age of the child.

Partly to test the associations alluded to in Currie and Stabile (2003) that differences in health systems may impact upon child health, we compare the US results to an English sample, an updated version of that used in Currie, Shields, and Price (2007). As in the US data, we do find non-persistent gradients in the standard age groups, although not as steep. There appears to be evidence across these developed countries that there is a child health gradient, related to income status, whether they have the resources to respond to health shocks (*i.e.* a universal health care system) or not.[5] It does appear, however, that there is some evidence that a universal health care system does lessen the gradient.[6] This would imply policies of expanding health

[5]In the US Medicaid coverage is extended to all children whose family income is below the poverty line. However individuals must still be aware of their eligibility, and have access to the care they require. The State Children's Health Insurance Program (SCHIP) extends coverage to certain families above the Medicaid threshold, but who are unable to afford private insurance. However, 8 million children in the US have no insurance coverage, even though up to 70% of them may be eligible for Medicaid or SCHIP Getzen (2007).

[6]This may help confirm evidence from the RAND experiment where the requirement to pay impacted upon use of services by lower income families. In addition, in a universal system there

insurance coverage further to children would be useful, as well as ensuring eligibility leads to take up. As stated by Currie and Stabile (2003), investigating further the causes of differential rates of health shocks to those in lower income classes would be useful.

We then take the analysis a significant step further. Moving away from the use of pre-determined breaks, we allow the data to choose the breaks, if any, and see if this has an impact on the relationship between health gradients and income. We find a significant break at age 5 for the US data, and two significant breaks at age 0 and 13 for the English data. There is a strong income gradient for those aged $0-5$ in the US sample, and the gradient worsens: poorer children are relatively worse off, compared to those from richer families, in the age group $0-5$, and as they age this inequality worsens across the age group $6-17$. These results confirm to a certain extent the earlier work of Case, Lubotsky, and Paxson (2002): information is 'hidden' when imposing pre-determined breaks.[7]

These findings have important, and potentially serious, policy implications as most children start school around age 5 in the US. As things seemingly get worse in terms of inequalities once children are at school, this will impact upon human capital accumulation. Policy makers may wish to direct resources at school age children, or families with school age children to help reduce these inequalities. Policies may be educational (for example, school resource allocation, teacher training incentives and school meals provision); transfer payments; housing policies (to reduce the frequency of health shocks to those less able to cope with them); or health promotion policies related to helping improve family lifestyle. Making universal coverage available for primary and secondary health care, and reducing barriers to access to such care, and public health activities such as immunization at school, may also help alleviate inequalities. Of course, reducing income inequalities themselves would also help, although relative differences will always exist.

are no eligibility criteria, meaning everyone is sure of their status in terms of access to care.

[7]Case, Lee, and Paxson (2008) on re-analysing their own and others data, find income plays a larger role in England than the US in terms of chronic conditions and child health. They use pre-determined breaks - we argue use of data-determined breaks adds valuable extra information.

In the English sample the data yields breaks at ages 0 and 13. Our results imply that there is a clear gradient, although less than in the US, and in fact the gradient improves past the age of 13, *i.e.* the relative difference between rich and poor, while still evident, lessens. Below the age of 1 there is also a clear gradient, but the relative difference between rich and poor is less than between ages $1-13$, and $14-15$, this could indicate that good universal access to care immediately post childbirth, and that factors other than access to care are more significant in England after the age of 1. As pointed out by Currie, Shields, and Price (2007), these results may have important implications, in terms of educational attainment and labor market entry. Our data determined breaks find stronger evidence of a gradient in England than earlier work, but still not as strong as in the US. We also confirm that the gradient does not always increase, as it seems to in the US. The break at age 13 follows entry into high school education, and this may be positively linked to reducing inequalities in the English system of comprehensive publicly funded education.

In terms of further investigation of the determinants of these gradients, we find parental education to be important. Both in the UK and US samples we find mothers and fathers education as significant determinants of their children's health. We find it reduces point estimates, but they still remain highly significant. This may be due to, as Case, Lubotsky, and Paxson (2002) point out, "true" household income being correlated with parental education. Currie, Shields, and Price (2007) also point out the protective effects of parents education levels. A further point may be related to imperfect information, *i.e.* that more highly educated parents may understand the benefits of health promotional activities, such as immunization or healthy eating, or the benefits of regular school attendance, as well as, of course, being able to do something about it. More highly educated parents may also be able to communicate more effectively with health care and educational professionals, potentially opening up more opportunities for their children.

Do poorer children with poorer health and worse educational levels become lower earning adults and is there a vicious cycle in evidence? This is not a question we can answer here, but it is an obvious implication. We have been one of the few studies to confirm the earlier, and seminal, findings of Case, Lubotsky, and Paxson (2002). Our use of data determined breaks has allowed this extra information, as we show information hidden using pre-determined age breaks, highlighted using more recent data. This persistence, and the evidence that it does not seemingly exist in the English data, raises interesting and important questions. Is this because of different rates of income inequality between the US and England, or differences in the health systems, or differences in the education systems? It is interesting that breaks in our two samples occur around the age that children start, or change, schools. It may be that all of these factors, and more, contribute to changes in the relationship between child health and income, and further investigation is warranted.

We should not lose sight of the fact that although the gradient does not increase persistently in the English sample, it still exists, and this is of course cause for concern. Currie, Shields, and Price (2007) point out that when using objective measures of health (such as blood tests and nurse measurements) there is no evidence of a family income gradient in England. They conclude that universal health care in England protects all children, both rich and poor. This may well be true, and our results also point in this direction. However, it would be interesting to compare this with objective measures in a comparative large US sample. Also of interest would be following data longitudinally, this would allow the impacts of policy and funding shocks to be monitored effectively.

In summary, we find that data determined age breaks provide critical new evidence supporting a family income effect persisting over age in the US, impacted upon by starting school, after which the gradient worsens. In contrast we find a lower gradient across the board in England, the situation improving somewhat after starting high school. Further research on environmental (in terms of, for example. a 'safe' society[8]), education, and housing factors as well as improving access to health care, and validation of results using objective measures of child health is recommended to further test our hypotheses, which as they stand may have important policy implications.

[8]The rate of deaths in childhood from external causes may in the US be double that of some European countries, see Currie (2000).

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Table 1: Selected Descriptive Statistics, US

Variable	Mean	Std. Dev.
Self Reported Health	1.7257	0.8443
Age	8.6117	5.1237
Male	0.5100	0.4999
Log Family Income	10.4808	0.8418
Highest Education of Mother: Low/Unknown	0.2857	0.4517
Highest Education of Mother: Year 12	0.2486	0.4322
Highest Education of Mother: Greater than Year 12	0.4657	0.4988
Highest Education of Father: Low/Unknown	0.4440	0.4969
Highest Education of Father: Year 12	0.1897	0.3921
Highest Education of Father: Greater than Year 12	0.3663	0.4818
Age of Mother	36.0368	7.8430
Age of Father	38.9535	8.2182
Mother Present	0.9393	0.2387
Father Present	0.7328	0.4425
Mother Respondent	0.5361	0.4987
Father Respondent	0.3661	0.4818
White	0.7757	0.4171
Black	0.1711	0.3766
Sample Size	26767	

§: Computed for children where father/mother is present

Table 2: Selected Descriptive Statistics, England

Variable	**Mean**	**Std. Dev.**
Self Reported Health	1.4812	0.6400
Age	7.9826	4.3229
Male	0.5051	0.5000
Log Family Income	9.9348	0.8357
Highest Education of Mother: Low/Unknown	0.6325	0.4821
Highest Education of Mother: O level	0.1550	0.3619
Highest Education of Mother: Greater than O level	0.2125	0.4091
Highest Education of Father: Low/Unknown	0.5098	0.4999
Highest Education of Father: O level	0.1923	0.3941
Highest Education of Father: Greater than O level	0.2979	0.4573
Mother Present	0.7018	0.4575
Father Present	0.9735	0.1606
Age of Mother	37.3045	6.8350
Age of Father	37.5122	7.6251
Other Ethnic Minority	0.0393	0.1943
Black	0.0285	0.1665
Asian	0.0476	0.2129
Sample Size	20644	

§: Computed for children where father/mother is present

Table 3: Raw Correlation between Household Income and Health Status

Age Category	**US**	**England**
$0-3$	-0.2082	-0.1257
$4-8$	-0.2016	-0.1945
$9-12$	-0.2286	-0.1674
$13-17$ (US)	-0.2208	
$13-15$ (England)		-0.1400

Table 4: The Income Gradient in Child Health Status, US. Pre-determined Breaks

	Specification 1	**Specification 2**	**Specification 3**
$LogIncome\left(\widehat{\beta}_0\right)$	-0.2606^{***}	-0.2517^{***}	-0.1430^{***}
	(0.0170)	(0.0175)	(0.0176)
$LogIncome \times AGE\,[4,8]\left(\widehat{\beta}_1\right)$	-0.0020	-0.0010	0.0030
	(0.0231)	(0.0231)	(0.0227)
$LogIncome \times AGE\,[4,8]\left(\widehat{\beta}_2\right)$	-0.0447^{*}	-0.0407^{*}	-0.0390
	(0.0243)	(0.0244)	(0.0243)
$LogIncome \times AGE\,[4,8]\left(\widehat{\beta}_3\right)$	-0.0450^{*}	-0.0383	-0.0462^{**}
	(0.0238)	(0.0240)	(0.0234)
Test: $\chi^2\,(1)$			
Break at Age 3 $\left(\widehat{\beta}_1 = 0\right)$	0.01	0.00	0.02
	[0.931]	[0.964]	[0.897]
Break at Age 8 $\left(\widehat{\beta}_1 = \widehat{\beta}_2\right)$	3.33	2.84	3.21
	[0.068]	[0.093]	[0.073]
Break at Age 12 $\left(\widehat{\beta}_2 = \widehat{\beta}_3\right)$	0.00	0.01	0.01
	[0.991]	[0.919]	[0.763]

Notes:
Robust Standard Errors in Parenthesis; $^{***}: p < 0.01, ^{**}: p < 0.05, ^{*}: p < 0.1$. *p-values* associated with the relevant $\chi^2\,(1)$ test in brackets.
Specification 2 includes dummies for the age and the presence of the father and mother in the household, for gender and race of the child, for mother or father as family respondent; and an interaction term between presence of mother or father and age of mother or father.
Specification 3 also includes dummies for the educational attainment of the father and the mother.
All specifications include the 3 age dummies: $AGE\,[4,8]\,, AGE\,[9,12]\,, AGE\,[13,17]\,.$

Table 5: The Income Gradient in Child Health Status, England. Pre-determined Breaks

	Specification 1	**Specification 2**	**Specification 3**
$LogIncome\left(\widehat{\beta}_0\right)$	-0.1696^{***}	-0.1368^{***}	-0.1087^{***}
	(0.0236)	(0.0241)	(0.0244)
$LogIncome \times AGE\,[4,8]\left(\widehat{\beta}_1\right)$	-0.1118^{***}	-0.1127^{***}	-0.1140^{***}
	(0.0295)	(0.0292)	(0.0292)
$LogIncome \times AGE\,[4,8]\left(\widehat{\beta}_2\right)$	-0.0724^{*}	-0.0756^{**}	-0.0787^{***}
	(0.0307)	(0.0304)	(0.0303)
$LogIncome \times AGE\,[4,8]\left(\widehat{\beta}_3\right)$	-0.0243	-0.0241	-0.0293
	(0.0325)	(0.0324)	(0.0324)
Test: $\chi^2\,(1)$			
Break at Age 3 $\left(\widehat{\beta}_1 = 0\right)$	14.36	14.86	15.27
	[0.000]	[0.000]	[0.000]
Break at Age 8 $\left(\widehat{\beta}_1 = \widehat{\beta}_2\right)$	2.24	2.02	1.83
	[0.135]	[0.156]	[0.176]
Break at Age 12 $\left(\widehat{\beta}_2 = \widehat{\beta}_3\right)$	2.62	3.03	2.79
	[0.108]	[0.082]	[0.095]

Notes:

Robust Standard Errors in Parenthesis; $^{***}: p < 0.01, ^{**}: p < 0.05, ^{*}: p < 0.1$. *p-values* associated with the relevant $\chi^2\,(1)$ test in brackets.

Specification 2 includes dummies for the age and the presence of the father and mother in the household, for gender and race of the child, for mother or father as family respondent; and an interaction term between presence of mother or father and age of mother or father.

Specification 3 also includes dummies for the educational attainment of the father and the mother.

All specifications include the 3 age dummies: $AGE\,[4,8]\,, AGE\,[9,12]\,, AGE\,[13,15]\,.$

Table 6: The Income Gradient in Child Health Status (Specification 1), US. Data Determined Break

	Break 1	**Break 2**
$LogIncome\left(\widehat{\beta}_0\right)$	-0.2479^{***}	-0.2480^{***}
	(0.0139)	((0.0139)
$LogIncome \times AGE\,[6,17]\left(\widehat{\beta}_1\right)$	-0.0521^{***}	
	(0.0174)	
$LogIncome \times AGE\,[6,10]\left(\widehat{\beta}_{11}\right)$		-0.0480^{***}
		(0.0209)
$LogIncome \times AGE\,[11,17]\left(\widehat{\beta}_{12}\right)$		-0.0585^{***}
		(0.0197)
Test: $\chi^2\,(1)$		
Break at age 5 $\left(\widehat{\beta}_1 = 0\right)$	9.00	
	[0.002]	
Break at Age 10 $\left(\widehat{\beta}_{11} = \widehat{\beta}_{12}\right)$		0.25
(Conditional on break at age 5)		[0.622]
	Preferred Specification	

Notes:
Robust Standard Errors in Parenthesis; $^{***}: p < 0.01, ^{**}: p < 0.05, ^{*}: p < 0.1$. Simulated *p-values* associated with the relevant $\chi^2\,(1)$ test in brackets. Thresholds are estimated. Relevant age dummies are included.

Table 7: The Income Gradient in Child Health Status (Specification 1), England. Data Determined Break

	Break 1	**Break 2**	**Break 3**
$LogIncome\left(\widehat{\beta}_0\right)$	-0.2375^{***}	-0.1032	-0.1031
	(0.0110)	(0.0630)	(0.0630)
$LogIncome \times AGE\,[1,13]\left(\widehat{\beta}_{12}\right)$		-0.1378^{***}	
		(0.0640)	
$LogIncome \times AGE\,[1,10]\left(\widehat{\beta}_{121}\right)$			-0.1474^{***}
			(0.0643)
$LogIncome \times AGE\,[11,13]\left(\widehat{\beta}_{122}\right)$			-0.1145^{***}
			(0.0670)
$LogIncome \times AGE\,[14,15]\left(\widehat{\beta}_1\right)$	0.0591^{***}	-0.0753	-0.0754
	(0.0296)	(0.0687)	(0.0687)
Test: $\chi^2(1)$			
Break at age 13 $\left(\widehat{\beta}_1 = 0\right)$	3.98		
	[0.035]		
Break at age 0 $\left(\widehat{\beta}_{12} = 0\right)$		4.64	
(Conditional on break at age 13)		[0.046]	
Break at Age 10 $\left(\widehat{\beta}_{121} = \widehat{\beta}_{122}\right)$			1.57
(Conditional on break at ages 0 and 13)			[0.213]
		Preferred Specification	

Notes:
Robust Standard Errors in Parenthesis; $^{***}: p < 0.01, ^{**}: p < 0.05, ^{*}: p < 0.1$. Simulated *p-values* associated with the relevant $\chi^2(1)$ test in brackets. Thresholds are estimated. Relevant age and year (reference year = 1999) dummies are included.

Table 8: The Income Gradient in Child Health Status (Specification 2), US. Data Determined Break

	Break 1	**Break 2**
$LogIncome\left(\widehat{\beta}_0\right)$	-0.2416^{***}	-0.2390^{***}
	(0.0146)	(0.0146)
$LogIncome \times AGE\,[6,17]\left(\widehat{\beta}_1\right)$	-0.0467^{***}	
	(0.0175)	
$LogIncome \times AGE\,[6,10]\left(\widehat{\beta}_{11}\right)$		-0.0442^{***}
		(0.0210)
$LogIncome \times AGE\,[11,17]\left(\widehat{\beta}_{12}\right)$		-0.0529^{***}
		(0.0199)
Test: $\chi^2\,(1)$		
Break at age 5 $\left(\widehat{\beta}_1 = 0\right)$	9.00	
	[0.001]	
Break at Age 10 $\left(\widehat{\beta}_{11} = \widehat{\beta}_{12}\right)$		0.17
(Conditional on break at age 5)		[0.677]
	Preferred Specification	

Notes:
Robust Standard Errors in Parenthesis; $^{***}: p < 0.01, ^{**}: p < 0.05, ^{*}: p < 0.1$. Simulated *p-values* associated with the relevant $\chi^2\,(1)$ test in brackets. Thresholds are estimated.
Also includes dummies for age; for the presence of the father and mother in the household; for gender and race of the child; for mother or father as the respondent. An interaction term between presence of father and mother in the household and age of father or mother is also included.

Table 9: The Income Gradient in Child Health Status (Specification 2), England. Data Determined Break

	Break 1	**Break 2**	**Break 3**
$LogIncome\left(\widehat{\beta}_0\right)$	-0.2038^{***}	-0.0681	-0.0690
	(0.0124)	(0.0632)	(0.0632)
$LogIncome \times AGE\,[1,13]\left(\widehat{\beta}_{12}\right)$		-0.1405^{**}	
		(0.0640)	
$LogIncome \times AGE\,[1,10]\left(\widehat{\beta}_{121}\right)$			-0.1501^{**}
			(0.0643)
$LogIncome \times AGE\,[11,13]\left(\widehat{\beta}_{122}\right)$			-0.1195^{*}
			(0.0671)
$LogIncome \times AGE\,[14,15]\left(\widehat{\beta}_1\right)$	0.0618^{***}	-0.0753	-0.0762
	(0.0296)	(0.0688)	(0.0688)
Test: $\chi^2(1)$			
Break at age 13 $\left(\widehat{\beta}_1 = 0\right)$	4.37		
	[0.033]		
Break at age 0 $\left(\widehat{\beta}_{12} = 0\right)$		4.82	
(Conditional on break at age 13)		[0.028]	
Break at Age 10 $\left(\widehat{\beta}_{121} = \widehat{\beta}_{122}\right)$			1.38
(Conditional on break at ages 0 and 13)			[0.245]
		Preferred Specification	

Notes:
Robust Standard Errors in Parenthesis; $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$. Simulated *p-values* associated with the relevant $\chi^2(1)$ test in brackets. Thresholds are estimated.
Also includes dummies for age and year (reference year = 1999); for the presence of the father and mother in the household; for gender and race of the child; for mother or father as the respondent. An interaction term between presence of father and mother in the household and age of father or mother is also included.

Table 10: The Income Gradient in Child Health Status (Specification 3), US. Data Determined Break

	Break 1	**Break 2**
$LogIncome\left(\widehat{\beta}_0\right)$	-0.1300^{***}	-0.1292^{***}
	(0.0149)	(0.0153)
$LogIncome \times AGE\,[6,17]\left(\widehat{\beta}_1\right)$	-0.0507^{***}	
	(0.0172)	
$LogIncome \times AGE\,[6,10]\left(\widehat{\beta}_{11}\right)$		-0.0419^{**}
		(0.0210)
$LogIncome \times AGE\,[11,17]\left(\widehat{\beta}_{12}\right)$		-0.0605^{***}
		(0.0200)
Test: $\chi^2(1)$		
Break at age 5 $\left(\widehat{\beta}_1 = 0\right)$	9.00	
	[0.001]	
Break at Age 10 $\left(\widehat{\beta}_{11} = \widehat{\beta}_{12}\right)$		0.25
(Conditional on break at age 5)		[0.422]
	Preferred Specification	

Notes:
Robust Standard Errors in Parenthesis; $^{***}: p < 0.01, ^{**}: p < 0.05, ^{*}: p < 0.1$. Simulated *p-values* associated with the relevant $\chi^2(1)$ test in brackets. Thresholds are estimated.
Also includes dummies for age; for the presence of the father and mother in the household; for gender and race of the child; for mother or father as the respondent; for the highest level of education attained by the mother and father. An interaction term between presence of father and mother in the household and age of father or mother is also included.

Table 11: The Income Gradient in Child Health Status (Specification 3), England. Data Determined Break

	Break 1	**Break 2**	**Break 3**
$LogIncome\left(\widehat{\beta}_0\right)$	-0.1786^{***}	-0.0370	-0.0973^{***}
	(0.0129)	(0.0638)	(0.0334)
$LogIncome \times AGE\,[1,13]\left(\widehat{\beta}_{12}\right)$		-0.1472^{**}	
		(0.0644)	
$LogIncome \times AGE\,[1,10]\left(\widehat{\beta}_{121}\right)$			-0.0947^{***}
			(0.0350)
$LogIncome \times AGE\,[11,13]\left(\widehat{\beta}_{122}\right)$			-0.0870^{**}
			(0.0430)
$LogIncome \times AGE\,[14,15]\left(\widehat{\beta}_1\right)$	0.0594^{***}	-0.0842	-0.0238
	(0.0296)	(0.0692)	(0.0427)
Test: $\chi^2(1)$			
Break at age 13 $\left(\widehat{\beta}_1 = 0\right)$	4.03		
	[0.057]		
Break at age 0 $\left(\widehat{\beta}_{12} = 0\right)$		5.23	
(Conditional on break at age 13)		[0.024]	
Break at Age 10 $\left(\widehat{\beta}_{121} = \widehat{\beta}_{122}\right)$			0.06
(Conditional on break at ages 0 and 13)			[0.820]
		Preferred Specification	

Notes:
Robust Standard Errors in Parenthesis; $^{***}: p < 0.01, ^{**}: p < 0.05, ^{*}: p < 0.1$. Simulated *p-values* associated with the relevant $\chi^2(1)$ test in brackets. Thresholds are estimated.
Also includes dummies for age and year (reference year = 1999); for the presence of the father and mother in the household; for gender and race of the child; for mother or father as the respondent; the highest education of the mother and father. An interaction term between presence of father and mother in the household and age of father or mother is also included.

Figure 1: Child Health Income Gradient by Age Groups. Pre-determined Breaks

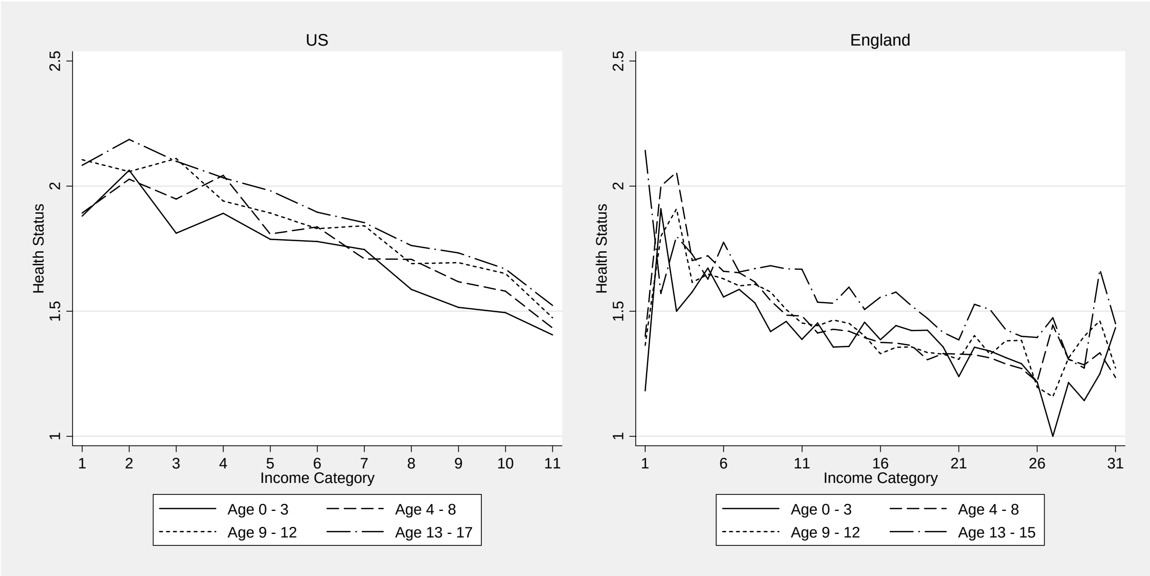


Figure 2: Child Health Income Gradient by Age Groups. Locally Weighted Regressions. Pre-determined Breaks.

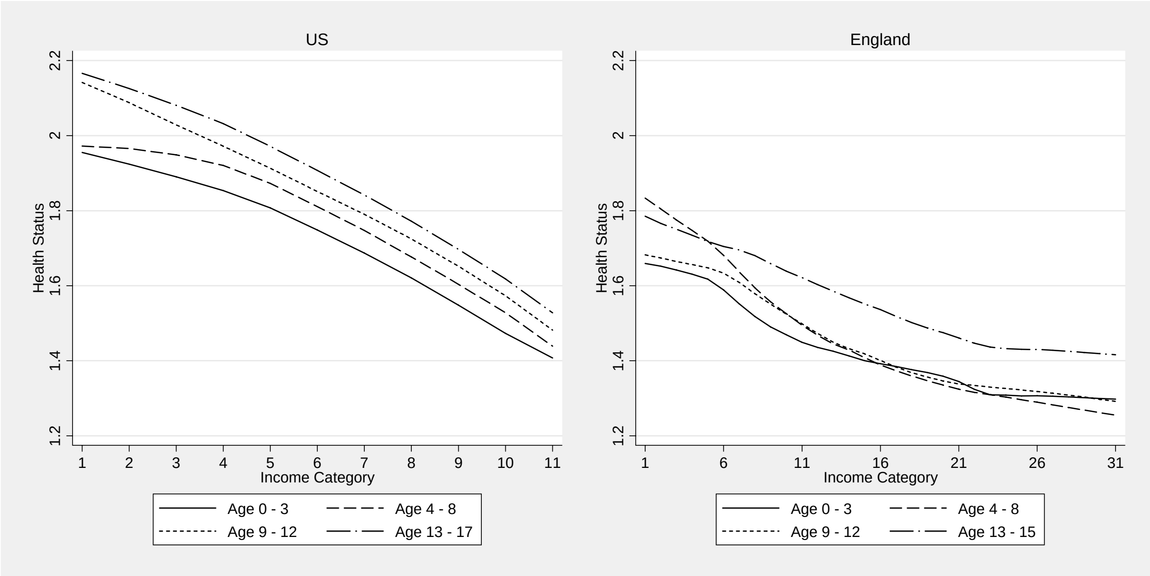


Figure 3: Predicted Probability of Excellent (Very Good) Health. Pre-determined Breaks.

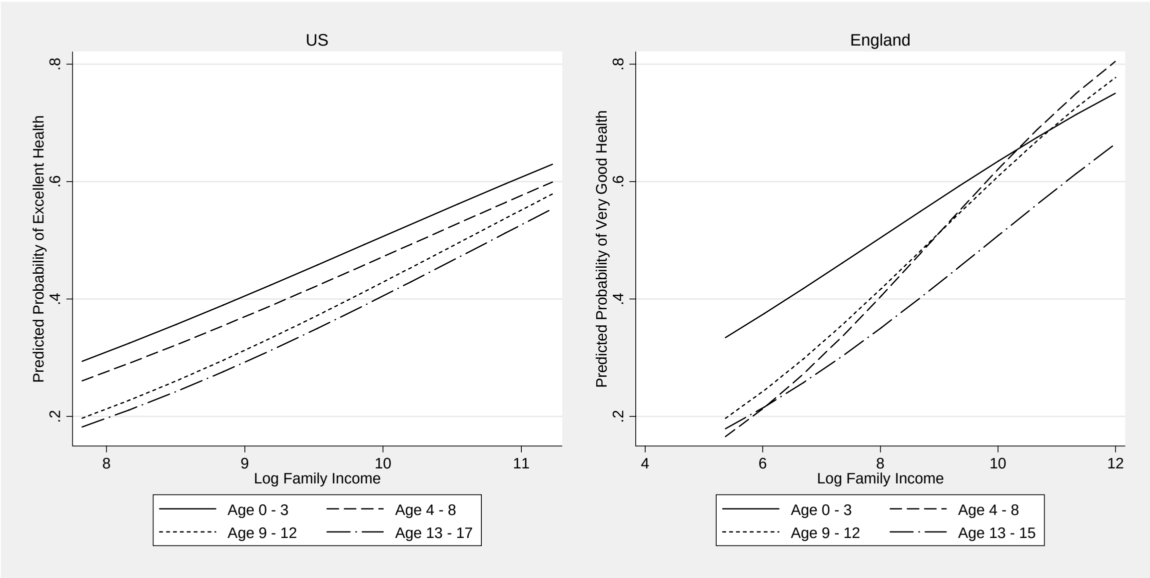


Figure 4: Child Health Income Gradient by Age Groups. Locally Weighted Regressions. Data Determined Breaks.

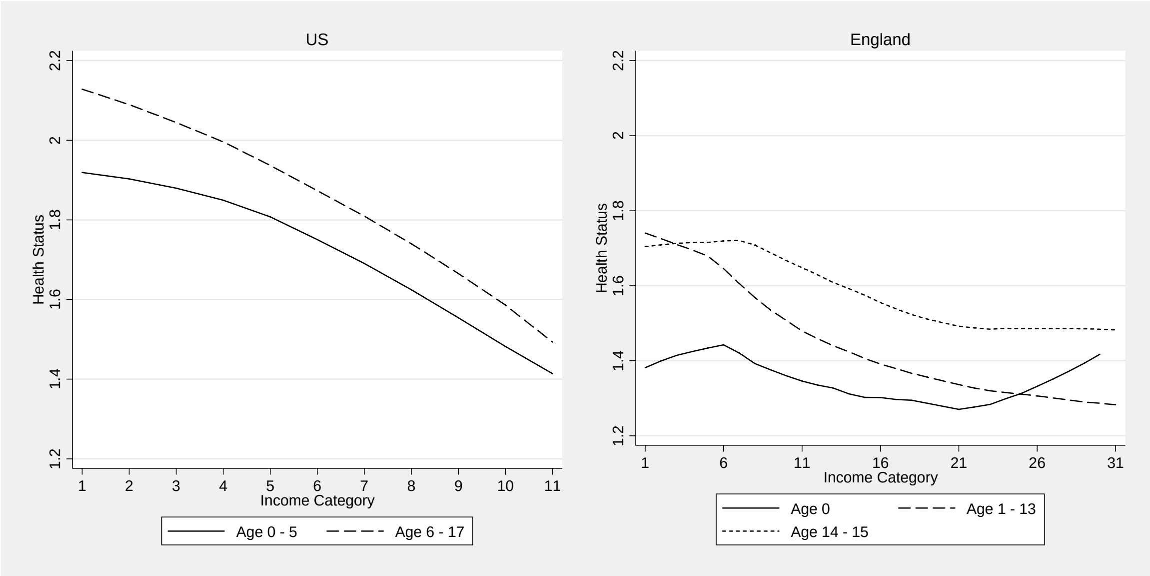


Figure 5: Predicted Probability of Excellent (Very Good) Health. Data Determined Breaks.

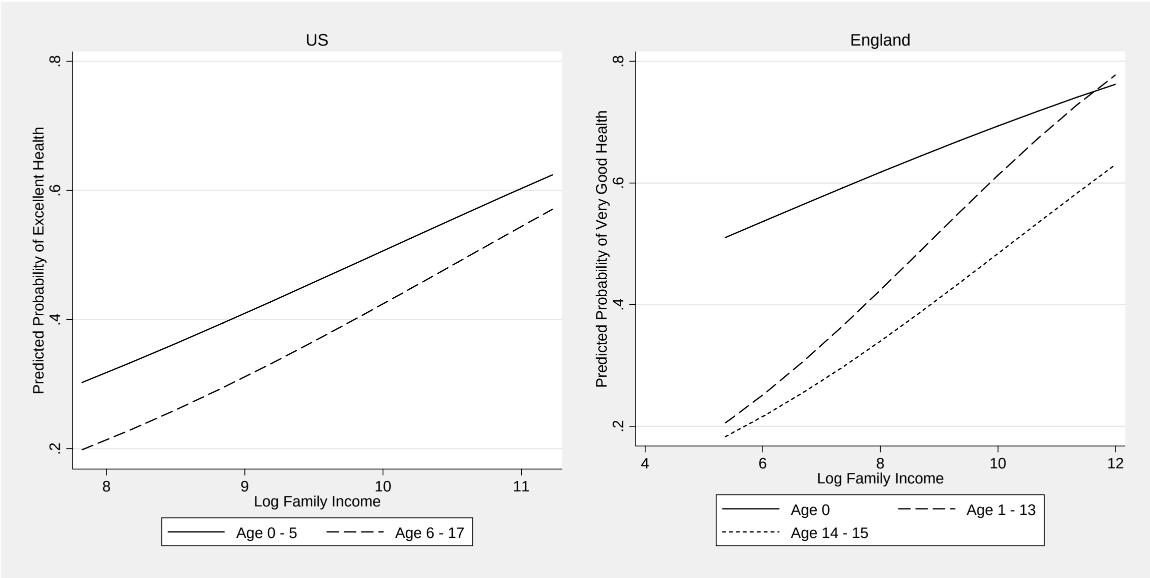


Figure 6: Comparisons with a Fully Flexible Approach

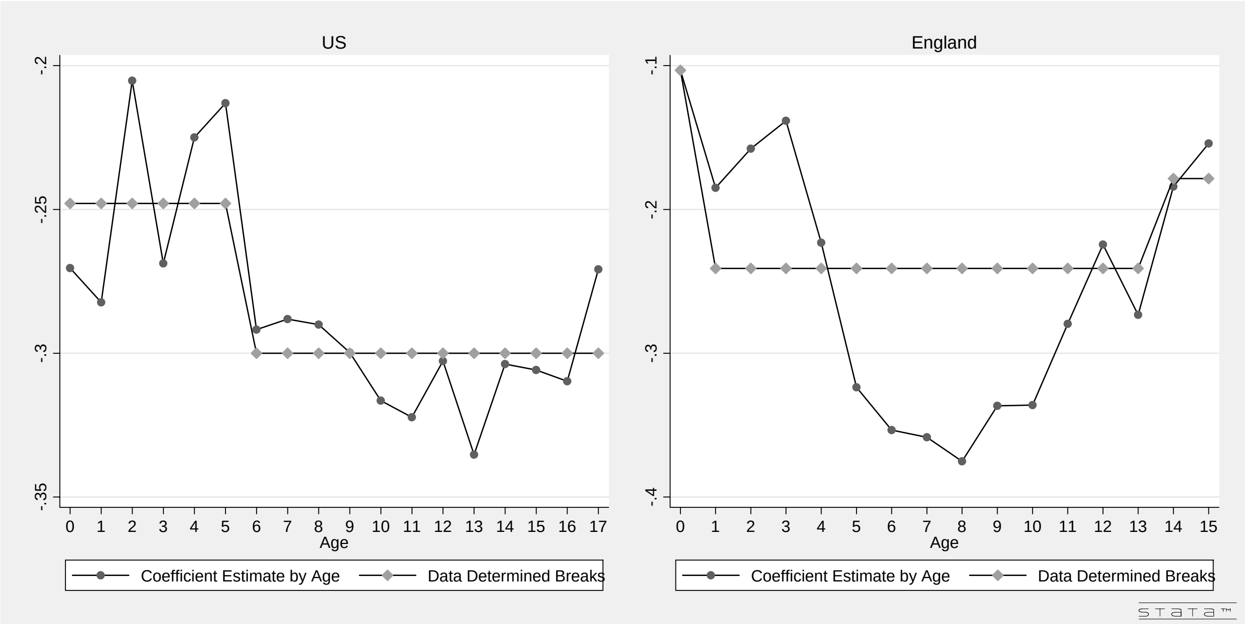
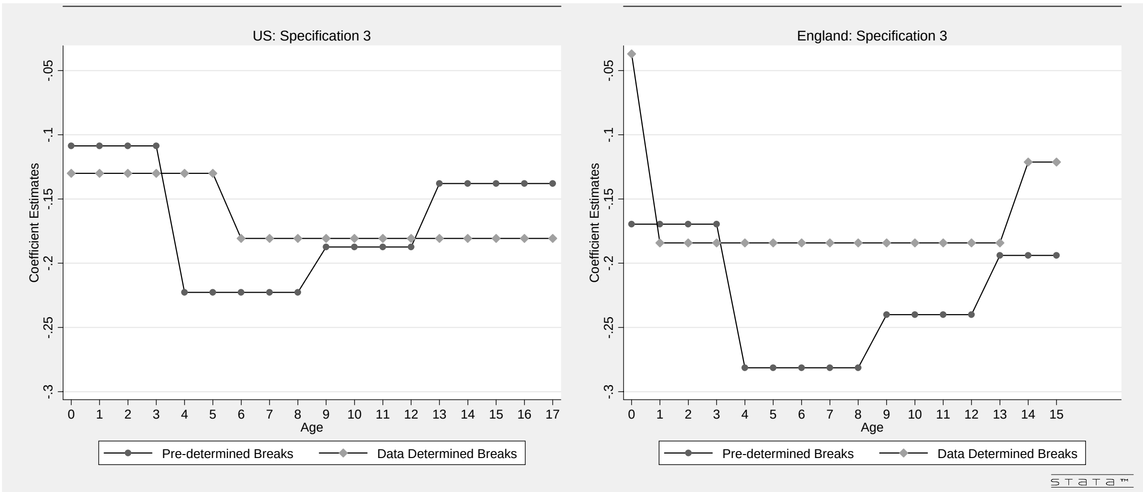


Figure 7: Coefficient Estimates Corresponding to Specification 3. Pre-determined and Data Determined Breaks.



A.1 Appendix A

Table A-1: Income Bands

US		England	
Income Code	**Income Band**	**Income Code**	**Income Band**
1	$\leq$ \$4,999	1	$<$ £ 520
2	\$5,000 − \$9,999	2	£ 520 − £ 1,600
3	\$10,000 − \$14,999	3	£ 1,600 − £ 2,600
4	\$15,000 − \$19,999	4	£ 2,600 − £ 3,600
5	\$20,000 − \$24,999	5	£ 3,600 − £ 5,200
6	\$25,000 − \$34,999	6	£ 5,200 − £ 7,800
7	\$35,000 − \$44,999	7	£ 7,800 − £ 10,400
8	\$45,000 − \$54,999	8	£ 10,400 − £ 13,000
9	\$55,000 − \$64,999	9	£ 13,000 − £ 15,600
10	\$65,000 − \$74,999	10	£ 15,600 − £ 18,200
11	\$75,000 or greater	11	£ 18,200 − £ 20,800
		12	£ 20,800 − £ 23,400
		13	£ 23,400 − £ 26,000
		14	£ 26,000 − £ 28,600
		15	£ 28,600 − £ 31,200
		16	£ 31,200 − £ 33,800
		17	£ 33,800 − £ 36,400
		18	£ 36,400 − £ 41,600
		19	£ 41,600 − £ 46,800
		20	£ 46,800 − £ 52,000
		21	£ 52,000 − £ 60,000
		22	£ 60,000 − £ 70,000
		23	£ 70,000 − £ 80,000
		24	£ 80,000 − £ 90,000
		25	£ 90,000 − £ 100,000
		26	£ 100,000 − £ 110,000
		27	£ 110,000 − £ 120,000
		28	£ 120,000 − £ 130,000
		29	£ 130,000 − £ 140,000
		30	£ 140,000 − £ 150,000
		31	$>$ £ 150,000