Better late than never? The Timing of Income and Human Capital Investments in Children.

by

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PRELIMINARY. PLEASE DO NOT CIRCULATE.

7th November 2010

Abstract

We measure household income and human capital outcomes across the entire childhood for over 500,000 children in Norway, estimating how the timing of income drives adolescent human capital . Such a large dataset enables us to estimate nonparametric regressions of adult outcomes on parental income in different periods of childhood. In order to interpret our findings we then simulate multiperiod models of parental investment in children under different assumptions about credit markets, labor supply, and the information sets of parents. We find that human capital is maximized when income is balanced across periods, although our results also suggest that there is a need for higher levels of income in late adolescence. Simple models emphasizing borrowing constraints do not explain our findings. More promising models are likely to feature uncertainty about income shocks, child endowments, and the technology of skill formation.

* We thank participants in the MFI Institute in Honor of James Heckman for useful comments. Carneiro gratefully acknowledges the financial support from the Economic and Social Research Council for the ESRC Centre for Microdata Methods and Practice (grant reference RES-589-28-0001), the support of the European Research Council through ERC-2009-StG-240910-ROMETA, the hospitality of Georgetown University, and the Poverty Unit of the World Bank Research Group. Salvanes thanks the Research Council of Norway for financial support. Tominey acknowledges the Research Council for Norway and the Leibniz Association, Bonn, in the research network 'Non-Cognitive Skills:Acquisition and Economic Consequences' for support.

1 Introduction

Take an economy where parents invest in the human capital of their children over multiple periods of childhood (e.g., Cunha, Heckman, and Schennach, 2010, Caucutt and Lochner, 2008). In this economy, the total human capital acquired during childhood depends on the whole history of investments. Investments at different points in time interact in the production of human capital, and they can be complements or substitutes (e.g., Cunha, Heckman, Schennach, 2010). As a result, the timing of investments may be as or more important than their sum.

In this economy parental incomes fluctuate over time, for both predictable and unpredictable reasons. Markets are incomplete, and therefore parents are only able to buy imperfect insurance against shocks. In such an economy, income fluctuations may affect investments in children at each point in time, and the timing of fluctuations matters.

In this paper we ask whether investments in children react to income shocks, and whether, keeping constant the permanent income of the family, the timing of income affects the human capital development of children. Are income shocks in different periods substitutes or complements in the production of human capital?

This is of central importance for the design of welfare systems. One important role welfare systems fulfill is to partially insure consumption against income shocks. However, if shocks to income also affect investments in children, we need to know how best to design welfare systems in order to provide insurance for human capital formation of children. In addition, by studying the importance of the timing of income shocks we are able to learn about the technology of skill formation, and about the structure of credit markets faced by parents.

Several papers compare the importance of early vs. late income shocks, such as: Duncan and Brooks Gunn (1997), Duncan et al (1998), Levy and Duncan (2000), Jenkins and Schluter (2002), Carneiro and Heckman (2002), Caucutt and Lochner (2005), Aakvik et al (2005), Humlum (2010). Most of them are for the US, but there are also papers for Germany, Norway and Denmark. Findings are fairly diverse. They range from *no effect of timing of income* (e.g., Carneiro and Heckman, 2002), to *the largest effect is that of early income* (e.g., Caucutt and Lochner, 2008), or to *the largest effect is that of late income* (e.g., Humlum, 2010). However, they deal with different countries, and outcomes are sometimes measured at different ages of the child.

This issue is far from settled in the literature. This paper uses particularly good data for this topic, which turns out to be quite important. The standard approach to studying the role of the timing of income in the literature divides childhood in a number of stages, say three (ages 0-5, 6-11, 12-17), and runs a regression of the following type:

$$Y_i = \alpha_0 + \alpha_P P_i + \alpha_2 I_{2,i} + \alpha_3 I_{3,i} + X_i \delta + u_i$$

where H is a measure of human capital at a given age, P is permanent income (over childhood), I_2 and I_3 are the average (discounted) values of income in periods 2 and 3, X is a set of other controls and u is the residual. Period 1 income is omitted since it is colinear to P once I_2 and I_3 are controlled for.

One simple and natural extension to this work considers many more periods of childhood (years), decomposes household income fluctuations into permanent and temporary shocks, and estimates how human capital development reacts to each type of shock in each time period. Following the literature on income dynamics and consumption, we take a standard model for household income dynamics and estimate it jointly with a human capital model:

$$\begin{aligned}
I_{it} &= X_{it}\beta + P_{it} + \upsilon_{it} \\
P_{it} &= P_{it-1} + \eta_t \\
\upsilon_{it} &= \varepsilon_{it} + \theta\varepsilon_{it-1} \\
Y_{iT} &= \sum_{t=1}^{T} X_{it}\delta + \sum_{t=1}^{T} \frac{\beta_t^P P_{it}}{(1+r)^t} + \sum_{t=1}^{T} \frac{\beta_t^T \upsilon_{it}}{(1+r)^t} + u_{iT} \\
&= \sum_{t=1}^{T} X_{it}\delta + \sum_{t=1}^{T} \frac{\beta_t^P}{(1+r)^t}\left(P_{i0} + \sum_{s=1}^{t}\eta_{is}\right) + \sum_{t=1}^{T} \frac{\beta_t^T \upsilon_{it}}{(1+r)^t} + u_{iT}
\end{aligned}$$

where Y_{it} is yearly income, P_{it} is the permanent component of earnings, υ_{it} is the transitory component, and β_t^P and β_t^T are the coefficients on the permanent and transitory components of income in each year.

We study this model in a companion paper, using registry data for Norway, which is the same data we use in this paper. We focus on the case where υ_{it} is MA(1), although we also experiment with an MA(2) for υ_{it}. We show that the human capital of an individual reacts to both permanent and transitory shocks to her parental income at different ages of childhood, but mainly to permanent shocks, as in the literature on consumption (e.g., Blundell, Preston and Pistaferri, 2008).

One problem with both this specification and the standard one in the literature is that they constrain income in different periods to be "perfect substitutes" and to have linear effects. This specification is used mainly for convenience, not because researchers believe in these assumptions. By using them we miss all the interactions between incomes in different periods. Evidence on the technology of skill formation shows that interactions between investments in different time periods are key to understanding the process of skill formation.

Therefore, in this paper we estimate instead nonparametric regressions of H on P and income at different periods of childhood using a very rich and large dataset (for Norway). Due to the curse of dimensionality we are forced to aggregate income into three different periods, as in most of the literature on this topic. In particular, we consider ages 0-5, 6-11, and 12-17. However, by aggregating income into these three periods we expect to average out transitory shocks to income. In summary, we estimate:

$$Y_i = h\left(P_i, I_{6-11i}, I_{12-17i}\right) + X_i\delta + \upsilon_i$$

where h is a nonparametric function of its arguments. Among other variables, our controls include age at birth and education, which means that we are controlling each parent's position in the age earnings profile, which is allowed to vary by education category.

There are at least three important potential problems we are faced with when estimating this model. First, age-income profiles may vary across households and be correlated with parental ability. We do not model this explicitly, but in one of our robustness checks we include pre-birth and post-18 parental income in the regression, in order to measure the slope of the age earnings profile taking two points just outside the relevant interval we are considering. There is hardly any change in our results. In addition, we note that in much of the later literature on estimating wage dynamics there is not a consensus on whether there exists or not important heterogeneity in the effect of age or experience on earnings. This is the stand we take here.

Second, related to this, it is possible that high ability mothers decide to spend the earlier years of the child at home, and later when they return to the labor market they have high earnings precisely because they have high ability. This would lead to a positive correlation between having a steep income profile and human capital development of the child, purely driven by maternal ability. Again, we do not model this explicitly, but we estimate models only with paternal income instead of total household income. Our empirical results are quite similar to the ones in our base specification. Similarly, if we take out age 0 from the analysis, to account for maternity leave, our results hardly change.

In response to the last two points it is also important to emphasize that it is possible to do a similar analysis using more aggregate data. In particular, we have estimated county business cycle shocks to household incomes, and then we have used them instead of income in our main regressions (present value of shocks, average shocks at ages 6-11, average shocks at ages 12-17). Although the standard errors are larger than in the original specification, the overall patterns are essentially the same.

Finally, the timing of births is endogenous and may be correlated with what stage of the career one is in. We showed above that our results are robust to the inclusion of pre-birth and post-18 parental income in the regression. Beyond that, results are robust to controls for age at birth (which we interact with education) and number of children. The data limits us to relatively simple solutions of the type we described. However, the remarkable robustness of our results to different specifications strongly suggests that we are including the most relevant controls in our models.

In the simplest setting with no uncertainty and no credit constraints, the timing of income should not matter. In more complex settings, the effects of the timing of income will depend on the response of investments to income fluctuations and on the technology of skill formation. We find that years of schooling of the child are maximized when: there is a balanced profile of earnings between periods 1 (0-5) and 2 (6-11); there is also some balance relatively to income in period 3 (12-17), but much income is shifted towards period 3 (at least over the support of the data). Similar patterns are found for several other outcomes This is true for multiple values of permanent income, and controlling for several family background variables, including parental education. Credit constraints are unlikely to be driving the results, because they would imply different patterns for different groups of families (grouped by permanent income, education), which we do not see.

The structure of the paper is as follows. In section 2 we outline our methodology and in section 3 our data. Section 4 discusses our results in light of simple models of investments in children. In section 5 we perform robustness checks. Finally, section 6 concludes.

2 Methodology

2.1 Empirical Strategy

We define the stock of human capital Y of child i as a function of parental income I in period t.

$$Y_i = m(\mathbf{I}_{it}) + \varepsilon_i \tag{1}$$

This is not a production function. A production function relates human capital Y to parental investments in human capital, which in turn are related to the history of parental income. Therefore this is a reduced form relationship that results from the combination of the production function and the reaction of investments in children to fluctuations in income.

$\mathbf{I}$ is defined as a *3* dimensional vector of income in periods 1, 2 and 3.

$$Y_i = m(I_{i1}, I_{i2}, I_{i3}) + \varepsilon_i \tag{2}$$

We allow this relationship to be fully flexible across I_i and make no assumptions on the distribution of the error term, except that it has a finite conditional variance: $E(\varepsilon_i^2|I_{i1}, I_{i2}, I_{i3}) \leq C < \infty$, and that it is additively separable from $m(.)$.

In order to draw any causal inference from our estimates, we require that

$$E(\varepsilon_i|I_{i1}, I_{i2}, I_{i3}) = 0 \quad (3)$$

This is unlikely to hold, as emphasized by many papers on this topic (e.g., Dahl and Lochner, 2010). However, our interest is on the timing of income, not on the level of income. Therefore, we introduce permanent income into the model. Household permanent income captures any fixed family traits, for example the education and occupational status of parents, therefore absorbing the omitted variable bias along this dimension.

With the extensive data on income covering the lifetime of the children, the definition of permanent income sums income across the lifetime of the child; $PI_i = I_{i1} + I_{i2} + I_{i3}$, thereby controlling for any parental traits fixed across the lifetime of the child and correlated to permanent income. So we estimate:

$$Y_i = m(PI_i, I_{i2}, I_{i3}) + \varepsilon_i \quad (4)$$

The consequence of controlling for PI in replacement of I_1 is that we will no longer be able to estimate the level effect of income across time, but rather the relative effects of the timing of income in period 2 and 3, relative to income in period 1[1]. Therefore, we examine which periods are more productive in producing child outcomes.

There are at least three important potential problems we are faced with when estimating this model. First, age-income profiles may vary across households and be correlated with parental ability. We do not model this explicitly, but in one of our robustness checks we include pre-birth and post-18 parental income in the regression, in order to measure the slope of the age earnings profile taking two points just outside the relevant interval we are considering. There is hardly any change in our results. In addition, we note that in much of the later literature on estimating wage dynamics there is not a consensus on whether there exists or not important heterogeneity in the effect of age or experience on earnings. This is the stand we take here.

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[1] See Appendix 1 for details

2.2 Semi Parametric Multivariate Local Linear Kernel Regression

We follow Ruppert & Wand (1994) and Fan & Gijbels (1996) to define the multivariate local kernel regression estimator. We aim to estimate the conditional mean function $m(I_i) = E(Y|I_i = x)$ for a vector $\mathbf{x}$, where $i = 1, .., n$.

The solution is the value which minimises the weighted least squares objective function

$$\sum_{i=1}^{n} \{Y_i - \alpha - \beta_1(I_i - x)\}^2 K_H(I_i - x) \tag{5}$$

where $\mathbf{H}$ is a *3x3* diagonal bandwidth matrix and *K(.)* is defined as the 3-dimensional product of a univariate Epanechnikov kernel function:

$$K(s) = \begin{cases} (1 - s^2) & if\ |s| < 1 \\ 0 & \text{otherwise} \end{cases}$$

where $s = \frac{I_i - x}{h}$ and h is the bandwidth.

This results in the estimator for each $\mathbf{x}$

$$\hat{\alpha} = e^T \left(I_x^T W_x I_x\right)^{-1} I_x^T W_x Y \tag{6}$$

where e^T is the vector with 1 in the first entry and 0 in all others and W_x is the weighting function at the point $\mathbf{x}$.

The choice of kernel is not important for the asymptotic properties of the estimator, as long as it is chosen to be a symmetric, unimodal density, such as the Epanechnikov kernel. However, there exists a trade-off in the choice of the number of observations entering the local kernel regressions, determined by the bandwidth h. A larger bandwidth increases the bias of the estimate but reduces the variance. Optimally $h \to 0$ as n$\to \infty$.

We use the following formula to choose our bandwidth, for each covariate:

$$h_j = C * 2 * \sigma_{x_j} h^{\frac{-1}{7}} \tag{7}$$

where C denotes a constant and σ_{x_j} the standard error of I_j. We allow C to vary between 0.5 and 4, in order to examine the robustness of our results to the choice of bandwidth.

Finally, we calculate the standard errors using the formula from Ruppert & Wand (1994).

$$var\left\{\hat{m}(x, H)|I_1, .., I_n)\right\} = \left\{n^{-1}|H|^{\frac{-1}{2}} R(K)/f(x)\right\} v(x) \{1 + o_p(1)\} \tag{8}$$

where $\mathbf{H}$ denotes the bandwidth matrix, $R(K) = \int K_H(s)^2 ds$, $f(x)$ denotes the conditional density of x and $v(x) = Var(Y|I = x)$ denotes the conditional variance. We estimate the conditional density and variance as follows:

$$\hat{f}(x) = \frac{1}{nh^d} \sum_{i=1}^{n} \frac{1}{h_1 h_2 h_3} K\left(\frac{I_{i1} - x_1}{h_1}, \frac{I_{i2} - x_2}{h_2}, \frac{I_{i3} - x_3}{h_3}\right) \tag{9}$$

$$\hat{v}(x) = e^T \left(I_x^T W_x I_x\right)^{-1} I_x^T W_x \hat{\epsilon}^2 \tag{10}$$

where $\hat{\epsilon}^2 = Y_i - \hat{m}(x)$.

Our nonparametric model controls for permanent income received during the lifetime of the children, hence we control for any traits of the parents that are fixed over the child's lifetime and can be subsumed in permanent income. Permanent income is correlated with many socioeconomic traits, such as the level of education and possibly even the age of the mother at birth, which may be likely to confound estimation of the effect of the timing of income. Note, this is what Carneiro & Heckman refer to as "lifetime credit constraints". Thus, we feasibly control for the socioeconomic status of parents until the child reaches adulthood. However, it is fairly easy to think of other traits which do vary across the child's lifetime which would also be correlated with the relationship between income received during different periods of time and the stock of child human capital. For example, the incidence of marital break up may change household income and studies have shown divorce to have an effect on the cognitive and non-cognitive development of children[2].

Following the model of Robinson (1988), we can extend our model from equation (8) to include a vector of covariates, z, where ζ denotes the error term.

$$Y_i = m(PI_i, I_{i2}, I_{i3}) + \delta' z_i + \zeta_i \tag{11}$$

Using this formulation, we are still able to estimate nonparametrically how income in the three periods drive child human capital. We allow a linear, parametric relationship between the remaining covariates and the dependent variable.

Robinson proposed a two-step method, where the first step estimates $E(Y|Z)$ and $E(I|Z)$ and secondly allows nonparametric estimation of the effect of the latter on the former. This is reminiscent to the OLS estimation of the following model

$$Y = I'\beta + Z'\delta' + U^3 \tag{12}$$

The coefficient $\hat{\beta}$ can be derived from a regression of the residuals $U_1 = Y - \hat{\gamma}_1 Z$ upon $U_2 = I - \hat{\gamma}_2 Z$.

We adapt the method slightly, to take account of the 3-dimensional I, as using directly the method of Robinson would require estimation of U_2 for each I. Rather, we estimate parametrically a regression given by equation (16) of Y on Z and a cubic function of I. Secondly, the fitted values of $Z'\hat{\delta}$ are subtracted from Y. We then estimate nonparametrically the following equation

$$Y_i - Z'\hat{\delta} = m(PI_i, I_{i2}, I_{i3}) + \varepsilon_i \tag{13}$$

The additional controls included in Z are the child's gender, a dummy variable for each time period determining whether there was a family break up, the number of siblings in the household at each period, maternal and paternal education and age at the birth of the child. We include a third order polynomial in income received in each time period.

3 Data

We utilise the wealth of information contained in merged administrative and education files, between 1971-2004 for the entire population of Norway.

We select all births in the period 1971-1980 and link unique identifiers of the mother and father taken from birth certificates, to map on annual household taxable earnings data for each year from the child's birth, through to their 17th year. This gives us information on 514,762 children.

The earnings values include wages and income from business activity but also unemployment, sickness and disability benefits. Therefore, our income measures include a degree of insurance against low income shocks and consequently, we expect the effect of the timing of taxable earnings to be lower than the effect of labour earnings

[2] see for example Joshi *et al* (1999)

[3] note, subscipts for time and individuals are excluded for ease of notation

alone. Household income is constructed as the real present value level as of the year of birth of the child. Following Aakvik *et al* (2005), we use the real interest rate of 4.26% to calculate real present value of income. Comparing the present value across periods of life for the child means that we can interpret our estimates as the relative effectiveness of a policy which aims to give a fixed real sum of money to parents in the most productive period.

To examine the differential effect of income at different stages in the child's lifetime, we sum household income over three periods of the child's life. According to Cunha & Heckman (2006, page 2) "It is important for studying the economics of skill formation to disaggregate the life cycle of the child and distinguish infancy, early schooling and adolescent outcomes". We divide the child's lifetime into three periods accordingly. In the first period of early childhood, the child is aged 0-5 years. In period 2 the children are aged 6-11 and the child is aged 12-17 in the third period, the period of adolescence.

A contribution of our paper is to estimate the effect of the timing of income upon a large range of child outcomes. The administrative data measures the traditional schooling outcomes of the years of education. We include also an indicator for dropping out of high school at the age of 16. The consequences of the early drop out are that individuals do not receive a certificate for vocational or academic achievement which, in the latter case, prohibits access to further education. We also measure whether the individuals enrolled in college (by which we mean enter themselves at university for a degree qualification). It is not possible to measure whether the degree was completed, unfortunately.

Military service is compulsory in Norway for males and, usually between the age of 18-20 males take an IQ test. This test is a composite of an arithmetic and words tests[4] and a figures test[5], all of which are recognised as tests of IQ. See Sundet *et al* (2004, 2005) and Black *et al* (2008) for more information on the tests.

For a sample of children, we observe the level of income they receive at age 30. This may provide interesting information as to the nature of the parent's utility function and therefore the mechanisms through which lifetime income translates into child outcomes. Firstly, a model in which the parent's utility is a function of the financial affluence of their child may mean that the timing of income is more important for the income of the child than for test score or educational outcomes. Alternatively, if parents care only about the ability level of their child, we will find the opposite result. Secondly, it is possible that parents with altruistic preferences will choose to invest to optimise their child's income level, rather than test scores of education, if they plan to extract a return to the investment in their old age.

Then, in a move away from the more traditional outcomes, we measure a health score taken also from the military tests upon entry to the Army. This test is designed to ascertain physical capabilities of the males. It is measured on a 9 point scale, with the top score of 9 indicating health sufficient to allow military service. Around 85% of individuals score the top measure. Finally, we include also an indicator for teen pregnancy. This takes the value of 1 if the individual has a child aged between 16 and 20.

In our semi-parametric estimation, we control for other inputs into the child's human capital production function. These include family background information of parental years of education and age at birth, marital status and family size in each year of the child's life. We observe also the year of birth of the child and the municipality of residence in each year of the child's life.

[4] which are most similar to the Wechsler Adult Intelligent Scale (WAIS)
[5] similar to the Raven Progressive matrix

4 Results

4.1 Descriptive Statistics

The descriptive statistics for the sample are reported in Table 1. There are over 500,000 child level observations in the dataset. There is large variation in income, as we would expect. Mean income falls across the three periods, owing to our choice of comparing the present value of income across time. The mean education of the mothers is slightly lower than that of the fathers, at 10.7 years compared to 11.3. Also, the mother tends to be younger than the father at the birth of the child.

Looking at the measures of child human capital, the mean education of the child is higher than that for both parents, at 12.8 years. 21% of children drop out from high school, after 12 years of schooling but 40% attend college pointing to very polarised education choices.. The mean earnings of the sample of children reporting a wage at age 30 is £19,771. As noted above, our IQ measure for males only[6] has been aggregated into a 9 point scale, and on average children score 5.24, with a standard deviation of 1.79. On the other hand, the average health score for the males is 8.44, indicating that the majority of children achieve perfect physical health on this scale. Finally, teen pregnancies occur for 4% of the population of children born in the 1970s.

The life cycle profiles for mothers and fathers are shown in Figures 1 & 2 for reference. They show substantial heterogeneity across cohorts in the slopes of wage profiles and across mothers and fathers. Maternal incomes tend to be lower and the profiles peak earlier than for the men.

It is necessary that income across the three periods display mobility, if our model is to identify the parameters of interest. Tables 2a) and 2b) report the mobility in income across a father's and mother's life respectively, by providing a transition matrix between the quartile in the income distribution at ages 30 and 40. The ranking in the income distribution was calculated for each parent in every year we observe their wage. Then for the mothers and fathers, we select their position at ages 30 and 40. We see that there is persistence, with 46% and 32% of men and women in the 1st quartile at 30 also in the 1st quartile at age 40. The same persistence is evident for those in the 4th quartile at age 30. 57% and 58% of these men and women will also be in the 4th quartile one decade later. However, despite this, there is evidence of mobility also. For example, of the men (women) in the 1st quartile at age 30, 27% (29%) were in the 2nd quartile at age 40, 15% (24%) were in the 3rd and 11% (15%) were in the 4th quartile. The same is true when we plot a transition matrices in Tables 2c)-2e) for income decile of households in the three periods of the child's life used in the bulk of our analysis. Whilst again there is persistence across periods in the household income decile, there is also substantial variation around this trend. We are therefore reassured that there is adequate variation in our data to estimate the how parental income received at three different periods if a child's life will drive their human capital.

4.2 Parametric Results

To provide a benchmark to the nonparametric results, we run OLS regressions of child outcomes on real, present value (at age 0) income in periods 2, 3 and permanent income.[7]. The results are reported in Table 3 for the seven child outcomes - years of schooling, high school drop out, college attendance, log earnings at age 30, IQ, health and teen pregnancy. Note, we report only the coefficients on the three income variables. Full regression results are in Appendix Tables 1a) &1b). The regressors are income in period 2 (I2 - aged 6-11), income in period 3 (I3 - aged 12-17) and permanent income (PI - aged 0-17). Including a control for permanent income results in the interpretation

[6] taken from the Armed Forces Test

[7] Recall children age aged 0-5 in period 1, 6-11 in period 2 and 12-17 in period 3. Permanent income is the sum of income across these three periods.

of a coefficient on I2 (I3) as the effect relative to I1, as shown in Appendix 2.

Unconditional results are shown in odd-numbered columns and in even columns, we condition on a set of family inputs, including parental years of schooling and age at birth, parent separation, measured by a dummy variable which takes the value of 1 if parents separated in each period and 0 otherwise, the number of children in the household in each period and dummy variables for child's year of birth (not reported).

The table shows that the raw effect of I2 and I3 upon child outcomes is quite different to the conditional effect. For example, from column 1, the raw effect of an increase in I2 by £10,000 keeping permanent income and I3 constant (implying a reduction in I1), is to lower years of schooling by 0.022 years. This implies that I1 is more productive than I2 in raising years of schooling. However, in column 2 this effect is insignificant once the family controls are included in the regression. A similar pattern is found for teen pregnancy, whereby the raw effect of an increase in I2 by £10,000 raises the probably of a teen pregnancy by 0.002, but this is not significant in the conditional regressions. For outcomes high school dropout, earnings and health the magnitude of the coefficient I2 falls in the conditional regression compared to the raw, but remains significant and for college attendance in the conditional regressions, the sign changes such that I2 is more productive than I1 in raising college attendance of children.

In contrast, the estimates of the effect of I3 (relative to I1) suggest that I3 is more productive at producing all outcomes, except for health, than I1 – even in the conditional regressions. Taking years of schooling again in column 1, an increase in I3 by £10,000 has no effect upon schooling, but in column 2 this change raises schooling by 0.016 years. The conditional effect of I3 also lowers the probability of high school drop out by 0.003, raises IQ by 0.016, earnings at age 30 by 0.5%, raises college attendance by 0.004 and lowers the probability of teen pregnancy by 0.001.

To give some order of magnitude to these numbers, a £10,000 change in I3 is around 1/12th of the median. Assuming a linear relationship between I3 and child outcomes, the effect of shifting income from the 90th percentile to the 10th percentile would raise years of schooling, lower drop out probability, raise IQ, earnings, college attendance and lower teen pregnancy by 0.2 years, 0.04, 0.20, 6.35%, 0.05 and 0.0127 respectively. These numbers are mostly equivalent to around 10% of a standard deviation in child outcomes, which is non-trivial but certainly not a large effect. The exception is health, for which the effect is I3 is particularly small.

A summary of the parametric results is that I2 is as productive as I1 at raising child human capital outcomes once we condition on a set of family traits. However, I3 remains slightly more productive than I1, although the magnitude of the effect is rather small. These parametric results suggest a need to control for covariates in our estimation. The next step therefore is to adopt a semi-parametric methodology, in order to allow for non-linearity in the relationship between the timing of income and child outcomes and for potential interactions across different periods, whilst controlling for covariates which have been found to be important.

4.3 Semi Parametric Results

We are interested in examining firstly whether there are any differential returns to parental income across periods of child lifetime, secondly whether any complementarities exist across time between income and thirdly whether there exist heterogeneity in these effects for credit constrained parents. In order to do so it is important to estimate flexible models of the impact of the timing of income on human capital development of children.

Note that an alternative approach to kernel regression is to estimate the mean level of education in cells, defined by the household's position in the income distribution in the three periods. However, the advantage of using this technique over a cell mean approach, is that we are able to smooth the education income profiles, by using a kernel weight for each combination of I2, I3 and P to include observations around these points. This allows us to estimate a smoother function. Additionally, the local kernel regression estimates have better asymptotic properties than a cell mean approach.

The method we use is as follows. We created a *3-D* **I** matrix for the timing of parental income, consisting of PI, I2 and I3. Therefore, we estimate the relative model, comparing the effect of both I2 and I3 to I1, in order to control for permanent income. We estimate a local regression, for 6,859 points within this matrix. The points were defined by taking for each income variable, the 19 points dividing the distribution equally, for the 3-D grid. At each point, we weight all observations using an Epanechnikov Kernel as described above. We trim the data of the smallest cells, such that we drop 2% of observations. This is to avoid spurious estimation in cells for which the density of **I** is low, as reported by Robinson (1988).

Kernel regression results are, in general, prone to sensitivity from the choice of bandwidth. Therefore we vary the bandwidth and estimate local linear kernel regressions allowing three differently sized criteria for selecting the observations to include for each regression. Table 4 below details the bandwidth choice, as we vary C, defined in equation (11) above. Note that we did additionally create a bandwidth labelled "1", where C=0.5. However, this proved too small and the support in the cells was too low for us to make any inference, so is excluded from the analysis. The main set of results choose the bandwidth sized 4 and we run robustness checks in Section 6.1 to show our results are not sensitive to this choice.

The results are rather complicated to graphically reproduce, given the 4-dimensional nature of the model - the outcome variable and household income measured in three time periods. Therefore, for either I2 or I3, we plot the estimates of the conditional mean function, holding constant the remaining two income measures at the third, fifth or seventh decile. This enables us to firstly evaluate the relative impact of each income measure, but also possible complementarities in income received across the child's lifetime. Dynamic complementarity between periods 2 and 3 will show up in the graph by comparing the return to income in period 2, for parents positioned in the third decile of income in period 3 compared to those in the fifth and seventh decile.

When analysing the graphs, we will look for different relative productivity of income across periods, for dynamic complementarity and finally for a differential relationship according to whether the parents were credit constrained, measured as being in the third decile of PI. Before explaining the results, we describe how to interpret such findings from the figures by looking at all potential hypothetical cases. Let us compare the effect of I2 and I1 in the two graphs of Figure 3. In each, I2 is shown on the x-axis and PI and I3 held constant. Hence moving from the left hand side to the right substitutes income from period 1 into period 2. Results similar to those in Figure 3i) would suggest a linear relationship between I2/I1 and the child output. We would interpret the blue line as evidence that I1 and I2 are equally as important, as substituting I1 for I2 leads to no change in the y-axis. However the red line would suggest that I2 is more productive than I1, as switching the latter for the former raises child outcomes. Figure 3ii) shows an example of complementarity between I1 and I2. If we start from point a), I1 is very high relative to I2 and substituting from I1 to I2 raises outcomes of the child. However, there is a threshold, I2*, beyond which this is no longer true and we see a decreasing relationship. This suggests that it is optimal to have an equal bundle of I1 and I2, relative to extreme bundles, indicating complementarity. Finally, we will investigate the presence of credit constraints, by observing whether these relationships differ when looking at parents in the 3rd decile of PI, compared to the 5th and 7th.

4.3.1 Years of Schooling

The results of a multivariate kernel analysis of the timing of income upon years of schooling are shown in Figures 4ai)-4jiii). Specifically, Figures 4ai)-4ciii) show how years of schooling change with I2, relative to I1. Figures 4di)-4fiii) display the results similarly for a change in I3 relative to I1 and Figures 4gi)-4jiii) report the effect of a change in I2 at the expense of I3, keeping constant I1 and PI. As discussed above, it is impossible to plot out the full set of results in the 4-dimensional set, therefore within each graph PI is held constant at decile 3, 5 or 7. Figures 4a), 4d) and 4g) hold PI at the 3rd decile of the income distribution, representing households poor over their lifetimes. Figures 4b), 4e) and 4h) display results for medium income households and finally in 4c), 4f) and 4j) households are grouped in the 7th decile of PI.

Note that on each graph, we plot the mean level of income for the period excluded from analysis. This demonstrates the point that by controlling for PI, we estimate the effect of income in one period at the expense of income in another.

We firstly analyse how raising I2 relative to I1 drives child years of schooling. The results are remarkably similar across several levels of PI and I3. They show a hump-shaped pattern, suggesting that years of schooling are maximized when income is balanced between periods 1 and 2. Similar patterns are found for relative incomes between periods 1 and 3, and periods 2 and 3. However, in the latter two cases there is a large region over which it is advantageous to shift income to period 3, suggesting that income in the last period of adolescence is particularly valuable, but that in general it is not desirable to shift all income towards period 3.

It is important to note that, for each given family, we observe almost no periods where income is equal to zero. Therefore, we are unable to infer what would happen if income shifted towards those periods. We can only infer behavior from the support we observe in the data.

4.3.2 High School Drop Out and College Attendance

We move attention towards students at the bottom of the education distribution, who drop out of high school. The outcome of high school drop-out indicates the students who leave schooling before obtaining a certificate for completed vocational qualification or requisite status for further education at college or university. From a policy point of view the decision to stay on at school is desirable, especially to groups of students with families from lower income groups.

The graphs will be inverted compared to the other outcomes, as this is the only negative indicator of human capital. That given, we see from Figures 5ai)-5fiii) that patterns are quite similar to the ones observed for schooling.

The acquisition of a degree has a positive personal benefit such as increased wages[8] and improved health[9]. Additionally, a large body of empirical work demonstrates that living in a household with an educated parent is unambiguously good for the human capital of its children. For example, children tend to have improved health[10], better behaviour and higher achievement[11].

Whilst the Norwegian administrative data does not measure whether individuals hold a degree, it does record attendance at college[12]. Figures 6a)-6j) plot out the effects of the timing of income upon college attendance. Again, there is basically a hump-shaped relationship between income in period 2 and college attendance. However, there is a stronger indication than before that income in period 3, the late adolescent years, is especially important.

4.3.3 Log Earnings at age 30

Figures 7ai)-7fiii) look at the log earnings of the Norwegian sample of children born in 1970-1980. For the case of earnings patterns are slightly different for the relationship between incomes in periods 1 and 2. Shifting resources away from period 1 and towards period 2 results in lower earnings for children when they are 30 years of age, which means that early resources are especially important for the development of skills that are important in the labor market. Period 3 income continues to have the same importance it had when we looked at schooling outcomes: it

[8] see, for example, Card (1999)
[9] See Grossman (2004) for a summary of the literature of the health benefits to education
[10] Doyle *et al* (2007)
[11] Carneiro *et al* (2007), Currie & Moretti (2003)
[12] equivalent to university attendance in some countries, such as the UK

is relatively more important than income in each of the other two earlier periods, but in the other end it is not productive to shift all income towards period 3.

4.3.4 IQ, Health and Teen

It is interesting to extend the analysis to look at the outcome of IQ. We may expect different results, as there is increased plasticity of child skills linked to the cognitive development at this stage. For example, the ability to learn a language declines sharply after age 5 and the cohort-ranking of IQ is set at around the age of 7. Note that we can only observe IQ for boys, as it is measured through the armed forces test.

Surprisingly, again we find quite similar patterns in the manifestation of income across the child's life into their IQ measured at around age 18 as we did for their educational attainment. These are shown in figures 8ai)-8fiii).

Recent developments in the child production function literature has extended measures of human capital beyond traditional schooling outcomes. For example, Heckman *et al* (1999) evaluate the effect of the Perry Pre School Programme on education, crime and welfare participation. Currie *et al* (2010) considers how early child physical and mental health problems drive adolescent achievement. Van den Berg *et al* (2006) estimates the effect of being born in a recession upon later life mortality rates. In a similar vein, we extend our analysis by incorporating two measures of social human capital - the physical health of a child and the incidence of teen pregnancy.

What Figures 9a)-9j) show are horizontal sloping relationships for all graphs. That is, as income shifts between any period, there is no effect on the health outcome. This suggests that for a given level of permanent income, the timing of income is irrelevant for the acquisition of health. A note of caution is needed, as recall from Table 1 that 85% of the sample of males taking the health test were scored as perfect physical health, enabling them to carry out their military service. It is possible that the finding of no effect of the timing of income indicates only that the health measure is too crude to pick up the true effect.

When evaluating the effect of the timing of income upon teen pregnancy, in Figures 10a)-10j), similarly to health, there are wide confidence intervals for the estimates. Consequently in most cases it is not possible to reject the hypothesis of a homogenous effect of household income, independently of the timing of the income. Despite the lack of significance however, the patterns of the effect of the timing of income is the same as we found in the schooling and wage outcomes above. That is, weak complementarity is found in the return of I1 and I2 and I2 and I3, but most especially for low permanent income families and I1 has an equal (or in some cases lower) effect on teen pregnancy than I3.

4.4 How large are these effects?

The magnitudes of the effects of the timing of income are not trivial. Take, for example, the case of college. Our results suggest that shifting income across periods by about £10000 leads to a 0.5-1% change in the college attendance rate. To put this in context, notice that average income in each of the three periods is between £120000 and £140000, and the college attendance rate for this cohort is 40%. However, how do the magnitudes of these effects compare to those of more permanent factors, such as permanent income, or family background?

It is useful to start with a simple set of graphs, based on the analysis of Carneiro and Heckman (2002) for the US. Suppose we group all individuals into tertiles of the IQ distribution and quartiles of the distribution of family income at ages 12-17, for a total of 12 cells. The left hand side panel of figure 11 plots college enrolment rates for each of these cells. Income in period 3 has a large effect on college attendance, even after controlling for IQ. In the right hand side panel of this figure we present a similar graph after controlling for a series of parental variables, namely permanent income, education, and age at birth. There remains an effect of income, especially at medium and high levels of IQ, but it is fairly small.

In summary, while the timing of parental income has non-trivial effects on human capital outcomes of children, these effects are much smaller than those of permanent factors. A similar statement can be made relatively to IQ. Figure 12 shows the relationship between income in period 3 and IQ before and after accounting for permanent family factors. While some effects remain after adjustment, they are fairly minor.

4.5 Interpretation of the Main Empirical Patterns

In order to interpret our finding we simulate models of parental investments in children with multiple periods and income fluctuations. Start with a simple model:

$$\max_{\{c_t,i_t,b_t\}_{t=1}^{T}} \sum_{t=0}^{T} \beta^t u\left(c_t\right) + \alpha V\left(H, b_{T+1}\right)$$

$$\begin{aligned} & s.t. \\ c_t + p_t i_t + b_{t+1} &\leq y_t + b_t\left(1+r_t\right) \\ H &= f\left(i_0 ... i_{T_H}\right) \\ c_t, i_t &\geq 0;\ b_t \geq \bar{b} \end{aligned}$$

where c is household consumption, i is parental investment in children, and b_t is assets. Parents maximize the present discounted value of consumption $(u(.))$ plus a function of child human capital (H) and bequests (b_{T+1}). They are subject to a budget constraint for each period, where y_t is income in period t, and p_t is the relative price of investment in period t. f is the human capital production function and depends on the whole history of investments. Consumption and investments in children are constrained to be non-negative, and in the general case parents may face borrowing constraints (depending on the value of $\bar{b}$).

This model cannot explain the data. In the absence of credit constraints ($\bar{b} = -\infty$) the timing of income is irrelevant. With credit constraints parents prefer all income in the first period. Simulations of the model, available on request, show odd cases where, with credit constraints, children would prefer a delay in income to prevent parents from consuming early on, but this is unlikely to be an empirically relevant case. The addition of labor supply and time investments in children does not help approximate the results of simulations and estimations of these models.

This model is not realistic anyway. We believe there are three important extensions to the model to consider:

1. There is uncertainty in income - parents face permanent and temporary shocks to income, which are not fully insurable.

2. There is uncertainty about child endowments and about the technology.

3. Do we expect all individuals to be forward looking and behave according to the Permanent Income Hypothesis?

The results of these simulations are still work in progress. Possible interpretations of our empirical patterns will become clearer when we finish it. In the meanwhile, there are several findings from the literature on consumption over the life-cycle on which we can draw on.

The consumption literature suggests that households can only partially insure against shocks. Temporary shocks are easier to insure against than permanent shocks (we aggregate income across periods so we may be averaging out temporary shocks). As mentioned above, in a companion paper we estimated an additive model examining how human capital responds to timing of temporary and permanent shocks. Both matter. The estimates for coefficients on the permanent component are noisy but suggest that shocks in later periods are more important. This is also true for transitory shocks. There is also mixed evidence about the response of consumption to anticipated income shocks. Evidence from tax rebates (and Japanese pensions) suggests that there is some contemporaneous response ($0.30 per $1). But evidence from the Alaskan permanent fund (and Spanish pensions) suggests perfect smoothing of predictable shocks.

It seems natural to presume that consumption responds somewhat to income fluctuations, especially if they are unpredictable and permanent. But if that is the case, it is also natural to expect responses from investments in children. There is one important obvious important difference between investments in children and consumption which comes from intertemporal non-separabilities. If investments are complements over time, we will have something that can be analogous to a habit formation model. If investments are substitutable over time, we will have something analogous to a durable good model. The reality probably combines both (see Cunha, Heckman and Schennach, 2010), which implies that the dynamics of this model will be quite complex.

Although there are several papers examining the response of consumption to income shocks, we are not aware of papers directly examining the response of investments in children to income shocks. There is, however, a large literature that focuses on the role of parental income in child development, but it is looking mainly at final outcomes rather than investments. One exception is a recent paper by Carneiro and Ginja (2010). They use the Children of the NLSY79, which has repeated measures of parental income and HOME scores, which are indices of parental investments and home environments. They show that after controlling for parental fixed effects (and other time varying characteristics such as labor supply or family size), changes in family income lead to changes in home investments.

Then, if investments in children track income then perhaps these empirical patterns tell us directly about the shape of the production function of skill. In particular, take the data on years of schooling, which shows that it is important that the timing of resources is balanced across different ages of the child, especially between ages 0-5 and ages 6-11. This suggests that there is complementarity between periods 1 and 2 investments. In some cases we cannot rule out that there is strong substitutability between period 3 investments and investments in earlier periods, given that there is not a very pronounced hump shape pattern in the corresponding figures. However, we cannot be sure because of lack of support.

It is important to make two additional points relatively to our empirical findings, which may explain why resources in the latest period of life are estimated to be so valuable. The first one is a rather trivial point, related to the age profile of child-rearing costs. Data from the CEX (Lino, 2010) shows that average expenditures on children grow with age. For example, the annual expenditure on children at ages 15-17 is estimated to be 15-25% higher than the annual expenditure on children at ages 0-2. This is also consistent with how child support payments are calculated: child support payments are higher for older children. This implies that parents may need positive income shocks towards later ages to support higher prices. Over time, parents learn new information about both and the returns to human capital investments become more certain. In such a setting there may be a temptation to delay investments, to wait for the unraveling of this uncertainty, and invest only if it pays off to do so. This temptation is balanced out by the potential importance of complementarity of investments across time. If complementarity is important then delaying investments can prove to be very costly, since investments are needed at early as well as later ages.

This is very similar to what happens in the study of inter-vivo transfers of Altonji, Hayashi and Kotlikoff (1996). Their theory suggests that there is a desire to delay in-vivo transfers and wait for revelation of earnings potential of child, and this is consistent with their empirical findings. However, this desire to postpone transfers to children is dampened by the potential importance of liquidity constraints that the child may be facing in young adulthood. If a child is facing severe credit constraints the parent may wish to transfer resources to her even in the face of strong uncertainty about the returns to these transfers.

5 Robustness Checks

5.1 Bandwidth Choice

It is very important in this context to check for the sensitivity of the bandwidth choice. An important part of our analysis is to examine the curvature of the function between the timing of income and child outcomes. The cell size for local estimation is increasing in the bandwidth and consequently, a large bandwidth may over smooth the function. This could lead us to conclude against complementarity when it is does exist and drive outcomes accordingly. As we wish to draw the correct policy implications from the results, we check the robustness by varying the bandwidth.

To save on space, we do not show the graphs for the different bandwidth choices, but results are available on request for all outcomes and bandwidth choices. We do see in the figures that a smoother function is estimated with the larger bandwidth, weakening the appearance of complementarity. Therefore, the complementarity between I1 and I2 is stronger with a bandwidth of 3 than 5. Confidence intervals tend to increase with the bandwidth, as the precision of the estimate falls. However, other than this the same patterns are repeated across different bandwidths. Complementarity exists between I1 and I2 and also I2 and I3, and the return to I2 is equal to that of I3.

We have also reestimated everything with a bandwidth of 2. In general, there is strong regularity between the estimated relationships as we vary the bandwidth, strengthening the validity of our results.

5.2 Time Investment in Children

It may be that the model considered above for the investment into child human capital is wrong in specifying only one investment good. If in fact relevant parental investment is composed of two factors - time and financial investment - the results of this paper may be misleading. Whilst parental income raises financial investment, assuming the constraint that total time is the sum of time in the labour market and time at home with children, it also implies a fall in time investment. Furthermore, time investment may be more important for young children than older. This would lead to a downward bias in the effect of early income, if it was easily insured by productive time investments.

The data available to us is rich in administrative data but sparse in time-use data and consequently we are unable to explicitly control for time parents spend with children. Despite this, it is possible to gain some understanding of the extent to which our results are driven by the substitutability between time and financial investments. Firstly, it is well documented that during the 1970s, labour supply of married women was relatively low, at around 40%[13], meaning that to an extent, time investment by mothers could be largely independent to family income. However, as still some mothers worked, we test for the robustness of our results by estimating the effect only of paternal income. This way, the effect of any fluctuations in income should reflect financial investment not time investment, given that a tiny proportion of fathers substitute time for financial investment in children.

The results, available at request from authors, are very similar to in the bulk of analysis. Obviously the scale of income in each period will be lower when excluding maternal income. Otherwise, the graphs tell an identical story to the results using household income.

6 Conclusion

In this paper we estimate the importance of the timing of income for the human capital development of children using Norwegian data. We group childhood in three period, ages 0-5, ages 6-11, and ages 12-17, and estimate semi-

[13] See Black *et al* (2008)

parametric regressions of human capital outcomes on permanent income and income in two other periods. We include several other controls in the regression. We find that human capital outcomes seem to be the highest when there is a balance between incomes in early childhood and early adolescence, but also when there is a shift from these two periods towards late adolescence, as long as it is not too extreme.

We considered some possible explanations, by simulating multi-period models of parental investments in children. The results suggest that credit constraints are unlikely to play an important role in explaining our results. Simple models emphasizing credit constraints do not explain the data. Furthermore, the fact that our results are similar for different levels of permanent income and different levels of parental education also suggest that credit constraints are not the main factor here, since these variables should be indicators of groups facing very different levels of credit constraints. Uncertainty about income, the technology and child endowments may be important, as well as a rising price of investments in children with age.

Our results suggest that the technology of skill formation is likely to exhibit complementarity between periods 1 and 2 investments. There may be complementarity of these two periods and period 3 investments, but it is weaker, and perhaps balanced by other considerations. It may also be hard to identify because of lack of support in the data.

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7 Figures & Tables

Figure 1

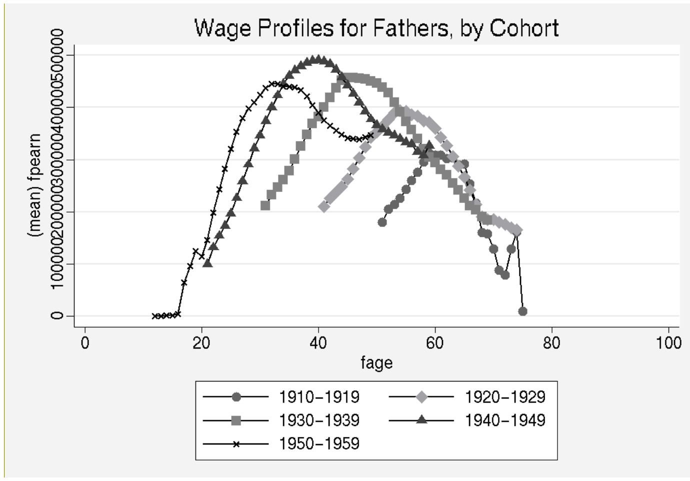


Figure 2

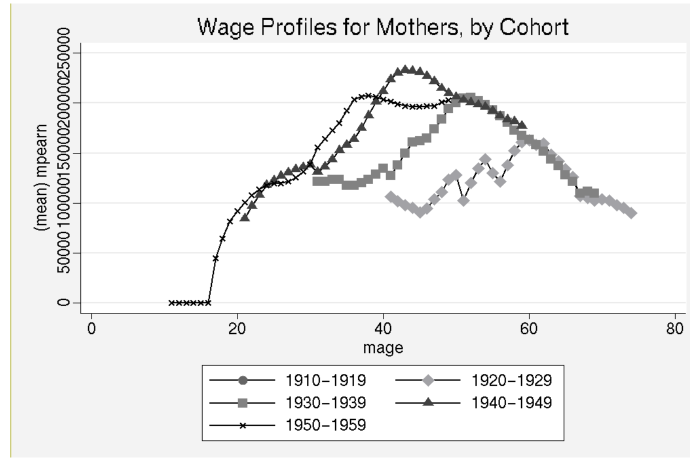
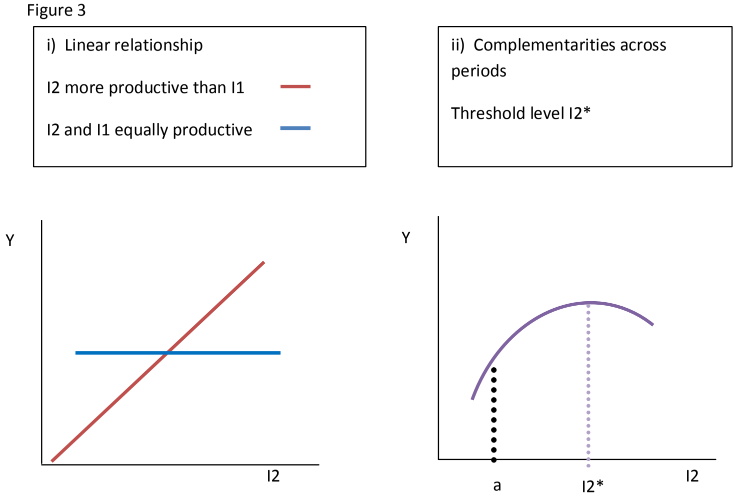


Figure 3

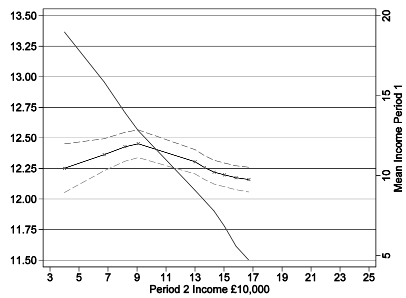


Note, PI and I3 held constant within graphs.

Figure 4: Semi Parametric Estimates. Dependent variable is Years of Schooling

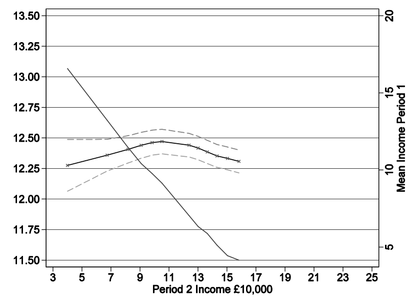
4ai) I3=9.35, PI=31.01

$\hat{\alpha}_1 = 0.13(0.11)\hat{\alpha}_2 = -\mathbf{0.26}(0.08)$



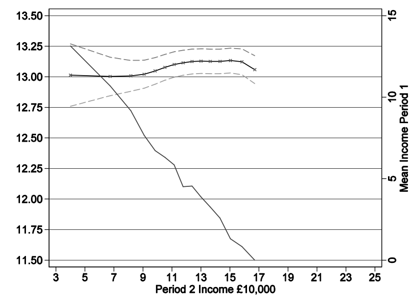
4aii) I3=11.67, PI=31.01

$\hat{\alpha}_1 = 0.19(0.12)\hat{\alpha}_2 = -\mathbf{0.16}(0.07)$



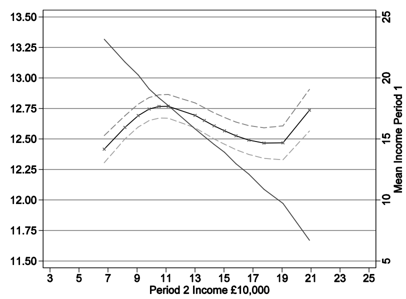
4aiii) I3=14.05, PI=31.01

$\hat{\alpha}_1 = 0.10(0.14)\hat{\alpha}_2 = -0.06(0.08)$



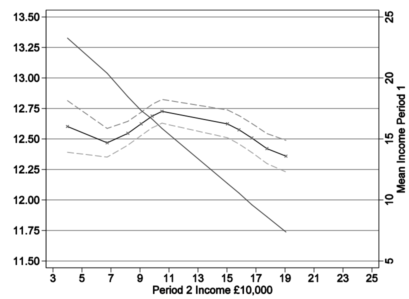
4bi) I3=9.35, PI=36.96

$\hat{\alpha}_1 = \mathbf{0.28}(0.08)\hat{\alpha}_2 = 0.04(0.10)$



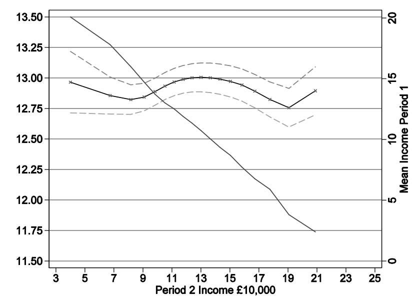
4bii) I3=11.67, PI=36.96

$\hat{\alpha}_1 = 0.14(0.12)\hat{\alpha}_2 = -\mathbf{0.38}(0.08)$



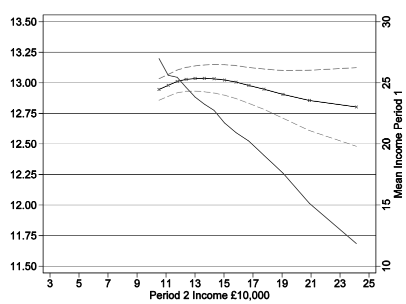
4biii) I3=14.05, PI=36.96

$\hat{\alpha}_1 = 0.04(0.14)\hat{\alpha}_2 = -0.11(0.12)$



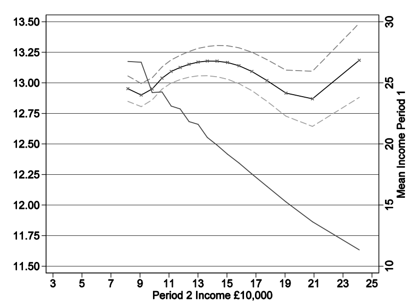
4ci) I3=9.35, PI=43.93

$\hat{\alpha}_1 = 0.09(0.07)\hat{\alpha}_2 = -0.23(0.17)$



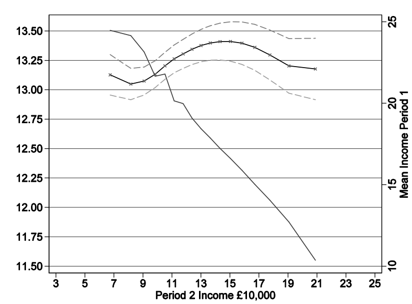
4cii) I3=11.67, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.23}(0.08)\hat{\alpha}_2 = 0.01(0.17)$



4ciii) I3=14.05, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.25}(0.11)\hat{\alpha}_2 = -0.20(0.15)$



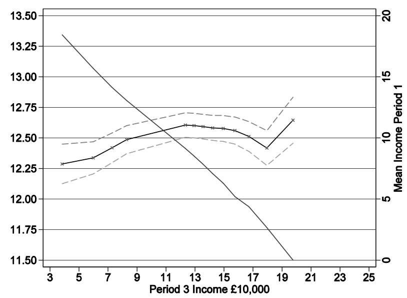
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 4: Semi Parametric Estimates. Dependent variable is Years of Schooling

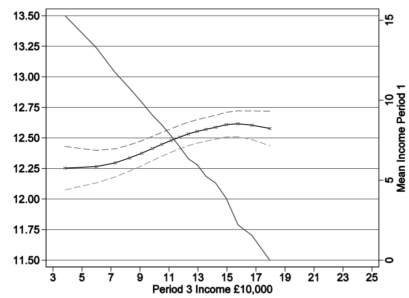
4di) I2=10.11, PI=31.01

$\hat{\alpha}_1 = \mathbf{0.32}(0.10)\hat{\alpha}_2 = 0.04(0.11)$



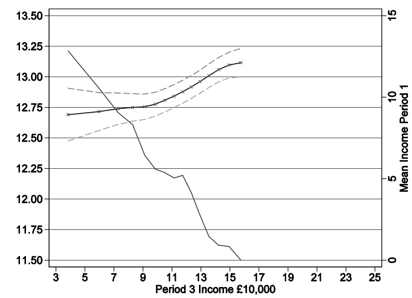
4dii) I2=12.39, PI=31.01

$\hat{\alpha}_1 = \mathbf{0.25}(0.10)\hat{\alpha}_2 = 0.07(0.09)$



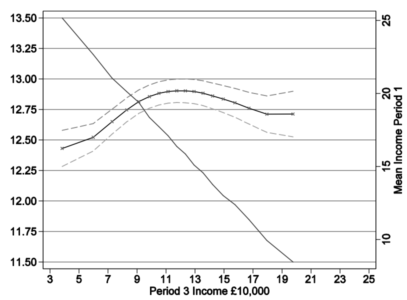
4diii) I2=14.98, PI=31.01

$\hat{\alpha}_1 = .15(0.12)\hat{\alpha}_2 = \mathbf{0.27}(0.08)$



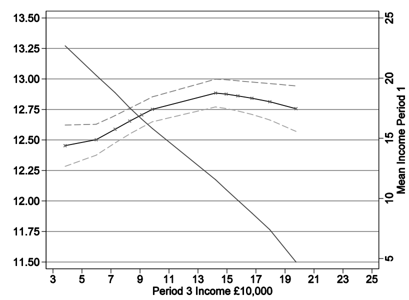
4ei) I2=10.11, PI=36.96

$\hat{\alpha}_1 = \mathbf{0.47}(0.09)\hat{\alpha}_2 = -\mathbf{0.19}(0.11)$



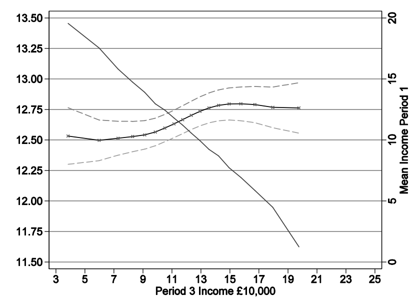
4eii) I2=12.39, PI=36.96

$\hat{\alpha}_1 = \mathbf{0.39}(0.10)\hat{\alpha}_2 = -0.09(0.11)$



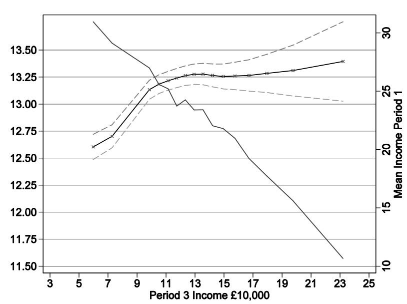
4eiii) I2=14.98, PI=36.96

$\hat{\alpha}_1 = 0.17(0.13)\hat{\alpha}_2 = \mathbf{0.72}(0.19)$



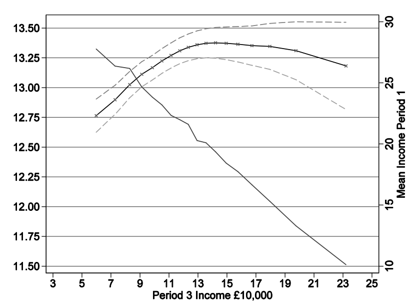
4fi) I2=10.11, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.67}(0.08)\hat{\alpha}_2 = 0.12(0.19)$



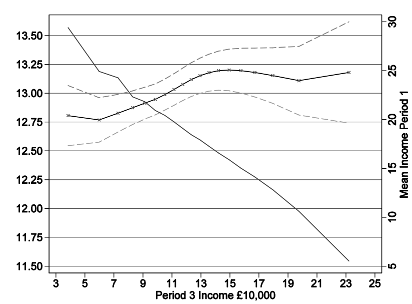
4fii) I2=12.39, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.57}(0.09)\hat{\alpha}_2 = -0.16(0.20)$



4fiii) I2=14.98, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.31}(0.15)\hat{\alpha}_2 = 0.06(0.24)$



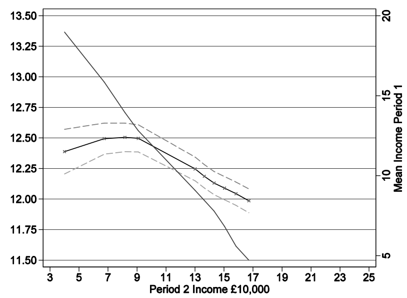
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 4: Semi Parametric Estimates. Dependent variable is Years of Schooling

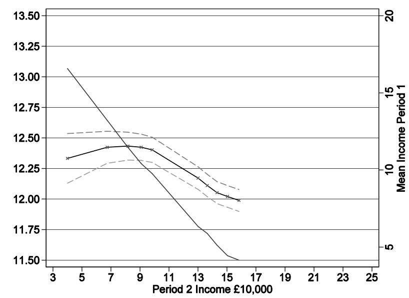
4gi) I1=10.91, PI=31.01

$\hat{\alpha}_1 = -0.03(0.11)\hat{\alpha}_2 = -\mathbf{0.78}(0.08)$



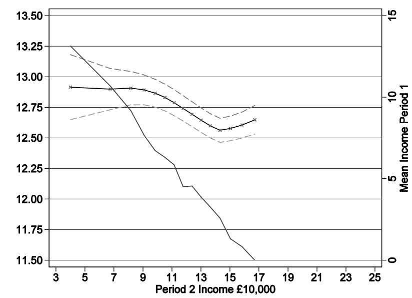
4gii) I1=13.02, PI=31.01

$\hat{\alpha}_1 = 0.00(0.12)\hat{\alpha}_2 = -\mathbf{0.34}(0.07)$



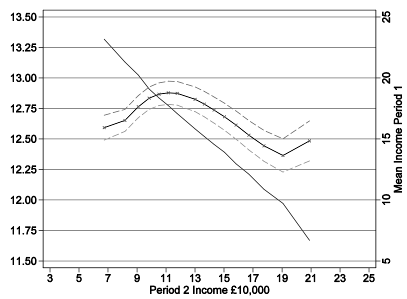
4giii) I1=15.64, PI=31.01

$\hat{\alpha}_1 = -0.17(0.15)\hat{\alpha}_2 = -0.09(0.08)$



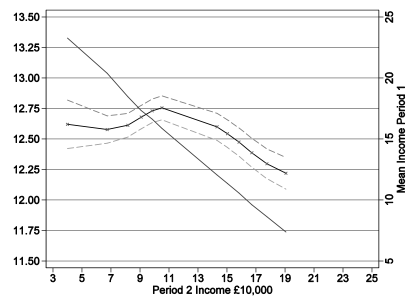
4hi) I1=10.91, PI=36.96

$\hat{\alpha}_1 = \mathbf{0.23}(0.07)\hat{\alpha}_2 = -\mathbf{0.34}(0.10)$



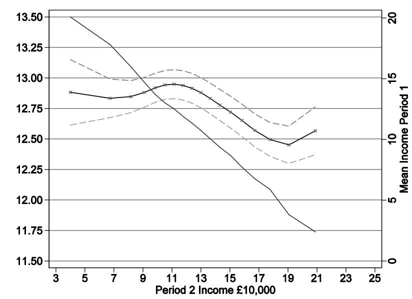
4hii) I1=13.02, PI=36.96

$\hat{\alpha}_1 = 0.11(0.11)\hat{\alpha}_2 = -\mathbf{0.51}(0.08)$



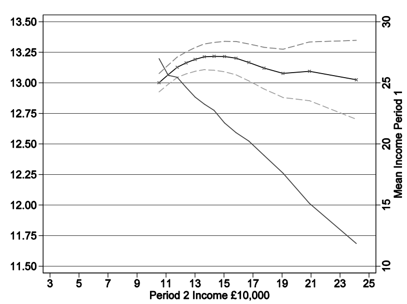
4hiii) I1=15.64, PI=36.96

$\hat{\alpha}_1 = 0.03(0.15)\hat{\alpha}_2 = -\mathbf{0.35}(0.12)$



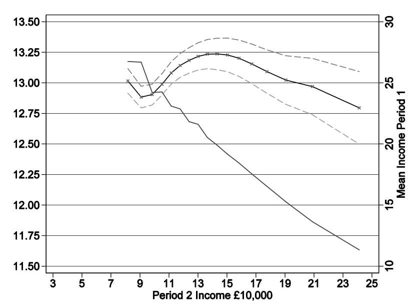
4ji) I1=10.91, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.22}(0.07)\hat{\alpha}_2 = -0.19(0.17)$



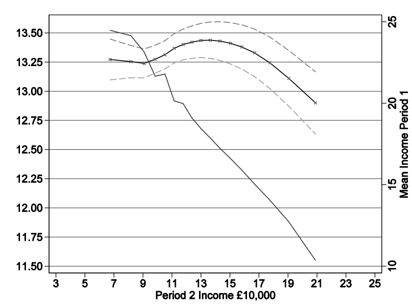
4jii) I1=13.02, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.22}(0.08)\hat{\alpha}_2 = -\mathbf{0.44}(0.16)$



4jiii) I1=15.64, PI=43.93

$\hat{\alpha}_1 = 0.16(0.12)\hat{\alpha}_2 = -\mathbf{0.54}(0.16)$



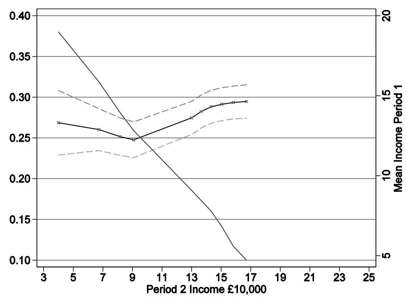
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 5: Semi Parametric Estimates. Dependent variable is High School Dropout

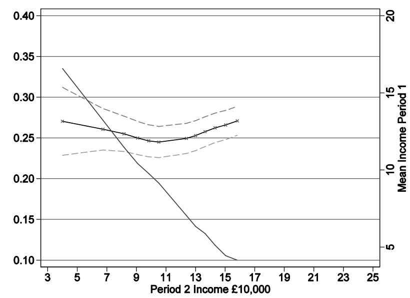
5ai) I3=9.35, PI=31.01

$\hat{\alpha}_1 = -0.01(0.02) \hat{\alpha}_2 = 0.03(0.02)$



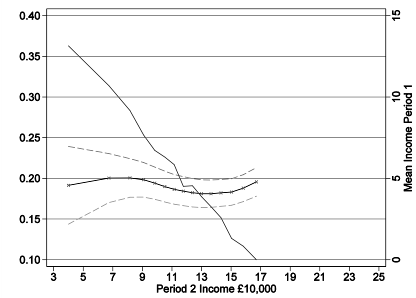
5aii) I3=11.67, PI=31.01

$\hat{\alpha}_1 = -0.03(0.02) \hat{\alpha}_2 = \mathbf{0.03}(0.01)$



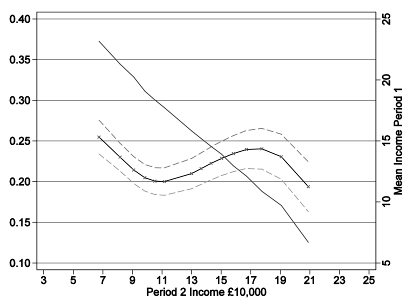
5aiii) I3=14.05, PI=31.01

$\hat{\alpha}_1 = -0.01(0.03) \hat{\alpha}_2 = 0.01(0.01)$



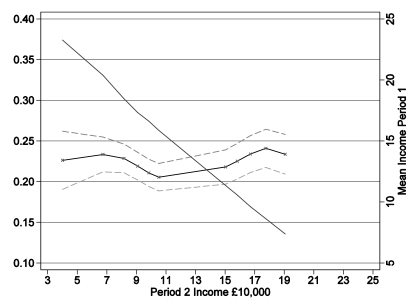
5bi) I3=9.35, PI=36.96

$\hat{\alpha}_1 = -\mathbf{0.04}(0.01) \hat{\alpha}_2 = -0.02(0.02)$



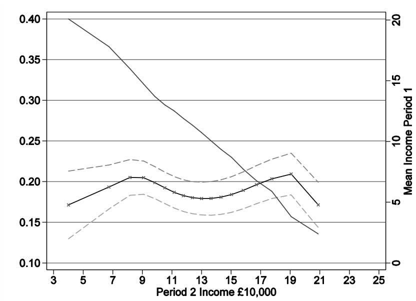
5bii) I3=11.67, PI=36.96

$\hat{\alpha}_1 = -0.02(0.02) \hat{\alpha}_2 = \mathbf{0.03}(0.02)$



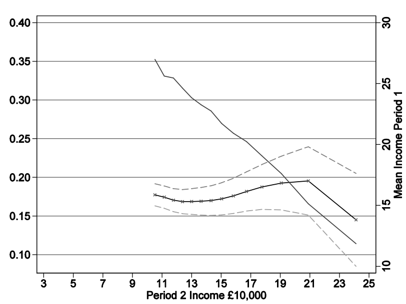
5biii) I3=14.05, PI=36.96

$\hat{\alpha}_1 = 0.01(0.02) \hat{\alpha}_2 = -0.01(0.02)$



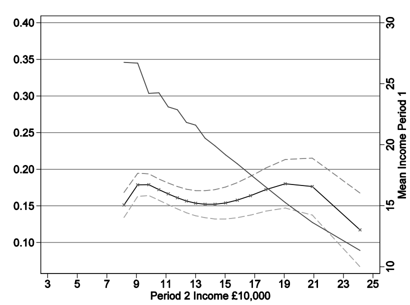
5ci) I3=9.35, PI=43.93

$\hat{\alpha}_1 = -0.01(0.01) \hat{\alpha}_2 = -0.02(0.03)$



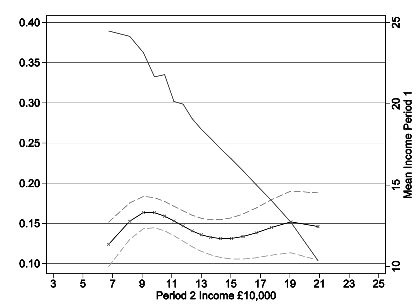
5cii) I3=11.67, PI=43.93

$\hat{\alpha}_1 = 0.00(0.01) \hat{\alpha}_2 = -0.04(0.03)$



5ciii) I3=14.05, PI=43.93

$\hat{\alpha}_1 = 0.01(0.02) \hat{\alpha}_2 = 0.01(0.02)$



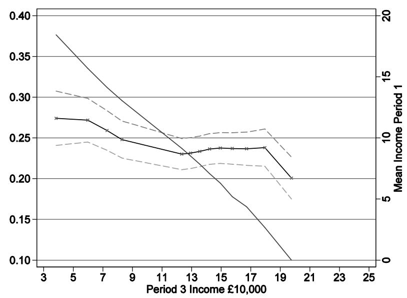
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 5: Semi Parametric Estimates. Dependent variable is High School Dropout

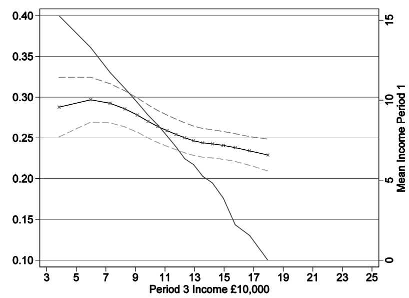
5di) I2=10.11, PI=31.01

$\hat{\alpha}_1 = -\mathbf{0.04}(0.02) \hat{\alpha}_2 = -\mathbf{0.03}(0.02)$



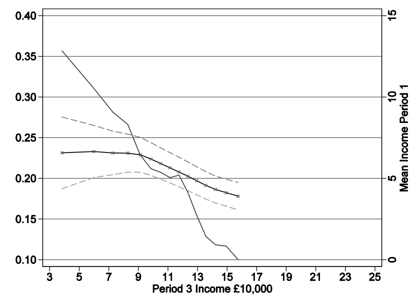
5dii) I2=12.39, PI=31.01

$\hat{\alpha}_1 = -\mathbf{0.03}(0.02) \hat{\alpha}_2 = -\mathbf{0.03}(0.01)$



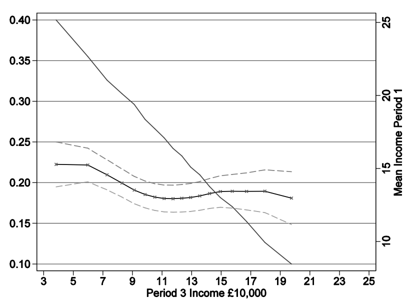
5diii) I2=14.98, PI=31.01

$\hat{\alpha}_1 = -0.02(0.02) \hat{\alpha}_2 = -\mathbf{0.03}(0.01)$



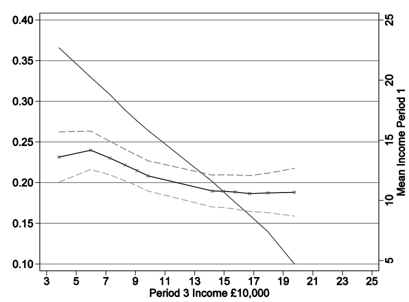
5ei) I2=10.11, PI=36.96

$\hat{\alpha}_1 = -\mathbf{0.04}(0.02) \hat{\alpha}_2 = 0.00(0.02)$



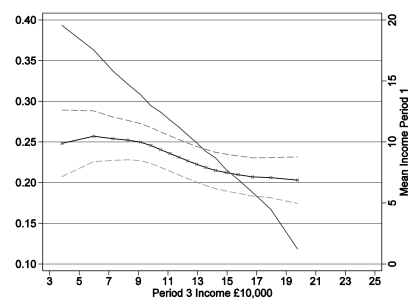
5eii) I2=12.39, PI=36.96

$\hat{\alpha}_1 = -\mathbf{0.04}(0.02) \hat{\alpha}_2 = -0.01(0.02)$



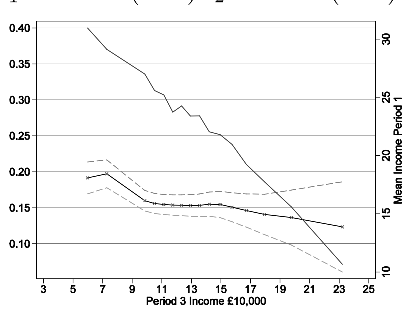
5eiii) I2=14.98, PI=36.96

$\hat{\alpha}_1 = -0.02(0.02) \hat{\alpha}_2 = -\mathbf{0.08}(0.02)$



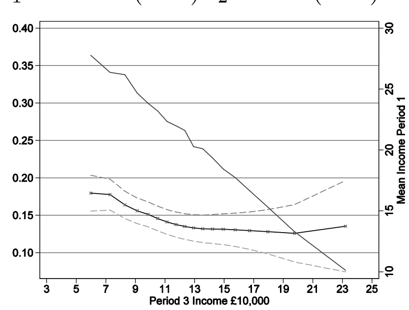
5fi) I2=10.11, PI=43.93

$\hat{\alpha}_1 = -\mathbf{0.04}(0.01) \hat{\alpha}_2 = -0.03(0.03)$



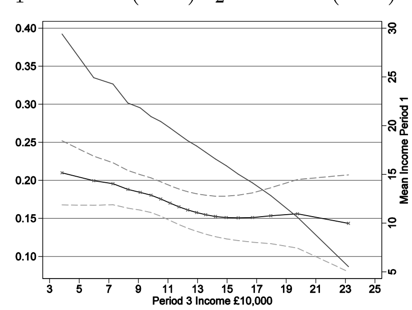
5fii) I2=12.39, PI=43.93

$\hat{\alpha}_1 = -\mathbf{0.04}(0.02) \hat{\alpha}_2 = 0.00(0.03)$



5fiii) I2=14.98, PI=43.93

$\hat{\alpha}_1 = -0.05(0.02) \hat{\alpha}_2 = -0.02(0.03)$



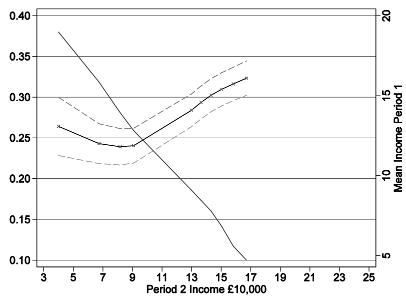
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 5: Semi Parametric Estimates. Dependent variable is High School Dropout

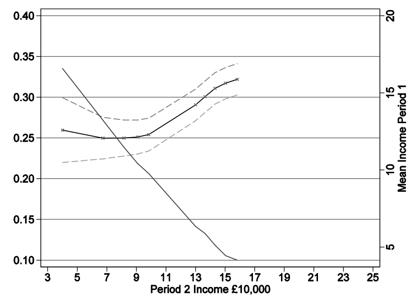
5gi) I1=10.91, PI=31.01

$\hat{\alpha}_1 = 0.00(0.02)\hat{\alpha}_2 = \mathbf{0.16}(0.02)$



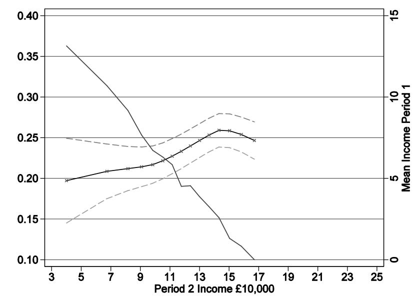
5gii) I1=13.02, PI=31.01

$\hat{\alpha}_1 = 0.01(0.02)\hat{\alpha}_2 = \mathbf{0.06}(0.01)$



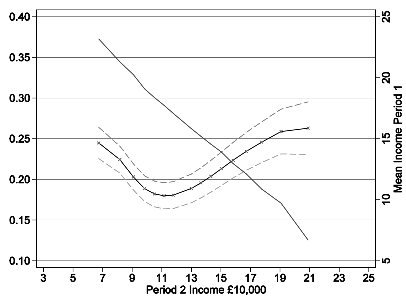
5giii) I1=15.64, PI=31.01

$\hat{\alpha}_1 = 0.04(0.03)\hat{\alpha}_2 = 0.01(0.02)$



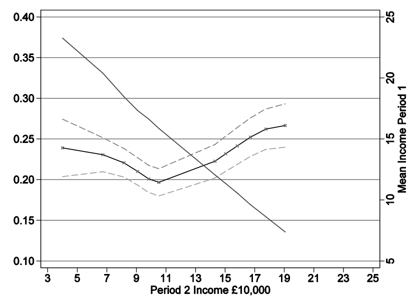
5hi) I1=10.91, PI=36.96

$\hat{\alpha}_1 = -\mathbf{0.06}(0.01)\hat{\alpha}_2 = 0.07(0.02)$



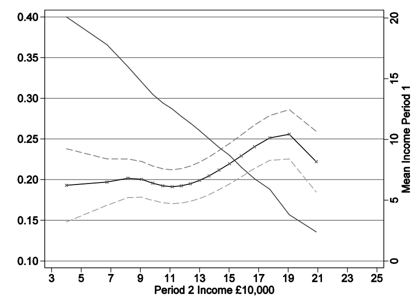
5hii) I1=13.02, PI=36.96

$\hat{\alpha}_1 = -\mathbf{0.04}(0.02)\hat{\alpha}_2 = \mathbf{0.06}(0.02)$



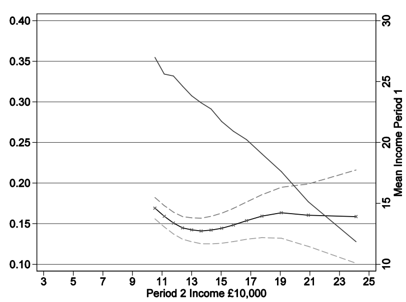
5hiii) I1=15.64, PI=36.96

$\hat{\alpha}_1 = 0.00(0.03)\hat{\alpha}_2 = 0.03(0.02)$



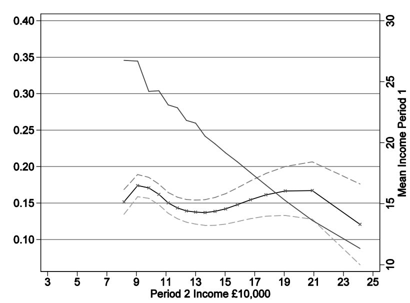
5ji) I1=10.91, PI=43.93

$\hat{\alpha}_1 = -\mathbf{0.03}(0.01)\hat{\alpha}_2 = 0.02(0.03)$



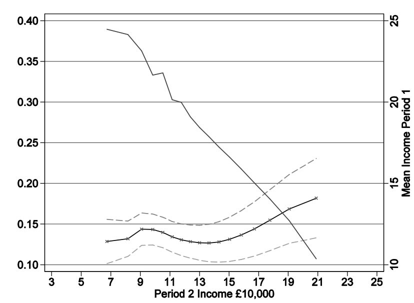
5jii) I1=13.02, PI=43.93

$\hat{\alpha}_1 = -0.01(0.01)\hat{\alpha}_2 = -0.02(0.03)$



5jiii) I1=15.64, PI=43.93

$\hat{\alpha}_1 = 0.00(0.02)\hat{\alpha}_2 = \mathbf{0.05}(0.03)$



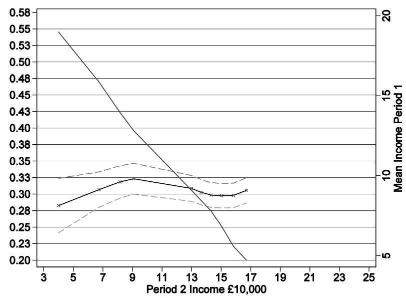
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 6: Semi Parametric Estimates. Dependent variable is College Attendance

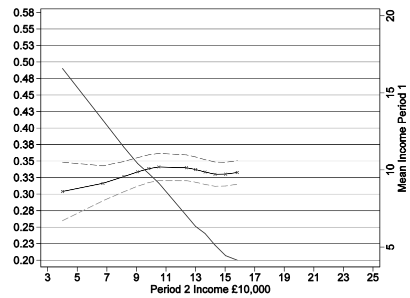
6ai) I3=9.35, PI=31.01

$\hat{\alpha}_1 = 0.04(0.02)\hat{\alpha}_2 = 0.01(0.02)$



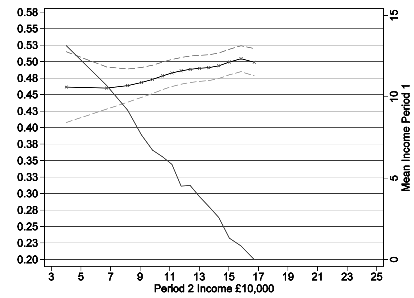
6aii) I3=11.67, PI=31.01

$\hat{\alpha}_1 = 0.04(0.02)\hat{\alpha}_2 = -0.01(0.01)$



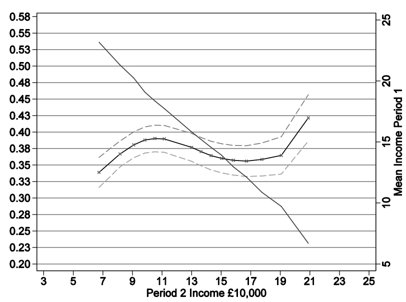
6aiii) I3=14.05, PI=31.01

$\hat{\alpha}_1 = 0.02(0.03)\hat{\alpha}_2 = 0.01(0.01)$



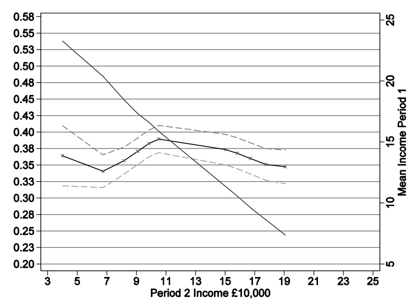
6bi) I3=9.35, PI=36.96

$\hat{\alpha}_1 = \mathbf{0.04}(0.02)\hat{\alpha}_2 = \mathbf{0.04}(0.02)$



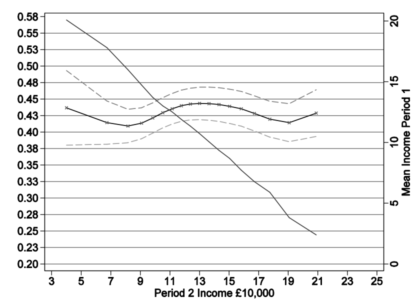
6bii) I3=11.67, PI=36.96

$\hat{\alpha}_1 = 0.03(0.03)\hat{\alpha}_2 = -\mathbf{0.04}(0.02)$



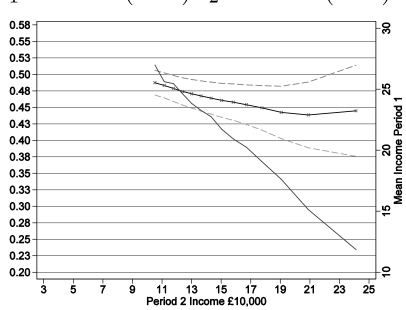
6biii) I3=14.05, PI=36.96

$\hat{\alpha}_1 = 0.01(0.03)\hat{\alpha}_2 = -0.01(0.02)$



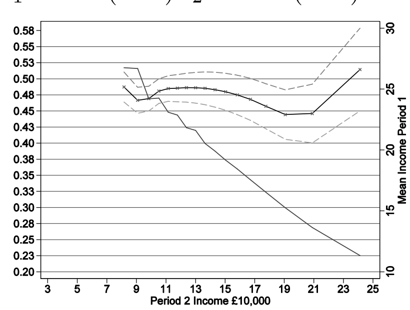
6ci) I3=9.35, PI=43.93

$\hat{\alpha}_1 = -0.02(0.02)\hat{\alpha}_2 = -0.02(0.04)$



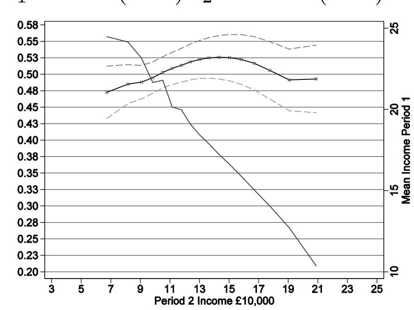
6cii) I3=11.67, PI=43.93

$\hat{\alpha}_1 = 0.00(0.02)\hat{\alpha}_2 = \mathbf{0.03}(0.04)$



6ciii) I3=14.05, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.05}(0.03)\hat{\alpha}_2 = -0.03(0.03)$



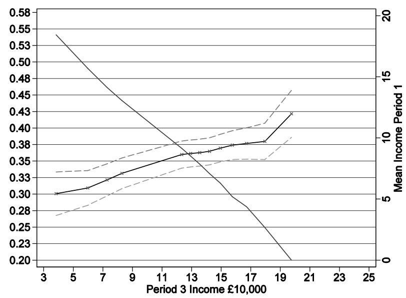
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 6: Semi Parametric Estimates. Dependent variable is College Attendance

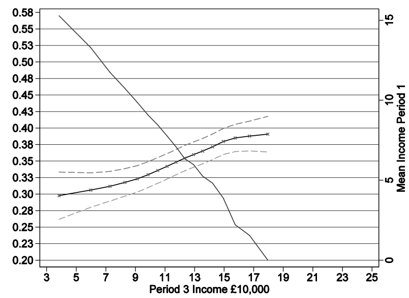
6di) I2=10.11, PI=31.01

$\hat{\alpha}_1 = \mathbf{0.06}(0.02) \hat{\alpha}_2 = \mathbf{0.06}(0.02)$



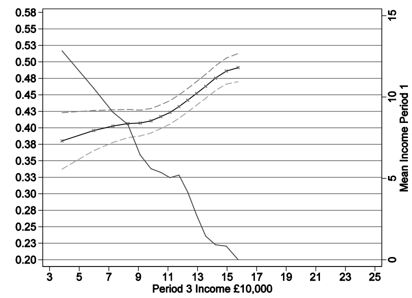
6dii) I2=12.39, PI=31.01

$\hat{\alpha}_1 = \mathbf{0.05}(0.02) \hat{\alpha}_2 = \mathbf{0.04}(0.02)$



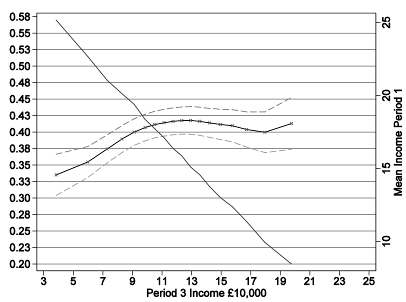
6diii) I2=14.98, PI=31.01

$\hat{\alpha}_1 = \mathbf{0.04}(0.02) \hat{\alpha}_2 = \mathbf{0.07}(0.01)$



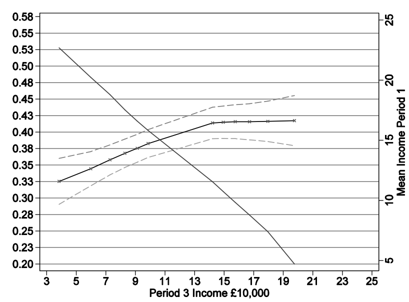
6ei) I2=10.11, PI=36.96

$\hat{\alpha}_1 = \mathbf{0.08}(0.02) \hat{\alpha}_2 = 0.00(0.02)$



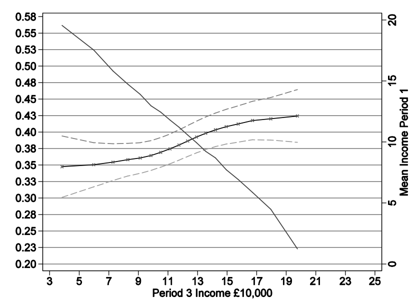
6eii) I2=12.39, PI=36.96

$\hat{\alpha}_1 = \mathbf{0.08}(0.02) \hat{\alpha}_2 = 0.02(0.02)$



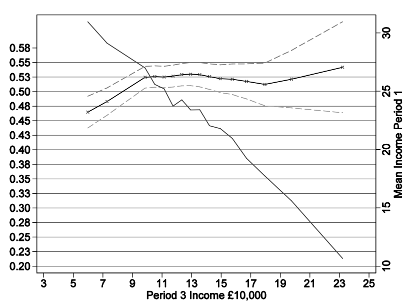
6eiii) I2=14.98, PI=36.96

$\hat{\alpha}_1 = \mathbf{0.04}(0.03) \hat{\alpha}_2 = \mathbf{0.15}(0.04)$



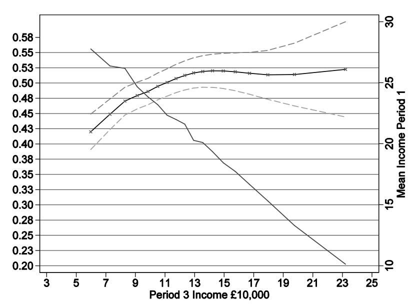
6fi) I2=10.11, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.07}(0.02) \hat{\alpha}_2 = 0.01(0.04)$



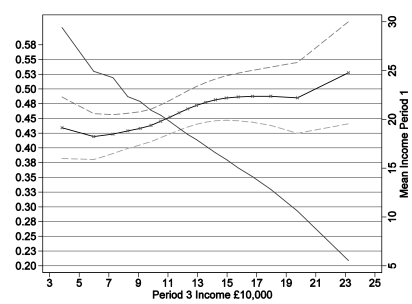
6fii) I2=12.39, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.09}(0.02) \hat{\alpha}_2 = 0.01(0.04)$



6fiii) I2=14.98, PI=43.93

$\hat{\alpha}_1 = 0.03(0.03) \hat{\alpha}_2 = 0.06(0.05)$



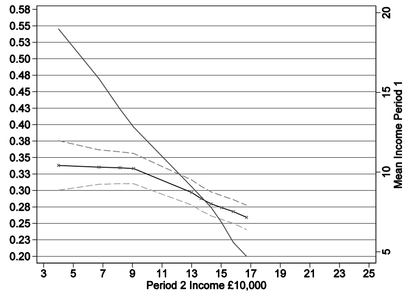
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 6: Semi Parametric Estimates. Dependent variable is College Attendance

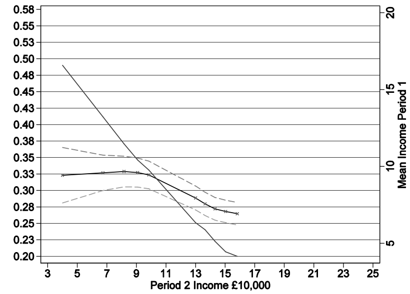
6gi) I1=10.91, PI=31.01

$\hat{\alpha}_1 = -0.02(0.02)\hat{\alpha}_2 = -\mathbf{0.12}(0.02)$



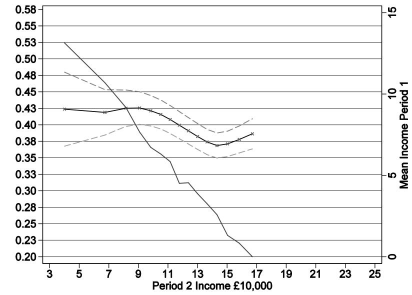
6gii) I1=13.02, PI=31.01

$\hat{\alpha}_1 = -0.01(0.02)\hat{\alpha}_2 = -\mathbf{0.05}(0.01)$



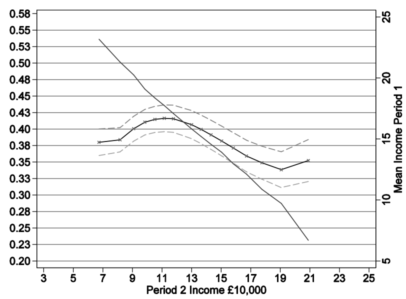
6giii) I1=15.64, PI=31.01

$\hat{\alpha}_1 = -0.02(0.03)\hat{\alpha}_2 = -0.01(0.02)$



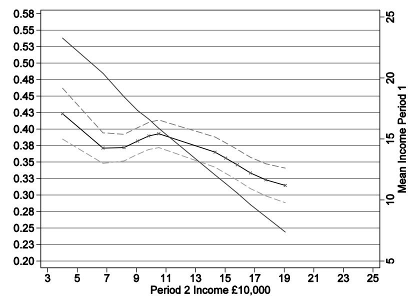
6hi) I1=10.91, PI=36.96

$\hat{\alpha}_1 = \mathbf{0.03}(0.01)\hat{\alpha}_2 = -\mathbf{0.05}(0.02)$



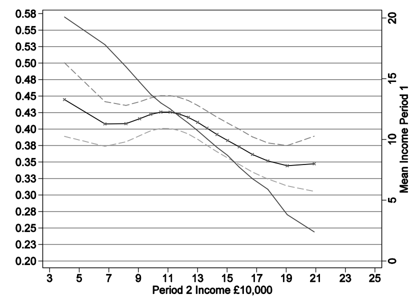
6hii) I1=13.02, PI=36.96

$\hat{\alpha}_1 = -0.04(0.02)\hat{\alpha}_2 = -\mathbf{0.07}(0.02)$



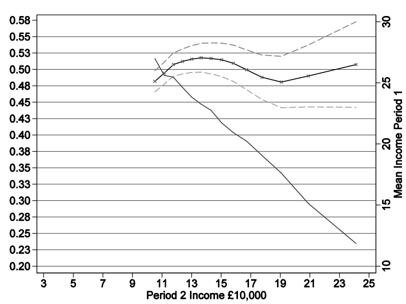
6hiii) I1=15.64, PI=36.96

$\hat{\alpha}_1 = -0.03(0.03)\hat{\alpha}_2 = -\mathbf{0.07}(0.02)$



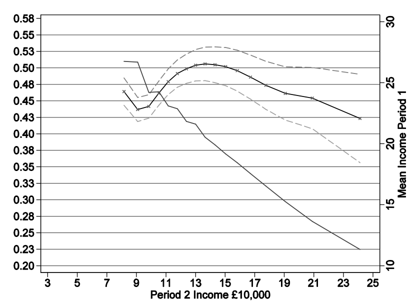
6ji) I1=10.91, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.03}(0.01)\hat{\alpha}_2 = -0.01(0.04)$



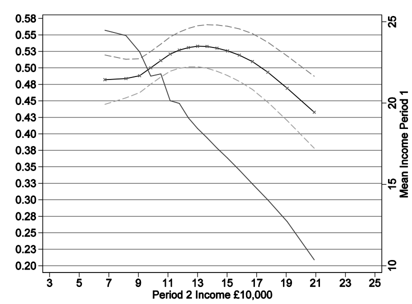
6jii) I1=13.02, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.04}(0.02)\hat{\alpha}_2 = -\mathbf{0.08}(0.04)$



6jiii) I1=15.64, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.05}(0.02)\hat{\alpha}_2 = -\mathbf{0.10}(0.03)$



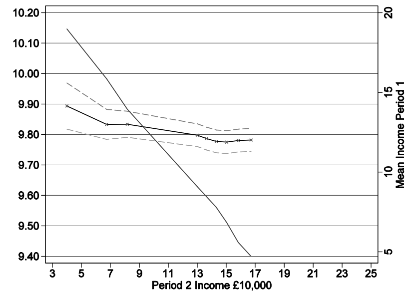
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 7: Semi Parametric Estimates. Dependent variable is Log Earnings age 30

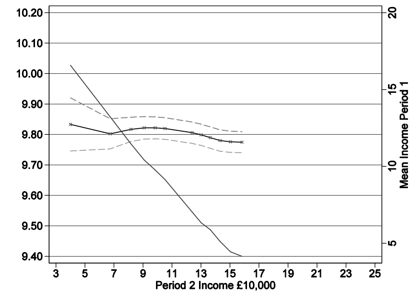
7ai) I3=9.35, PI=31.01

$\hat{\alpha}_1 = -\mathbf{0.08}(0.04)\hat{\alpha}_2 = -\mathbf{0.06}(0.03)$



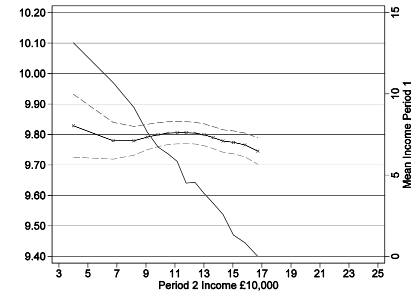
7aii) I3=11.67, PI=31.01

$\hat{\alpha}_1 = -0.02(0.05)\hat{\alpha}_2 = -\mathbf{0.04}(0.03)$



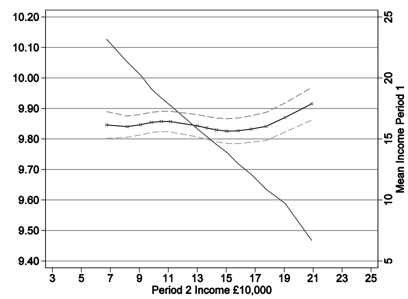
7aiii) I3=14.05, PI=31.01

$\hat{\alpha}_1 = -0.02(0.06)\hat{\alpha}_2 = -\mathbf{0.06}(0.03)$



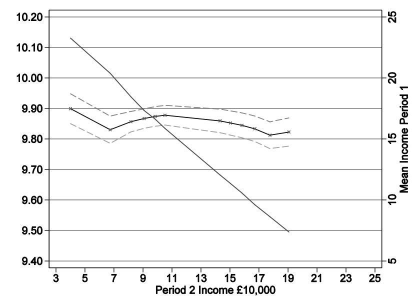
7bi) I3=9.35, PI=36.96

$\hat{\alpha}_1 = 0.00(0.03)\hat{\alpha}_2 = \mathbf{0.07}(0.03)$



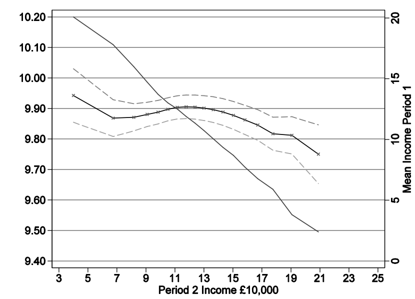
7bii) I3=11.67, PI=36.96

$\hat{\alpha}_1 = -0.03(0.03)\hat{\alpha}_2 = -\mathbf{0.05}(0.03)$



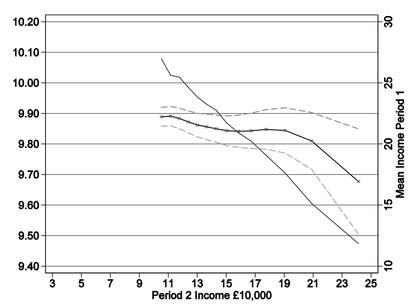
7biii) I3=14.05, PI=36.96

$\hat{\alpha}_1 = -0.04(0.05)\hat{\alpha}_2 = -\mathbf{0.15}(0.05)$



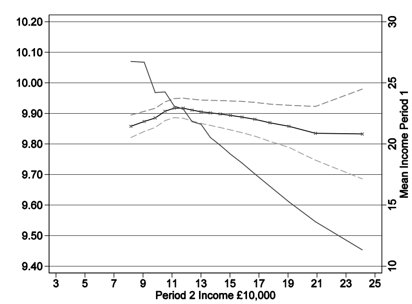
7ci) I3=9.35, PI=43.93

$\hat{\alpha}_1 = -0.04(0.03)\hat{\alpha}_2 = -\mathbf{0.17}(0.09)$



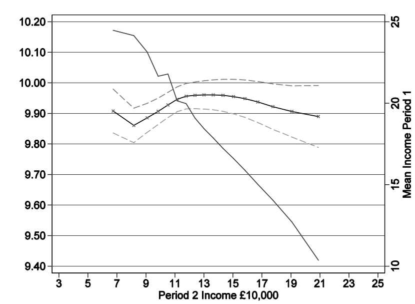
7cii) I3=11.67, PI=43.93

$\hat{\alpha}_1 = 0.04(0.03)\hat{\alpha}_2 = -0.07(0.08)$



7ciii) I3=14.05, PI=43.93

$\hat{\alpha}_1 = 0.05(0.04)\hat{\alpha}_2 = -0.07(0.06)$



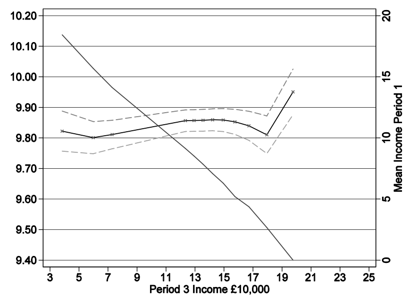
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 7: Semi Parametric Estimates. Dependent variable is Log Earnings age 30

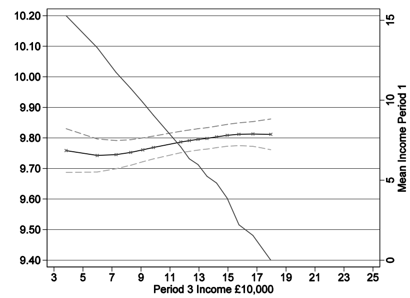
7di) I2=10.11, PI=31.01

$\hat{\alpha}_1 = 0.03(0.04) \hat{\alpha}_2 = \mathbf{0.10}(0.04)$



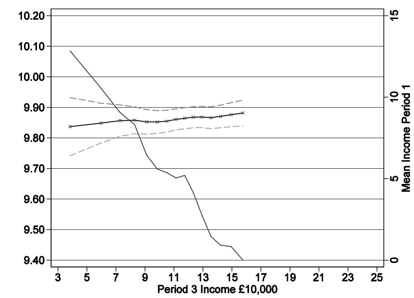
7dii) I2=12.39, PI=31.01

$\hat{\alpha}_1 = 0.03(0.04) \hat{\alpha}_2 = 0.02(0.03)$



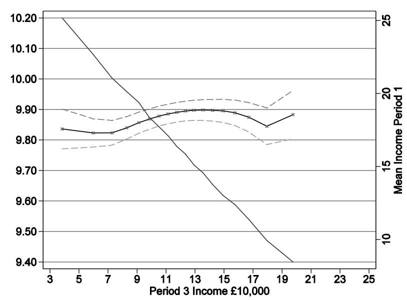
7diii) I2=14.98, PI=31.01

$\hat{\alpha}_1 = 0.02(0.05) \hat{\alpha}_2 = 0.02(0.03)$



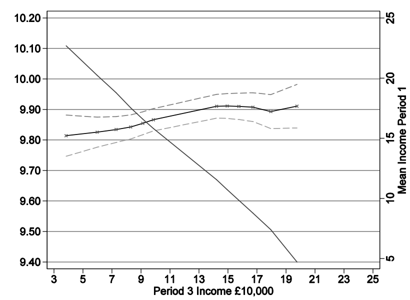
7ei) I2=10.11, PI=36.96

$\hat{\alpha}_1 = 0.05(0.04) \hat{\alpha}_2 = -0.01(0.04)$



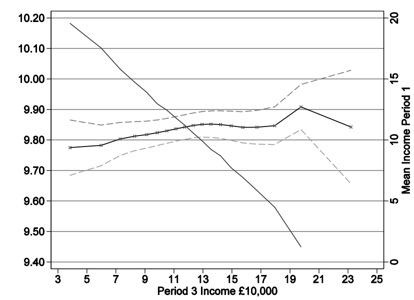
7eii) I2=12.39, PI=36.96

$\hat{\alpha}_1 = \mathbf{0.08}(0.04) \hat{\alpha}_2 = 0.02(0.04)$



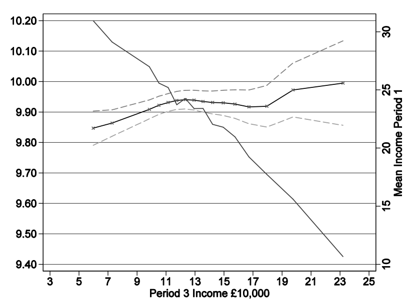
7eiii) I2=14.98, PI=36.96

$\hat{\alpha}_1 = 0.07(0.05) \hat{\alpha}_2 = -0.01(0.10)$



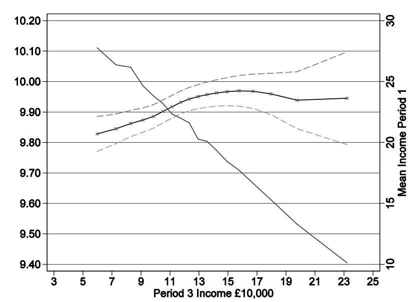
7fi) I2=10.11, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.09}(0.03) \hat{\alpha}_2 = 0.06(0.07)$



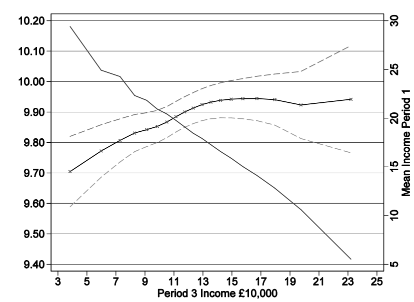
7fii) I2=12.39, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.11}(0.04) \hat{\alpha}_2 = 0.00(0.08)$



7fiii) I2=14.98, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.21}(0.06) \hat{\alpha}_2 = 0.03(0.09)$



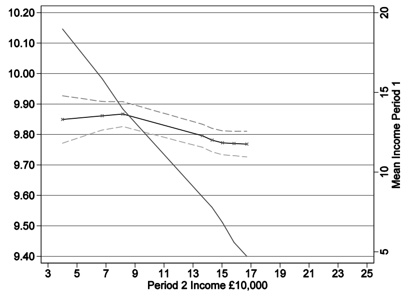
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 7: Semi Parametric Estimates. Dependent variable is Log Earnings age 30

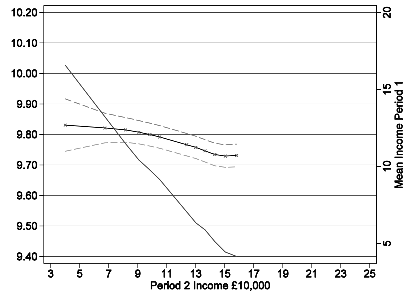
7gi) I1=9.35, PI=31.01

$\hat{\alpha}_1 = -0.02(0.04)\hat{\alpha}_2 = -\mathbf{0.08}(0.04)$



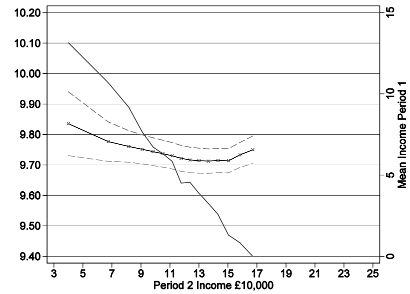
7gii) I1=13.02, PI=31.01

$\hat{\alpha}_1 = -0.05(0.05)\hat{\alpha}_2 = -\mathbf{0.05}(0.03)$



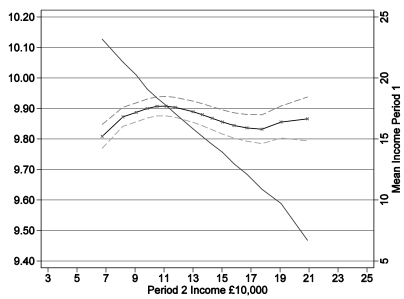
7giii) I1=15.64, PI=31.01

$\hat{\alpha}_1 = -\mathbf{0.11}(0.06)\hat{\alpha}_2 = 0.03(0.03)$



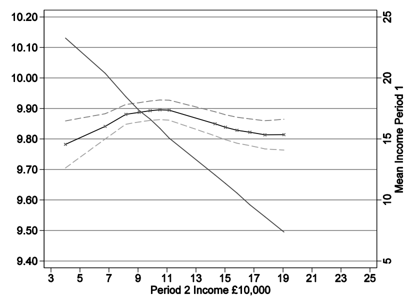
7hi) I1=9.35, PI=36.96

$\hat{\alpha}_1 = \mathbf{0.08}(0.03)\hat{\alpha}_2 - 0.02(0.04)$



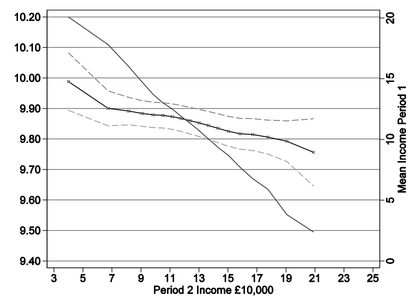
7hii) I1=13.02, PI=36.96

$\hat{\alpha}_1 = \mathbf{0.10}(0.04)\hat{\alpha}_2 = -\mathbf{0.07}(0.03)$



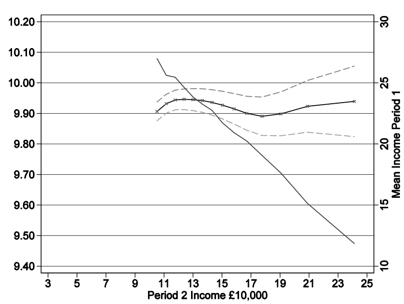
7hiii) I1=15.64, PI=36.96

$\hat{\alpha}_1 = -\mathbf{0.13}(0.05)\hat{\alpha}_2 = -\mathbf{0.10}(0.06)$



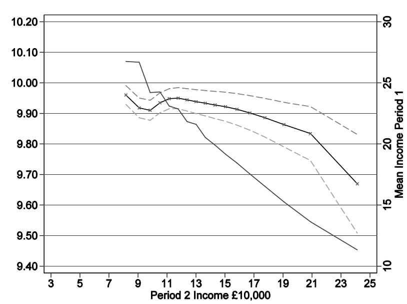
7ji) I1=9.35, PI=43.93

$\hat{\alpha}_1 = 0.03(0.03)\hat{\alpha}_2 = 0.00(0.06)$



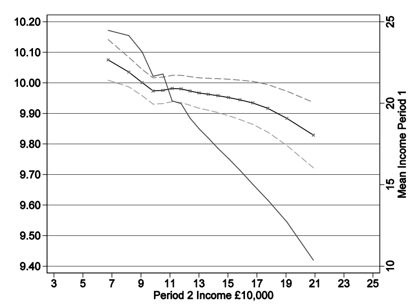
7jii) I1=13.02, PI=43.93

$\hat{\alpha}_1 = -0.03(0.03)\hat{\alpha}_2 = -\mathbf{0.26}(0.09)$



7jiii) I1=15.64, PI=43.93

$\hat{\alpha}_1 = -\mathbf{0.11}(0.04)\hat{\alpha}_2 = -\mathbf{0.14}(0.06)$



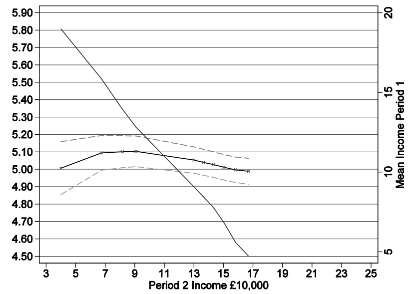
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 8: Semi Parametric Estimates. Dependent variable is IQ

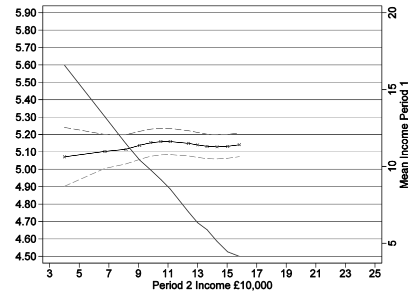
8ai) I3=9.35, PI=31.01

$\hat{\alpha}_1 = 0.07(0.09)\hat{\alpha}_2 = 0.00(0.06)$



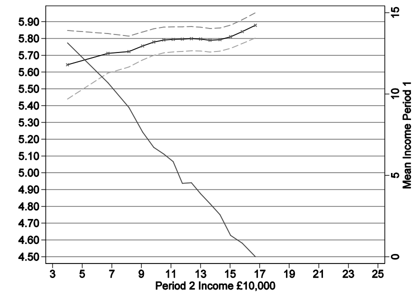
8aii) I3=11.67, PI=31.01

$\hat{\alpha}_1 = 0.09(0.09)\hat{\alpha}_2 = -0.02(0.05)$



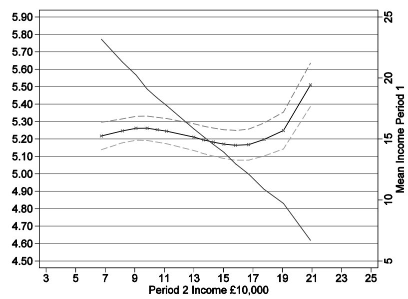
8aiii) I3=14.05, PI=31.01

$\hat{\alpha}_1 = 0.15(0.11)\hat{\alpha}_2 = 0.08(0.05)$



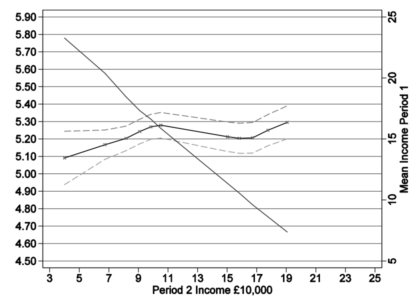
8bi) I3=9.35, PI=36.96

$\hat{\alpha}_1 = -0.01(0.06)\hat{\alpha}_2 = \mathbf{0.30}(0.07)$



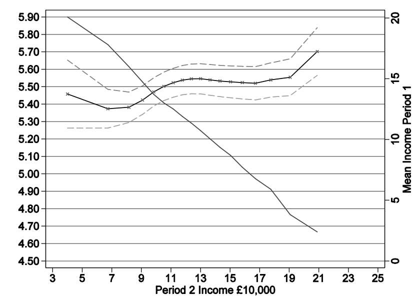
8bii) I3=11.67, PI=36.96

$\hat{\alpha}_1 = \mathbf{0.18}(0.09)\hat{\alpha}_2 = 0.03(0.06)$



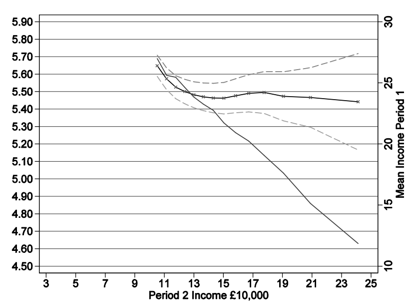
8biii) I3=14.05, PI=36.96

$\hat{\alpha}_1 = 0.09(0.11)\hat{\alpha}_2 = \mathbf{0.16}(0.08)$



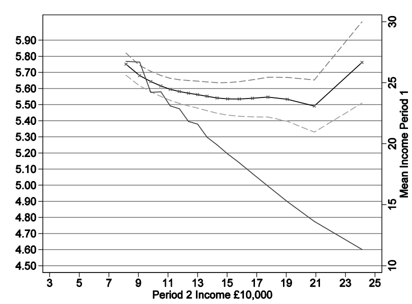
8ci) I3=9.35, PI=43.93

$\hat{\alpha}_1 = -\mathbf{0.18}(0.05)\hat{\alpha}_2 = -0.02(0.15)$



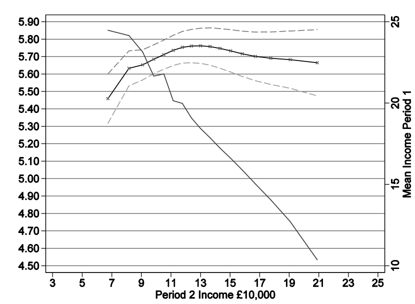
8cii) I3=11.67, PI=43.93

$\hat{\alpha}_1 = -\mathbf{0.20}(0.06)\hat{\alpha}_2 = 0.21(0.14)$



8ciii) I3=14.05, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.30}(0.09)\hat{\alpha}_2 = -0.10(0.11)$



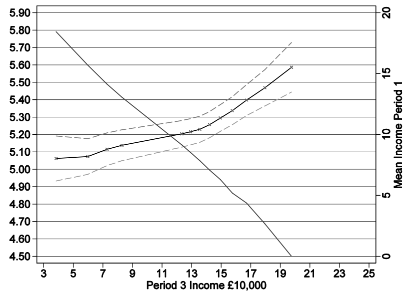
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 8: Semi Parametric Estimates. Dependent variable is IQ

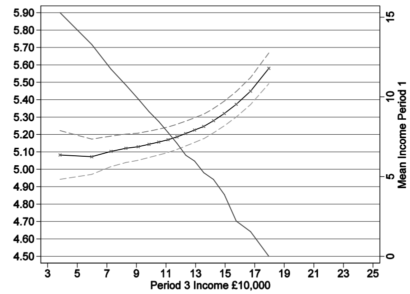
8di) I2=10.11, PI=31.01

$\hat{\alpha}_1 = \mathbf{0.13}(0.08)\hat{\alpha}_2 = \mathbf{0.39}(0.08)$



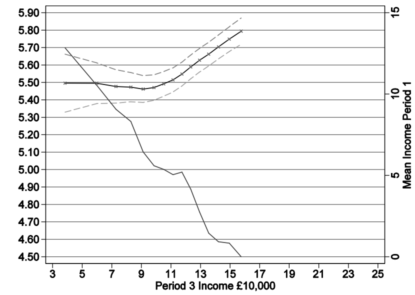
8dii) I2=12.39, PI=31.01

$\hat{\alpha}_1 = 0.10(0.08)\hat{\alpha}_2 = \mathbf{0.39}(0.06)$



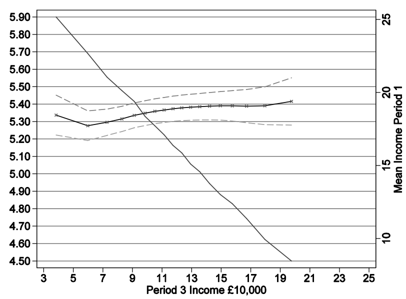
8diii) I2=14.98, PI=31.01

$\hat{\alpha}_1 = 0.02(0.09)\hat{\alpha}_2 = \mathbf{0.28}(0.05)$



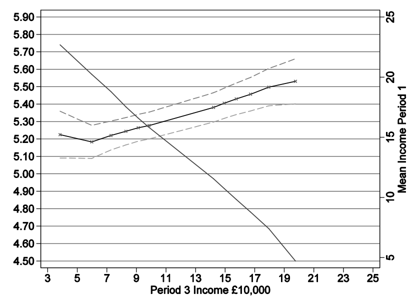
8ei) I2=10.11, PI=36.96

$\hat{\alpha}_1 = 0.04(0.07)\hat{\alpha}_2 = 0.04(0.08)$



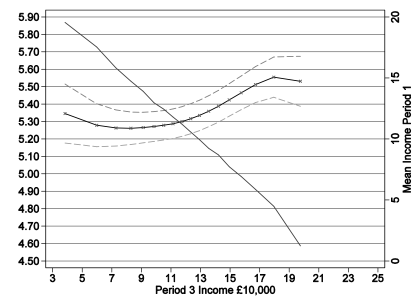
8eii) I2=12.39, PI=36.96

$\hat{\alpha}_1 = 0.09(0.08)\hat{\alpha}_2 = \mathbf{0.22}(0.08)$



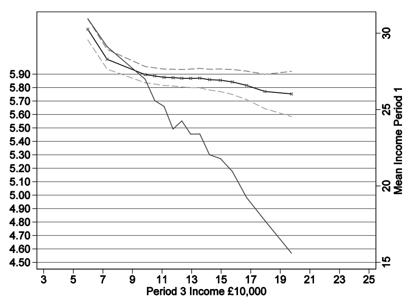
8eiii) I2=14.98, PI=36.96

$\hat{\alpha}_1 = -0.03(0.10)\hat{\alpha}_2 = \mathbf{0.41}(0.14)$



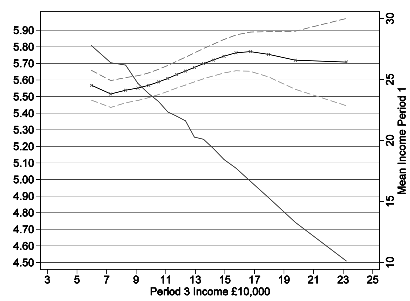
8fi) I2=10.11, PI=43.93

$\hat{\alpha}_1 = \mathbf{-0.36}(0.05)\hat{\alpha}_2 = 0.06(0.13)$



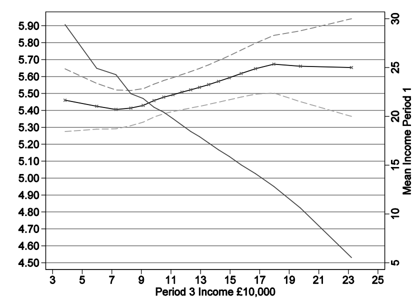
8fii) I2=12.39, PI=43.93

$\hat{\alpha}_1 = 0.09(0.06)\hat{\alpha}_2 = 0.05(0.14)$



8fiii) I2=14.98, PI=43.93

$\hat{\alpha}_1 = 0.06(0.11)\hat{\alpha}_2 = 0.13(0.16)$



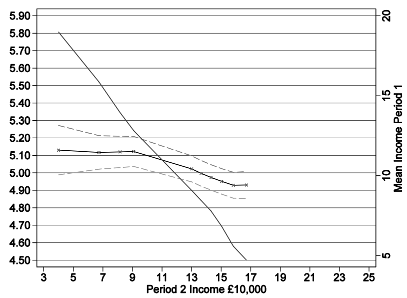
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 8: Semi Parametric Estimates. Dependent variable is IQ

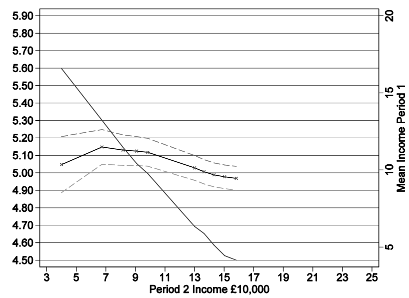
8gi) I1=9.3, PI=31.01

$\hat{\alpha}_1 = -0.06(0.08)\hat{\alpha}_2 = 0.02(0.07)$



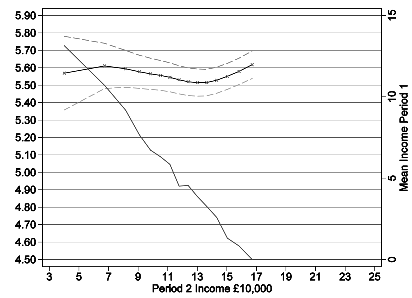
8gii) I1=13.02, PI=31.01

$\hat{\alpha}_1 = 0.04(0.09)\hat{\alpha}_2 = -\mathbf{0.12}(0.05)$



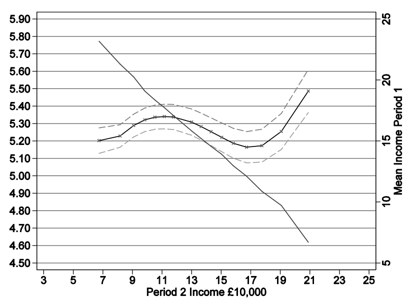
8giii) I1=15.64, PI=31.01

$\hat{\alpha}_1 = -0.04(0.12)\hat{\alpha}_2 = 0.09(0.06)$



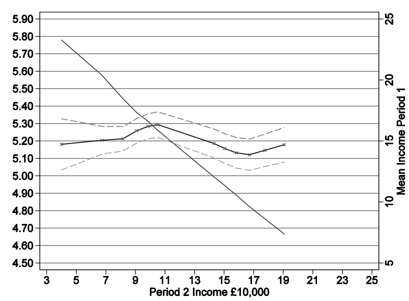
8hi) I1=9.35, PI=36.96

$\hat{\alpha}_1 = \mathbf{0.11}(0.05)\hat{\alpha}_2 = \mathbf{0.18}(0.07)$



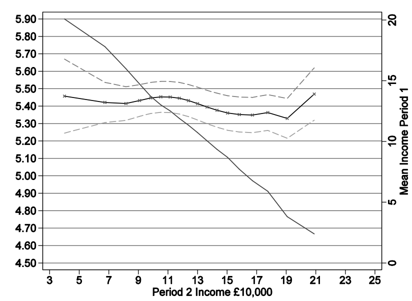
8hii) I1=13.02, PI=36.96

$\hat{\alpha}_1 = 0.09(0.08)\hat{\alpha}_2 = -0.09(0.06)$



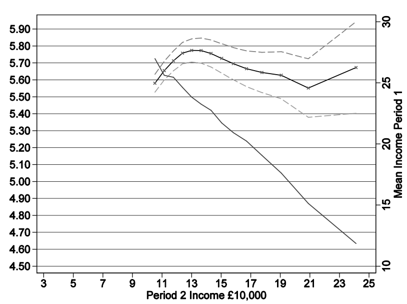
8hiii) I1=15.64, PI=36.96

$\hat{\alpha}_1 = -0.03(0.12)\hat{\alpha}_2 = 0.04(0.09)$



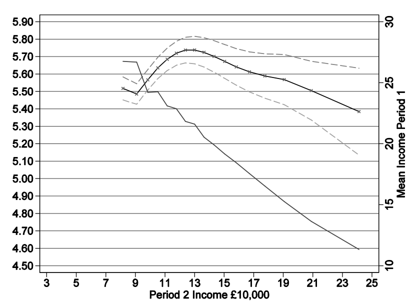
8ji) I1=9.35, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.18}(0.05)\hat{\alpha}_2 = -0.08(0.14)$



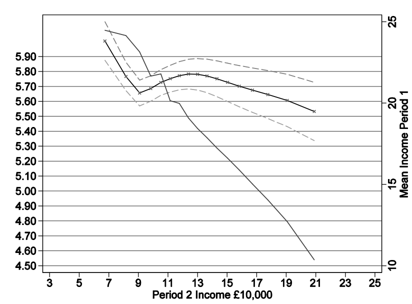
8jii) I1=13.02, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.21}(0.05)\hat{\alpha}_2 = -\mathbf{0.34}(0.13)$



8jiii) I1=15.64, PI=43.93

$\hat{\alpha}_1 = -\mathbf{0.22}(0.09)\hat{\alpha}_2 = -\mathbf{0.25}(0.11)$



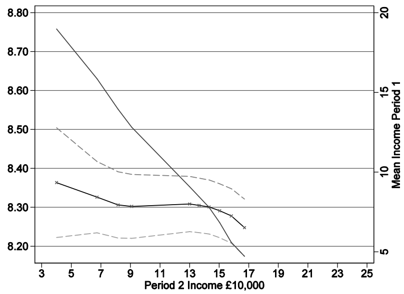
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 9: Semi Parametric Estimates. Dependent variable is Health

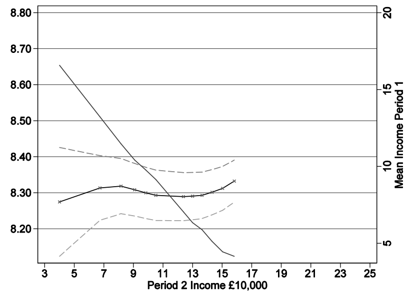
9ai) I3=9.35, PI=31.01

$\hat{\alpha}_1 = -0.06(0.08)\hat{\alpha}_2 = -\mathbf{0.22}(0.06)$



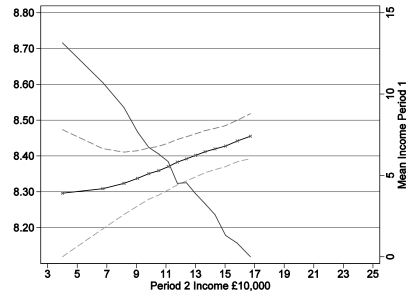
9aii) I3=11.67, PI=31.01

$\hat{\alpha}_1 = 0.01(0.08)\hat{\alpha}_2 = 0.04(0.05)$



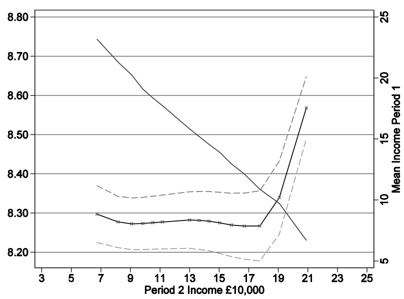
9aiii) I3=14.05, PI=31.01

$\hat{\alpha}_1 = 0.09(0.10)\hat{\alpha}_2 = 0.07(0.05)$



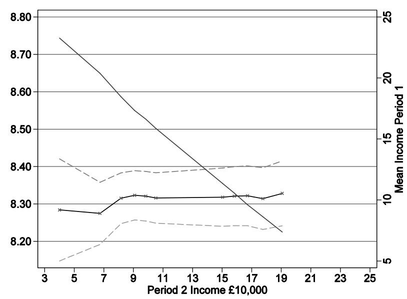
9bi) I3=9.35, PI=36.96

$\hat{\alpha}_1 = -0.02(0.05)\hat{\alpha}_2 = \mathbf{0.29}(0.05)$



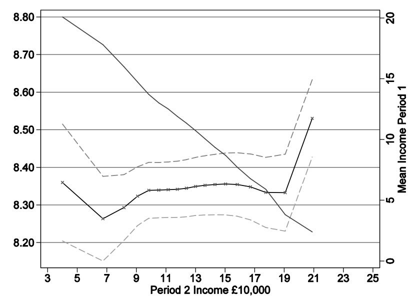
9bii) I3=11.67, PI=36.96

$\hat{\alpha}_1 = 0.03(0.08)\hat{\alpha}_2 = 0.02(0.06)$



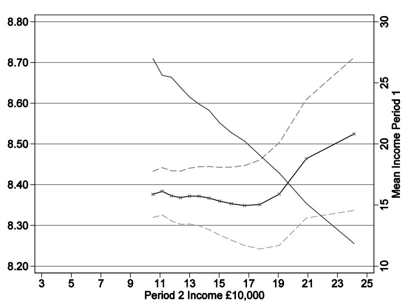
9biii) I3=14.05, PI=36.96

$\hat{\alpha}_1 = -0.02(0.09)\hat{\alpha}_2 = \mathbf{0.19}(0.07)$



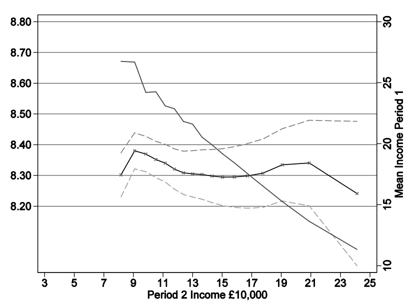
9ci) I3=9.35, PI=43.93

$\hat{\alpha}_1 = -0.01(0.05)\hat{\alpha}_2 = 0.16(0.10)$



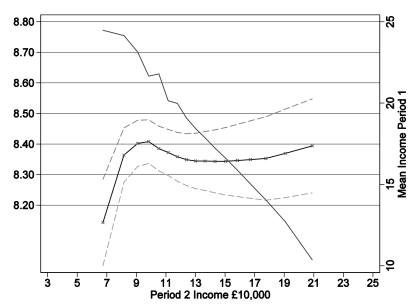
9cii) I3=11.67, PI=43.93

$\hat{\alpha}_1 = 0.00(0.05)\hat{\alpha}_2 = -0.06(0.13)$



9ciii) I3=14.05, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.20}(0.09)\hat{\alpha}_2 = 0.05(0.09)$



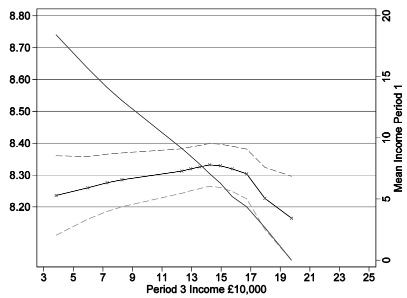
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 9: Semi Parametric Estimates. Dependent variable is Health

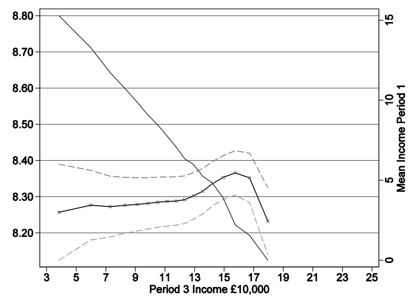
9di) I2=10.11, PI=31.01

$\hat{\alpha}_1 = 0.07(0.07)\hat{\alpha}_2 = \mathbf{-0.14}(0.08)$



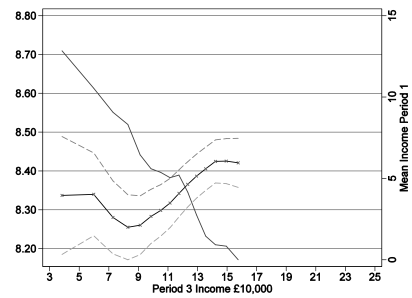
9dii) I2=12.39, PI=31.01

$\hat{\alpha}_1 = 0.03(0.08)\hat{\alpha}_2 = -0.06(0.06)$



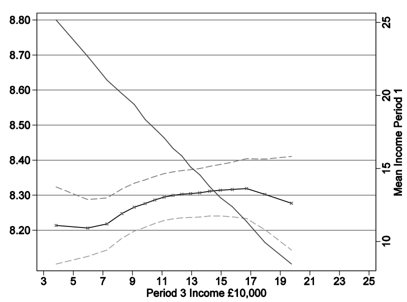
9diii) I2=14.98, PI=31.01

$\hat{\alpha}_1 = -0.02(0.08)\hat{\alpha}_2 = \mathbf{0.10}(0.05)$



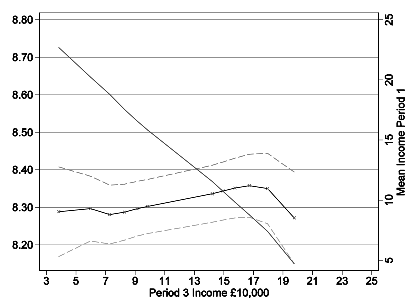
9ei) I2=10.11, PI=36.96

$\hat{\alpha}_1 = 0.09(0.07)\hat{\alpha}_2 = -0.02(0.08)$



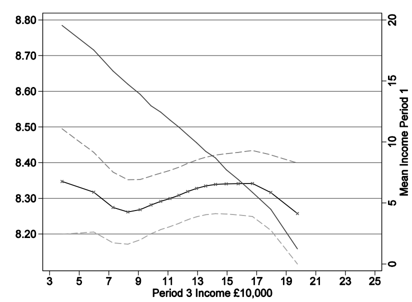
9eii) I2=12.39, PI=36.96

$\hat{\alpha}_1 = 0.03(0.07)\hat{\alpha}_2 = -0.04(0.07)$



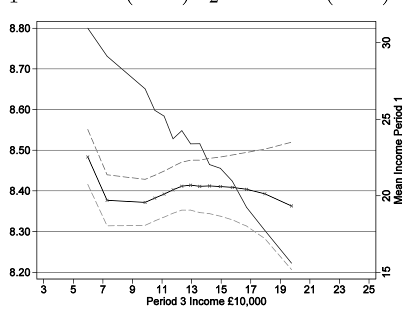
9eiii) I2=14.98, PI=36.96

$\hat{\alpha}_1 = -0.03(0.09)\hat{\alpha}_2 = -0.14(0.13)$



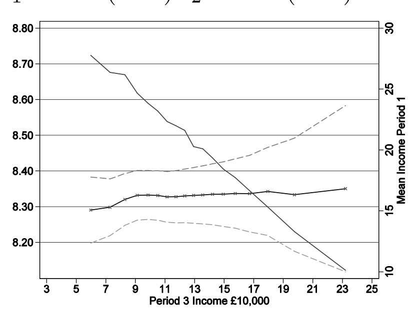
9fi) I2=10.11, PI=43.93

$\hat{\alpha}_1 = -0.07(0.05)\hat{\alpha}_2 = -0.19(0.15)$



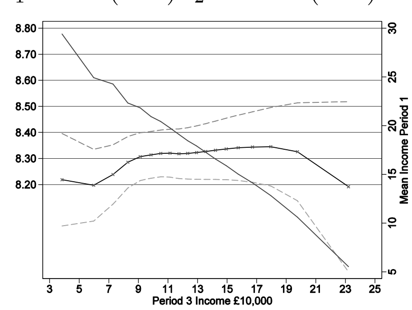
9fii) I2=12.39, PI=43.93

$\hat{\alpha}_1 = 0.04(0.06)\hat{\alpha}_2 = 0.02(0.12)$



9fiii) I2=14.98, PI=43.93

$\hat{\alpha}_1 = 0.10(0.10)\hat{\alpha}_2 = -0.13(0.17)$



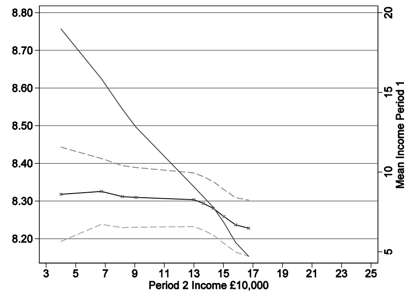
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 9: Semi Parametric Estimates. Dependent variable is Health

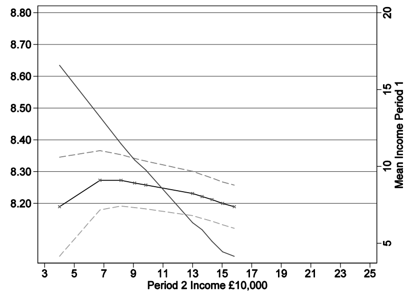
9gi) I1=9.35, PI=31.01

$\hat{\alpha}_1 = -0.01(0.07)\hat{\alpha}_2 = 0.01(0.05)$



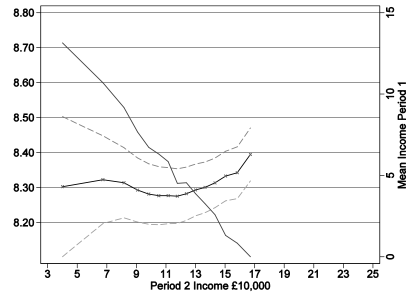
9gii) I1=13.02, PI=31.01

$\hat{\alpha}_1 = 0.06(0.09)\hat{\alpha}_2 = -0.06(0.05)$



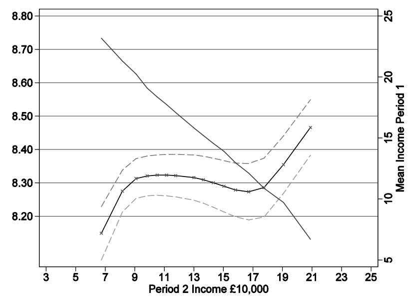
9giii) I1=15.64, PI=31.01

$\hat{\alpha}_1 = -0.03(0.11)\hat{\alpha}_2 = \mathbf{0.12}(0.06)$



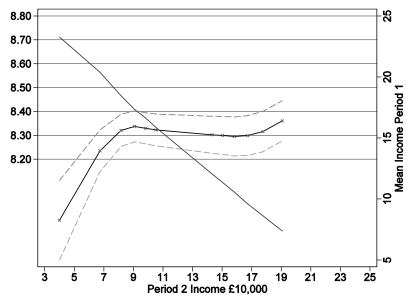
9hi) I1=9.35, PI=36.96

$\hat{\alpha}_1 = \mathbf{0.17}(0.05)\hat{\alpha}_2 = \mathbf{0.15}(0.05)$



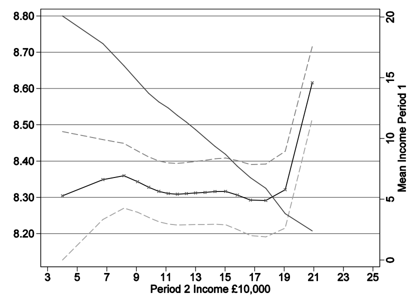
9hii) I1=13.02, PI=36.96

$\hat{\alpha}_1 = \mathbf{0.37}(0.09)\hat{\alpha}_2 = 0.05(0.06)$



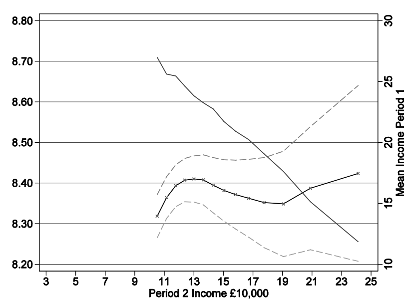
9hiii) I1=15.64, PI=36.96

$\hat{\alpha}_1 = 0.01(0.10)\hat{\alpha}_2 = \mathbf{0.31}(0.07)$



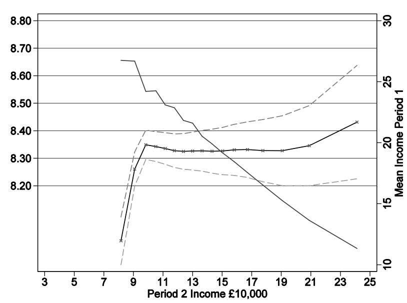
9ji) I1=9.35, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.08}(0.04)\hat{\alpha}_2 = 0.03(0.12)$



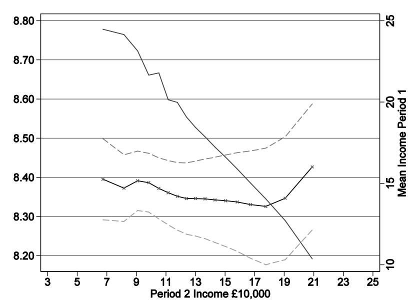
9jii) I1=13.02, PI=43.93

$\hat{\alpha}_1 = \mathbf{0.33}(0.06)\hat{\alpha}_2 = 0.10(0.11)$



9jiii) I1=15.64, PI=43.93

$\hat{\alpha}_1 = -0.05(0.07)\hat{\alpha}_2 = 0.08(0.10)$



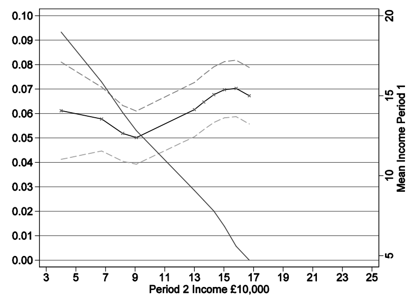
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 10: Semi Parametric Estimates. Dependent variable is Teen Pregnancy

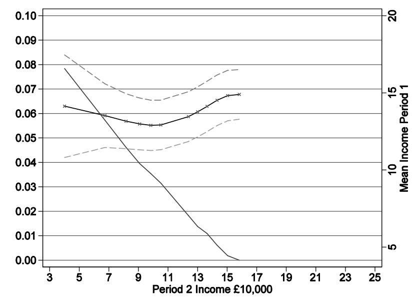
10ai) I3=9.35, PI=31.01

$\hat{\alpha}_1 = -0.01(0.01)\hat{\alpha}_2 = -0.01(0.01)$



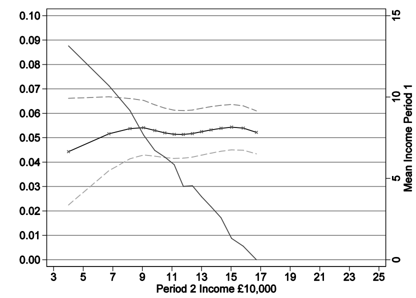
10aii) I3=11.67, PI=31.01

$\hat{\alpha}_1 = -0.01(0.01)\hat{\alpha}_2 = 0.01(0.01)$



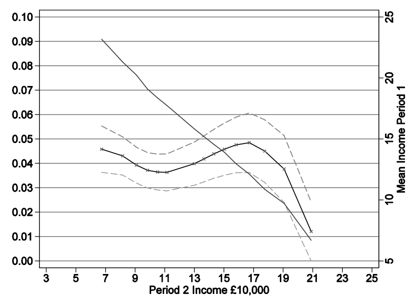
109aiii) I3=14.05, PI=31.01

$\hat{\alpha}_1 = 0.01(0.01)\hat{\alpha}_2 = 0.00(0.01)$



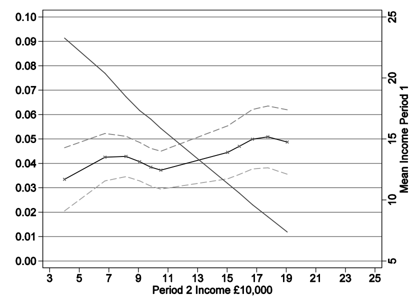
10bi) I3=9.35, PI=36.96

$\hat{\alpha}_1 = -0.01(0.01)\hat{\alpha}_2 = -\mathbf{0.03}(0.01)$



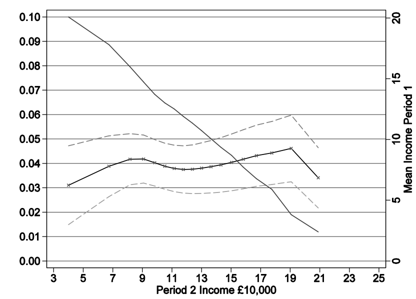
10bii) I3=11.67, PI=36.96

$\hat{\alpha}_1 = 0.00(0.01)\hat{\alpha}_2 = 0.01(0.01)$



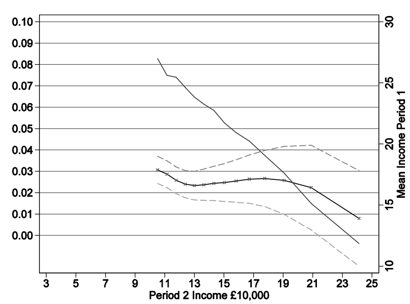
10biii) I3=14.05, PI=36.96

$\hat{\alpha}_1 = 0.01(0.01)\hat{\alpha}_2 = 0.00(0.01)$



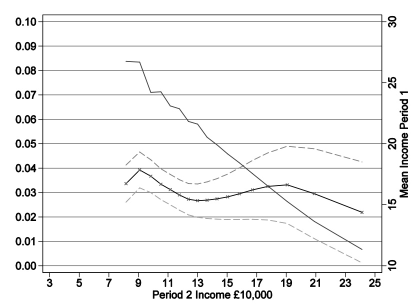
10ci) I3=9.35, PI=43.93

$\hat{\alpha}_1 = -0.01(0.01)\hat{\alpha}_2 = -0.02(0.01)$



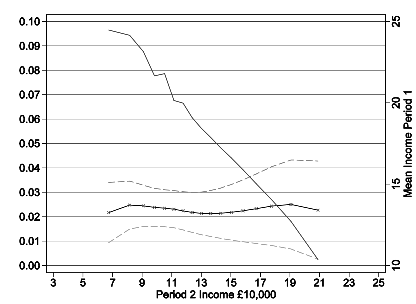
10cii) I3=11.67, PI=43.93

$\hat{\alpha}_1 = -0.01(0.01)\hat{\alpha}_2 = 0.00(0.01)$



10ciii) I3=14.05, PI=43.93

$\hat{\alpha}_1 = 0.00(0.01)\hat{\alpha}_2 = 0.00(0.01)$



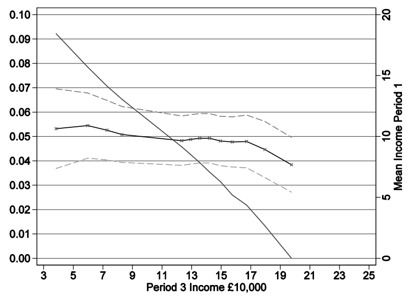
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 10: Semi Parametric Estimates. Dependent variable is Teen Pregnancy

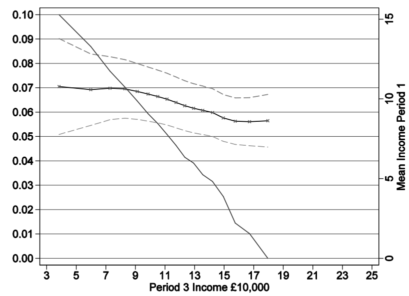
10di) I2=10.11, PI=31.01

$\hat{\alpha}_1 = -0.01(0.01)\hat{\alpha}_2 = -0.01(0.01)$



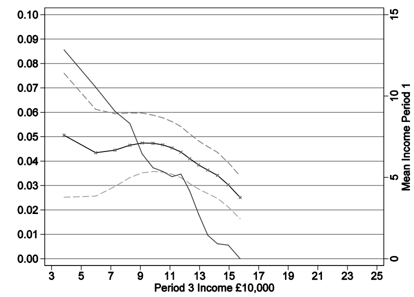
10dii) I2=12.39, PI=31.01

$\hat{\alpha}_1 = -0.01(0.01)\hat{\alpha}_2 = -0.01(0.01)$



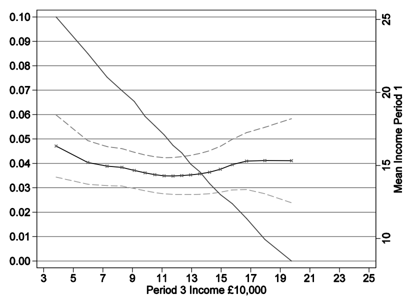
109diii) I2=14.98, PI=31.01

$\hat{\alpha}_1 = -0.01(0.01)\hat{\alpha}_2 = -\mathbf{0.02}(0.01)$



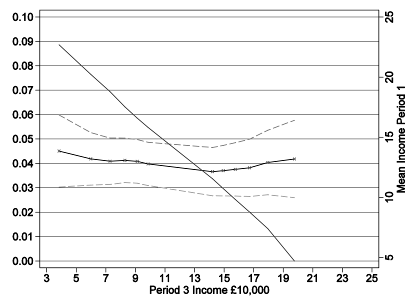
10ei) I2=10.11, PI=36.96

$\hat{\alpha}_1 = -\mathbf{0.01}(0.01)\hat{\alpha}_2 = 0.01(0.01)$



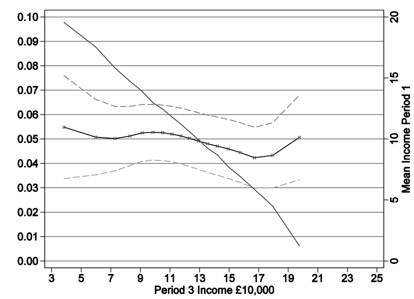
10eii) I2=12.39, PI=36.96

$\hat{\alpha}_1 = -0.01(0.01)\hat{\alpha}_2 = 0.00(0.01)$



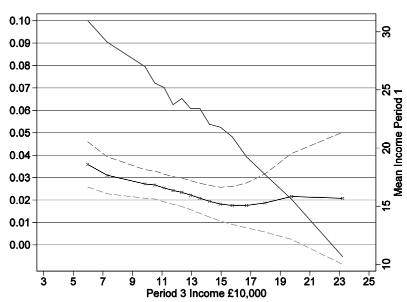
10eiii) I2=14.98, PI=36.96

$\hat{\alpha}_1 = 0.00(0.01)\hat{\alpha}_2 = 0.00(0.01)$



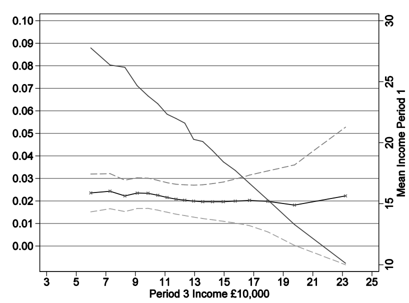
10fi) I2=10.11, PI=43.93

$\hat{\alpha}_1 = -\mathbf{0.01}(0.01)\hat{\alpha}_2 = 0.00(0.02)$



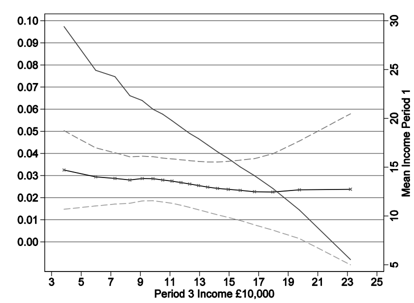
10fii) I2=12.39, PI=43.93

$\hat{\alpha}_1 = 0.00(0.01)\hat{\alpha}_2 = 0.00(0.02)$



10fiii) I2=14.98, PI=43.93

$\hat{\alpha}_1 = -0.01(0.00)\hat{\alpha}_2 = 0.00(0.02)$



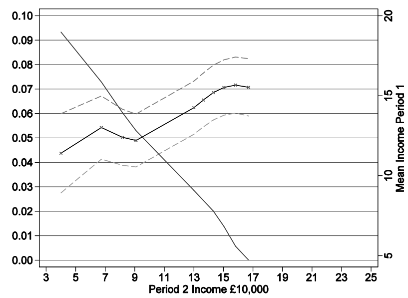
Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 10: Semi Parametric Estimates. Dependent variable is Teen Pregnancy

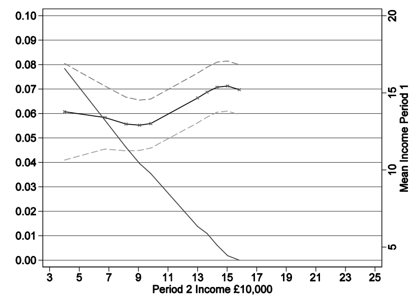
10gi) I1=9.35, PI=31.01

$\hat{\alpha}_1 = 0.01(0.01)\hat{\alpha}_2 = \mathbf{0.02}(0.01)$



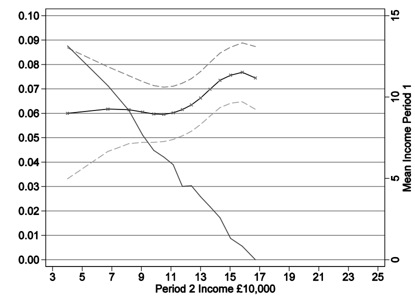
10gii) I1=13.02, PI=31.01

$\hat{\alpha}_1 = 0.00(0.01)\hat{\alpha}_2 = 0.01(0.01)$



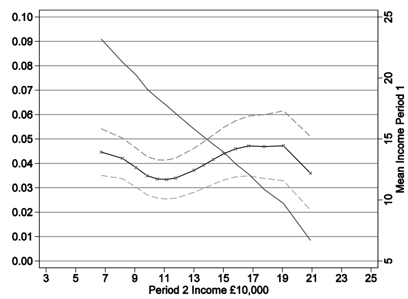
10giii) I1=15.64, PI=31.01

$\hat{\alpha}_1 = 0.00(0.01)\hat{\alpha}_2 = 0.01(0.01)$



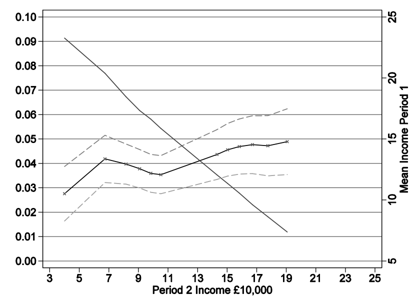
10hi) I1=9.35, PI=36.96

$\hat{\alpha}_1 = -0.01(0.01)\hat{\alpha}_2 = 0.00(0.01)$



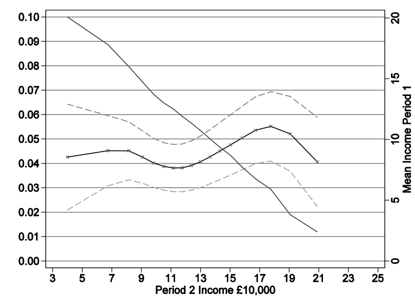
10hii) I1=13.02, PI=36.96

$\hat{\alpha}_1 = 0.01(0.01)\hat{\alpha}_2 = 0.01(0.01)$



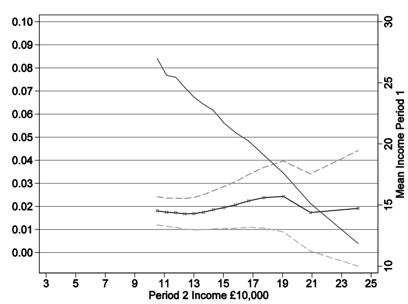
10hiii) I1=15.64, PI=36.96

$\hat{\alpha}_1 = 0.00(0.01)\hat{\alpha}_2 = 0.00(0.01)$



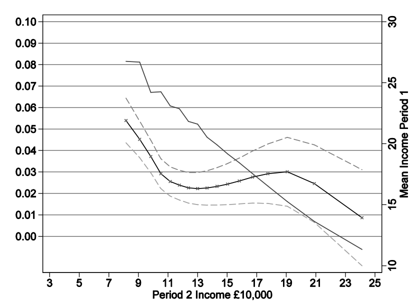
10ji) I1=9.35, PI=43.93

$\hat{\alpha}_1 = 0.00(0.01)\hat{\alpha}_2 = 0.00(0.01)$



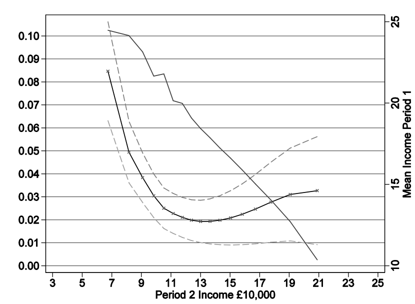
10jii) I1=13.02, PI=43.93

$\hat{\alpha}_1 = -\mathbf{0.03}(0.01)\hat{\alpha}_2 = -0.01(0.01)$



10jiii) I1=15.64, PI=43.93

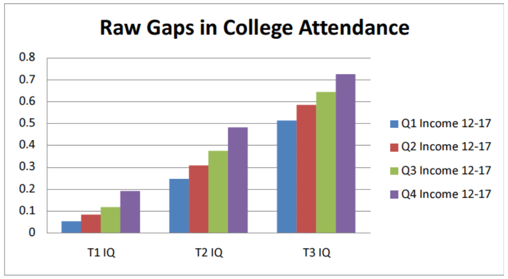
$\hat{\alpha}_1 = -\mathbf{0.07}(0.01)\hat{\alpha}_2 = 0.01(0.01)$

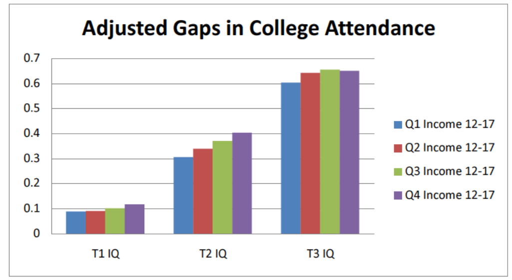


Note: 95% confidence intervals shown. Income variables in 2006 prices, UK £10,000s.

$\hat{\alpha}_1(\hat{\alpha}_2)$: difference in means between mid point and first (last) point. Standard errors in parentheses

Figure 11 - College Attendance and Family Income





Q_1 =£65335, Q_2 =£105047, Q_3 =£132550, Q_4 =£190735

Figure 12 - IQ and Family Income

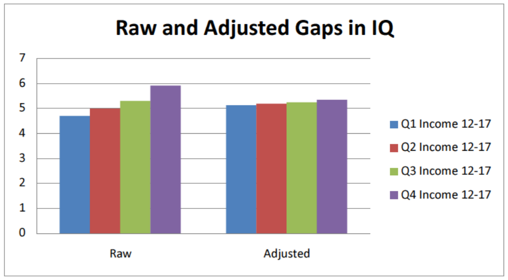


Table 1: Descriptive Statistics

	N	Mean	Standard deviation
Income Period 1, Age 0-5	514412	14.04	5.29
Income Period 2, Age 6-11	514762	13.29	5.40
Income Period 3, Age 12-17	514762	12.42	5.57
Permanent Income, Aged 0-17	514762	39.74	14.50
Mother Education	514762	10.74	2.43
Father Education	514762	11.32	2.92
Mother Age at Birth	514762	26.23	5.07
Father Age at Birth	514762	29.00	5.83
Child Year of Birth	514762	1975.25	2.89
Years of Schooling	513278	12.75	2.42
High School Drop Out	514762	0.21	0.41
College Attendance	514762	0.40	0.49
Log Earnings age 30	254402	9.89	0.81
IQ	230569	5.24	1.79
Health	261965	8.44	1.52
Teenage Pregnancy	514353	0.04	0.20

Note: Income values are in 2006 prices, in UK sterling

Table 2a: Income Mobility of Fathers in Norway

				40	Quartile		
30	Quartile		1	2	3	4	Total
		1	22,623	12,946	7,784	5,480	48,833
			46.33	26.51	15.94	11.22	100
		2	17,030	25,082	17,350	7,626	67,088
			25.38	37.39	25.86	11.37	100
		3	10,348	19,042	26,070	18,641	74,101
			13.96	25.7	35.18	25.16	100
		4	7,094	7,073	16,733	40,852	71,752
			9.89	9.86	23.32	56.93	100
	Total		57,095	64,143	67,937	72,599	261,774
			21.81	24.5	25.95	27.73	100

Table 2b: Income Mobility of Mothers in Norway

		40 Quartile				
30	Quartile	1	2	3	4	Total
	1	20,636	10,683	5,036	2,776	39,131
		52.74	27.3	12.87	7.09	100
	2	15,726	21,832	12,912	5,039	55,509
		28.33	39.33	23.26	9.08	100
	3	9,059	16,657	18,683	10,775	55,174
		16.42	30.19	33.86	19.53	100
	4	5,347	5,949	11,428	17,631	40,355
		13.25	14.74	28.32	43.69	100
Total		50,768	55,121	48,059	36,221	190,169
		26.7	28.99	25.27	19.05	100

Table 2c: Household Income Mobility in Norway

		Income Period 1									
		1	2	3	4	5	6	7	8	9	10
Income Period 2	1	57.55	16.02	7.64	4.59	3.36	2.43	1.84	1.4	0.96	0.57
	2	18.05	29.59	21.57	12.3	7.37	4.68	3.16	1.92	1.13	0.53
	3	7.87	19.34	22.78	20.18	13.38	7.7	4.68	2.66	1.28	0.53
	4	4.98	12.8	17.3	19.82	18.05	12.84	7.75	4.11	2.03	0.72
	5	3.63	8.51	12.34	16.49	18.44	17.09	12.51	7.27	3.26	0.91
	6	2.65	5.6	8.25	11.82	16.03	18.96	17.69	12.39	5.55	1.5
	7	2.09	3.67	5.01	7.57	11.82	16.74	20.29	19.33	11.13	2.78
	8	1.55	2.36	2.86	4.28	7.04	11.67	17.69	23.85	22.35	6.78
	9	1.03	1.42	1.6	2.14	3.31	5.91	10.77	19.39	32.85	22
	10	0.6	0.7	0.65	0.81	1.2	1.99	3.63	7.68	19.46	63.69
Total		100	100	100	100	100	100	100	100	100	100

Table 2d: Household Income Mobility in Norway

		Income Period 1									
		1	2	3	4	5	6	7	8	9	10
Income Period 3	1	48.12	16.29	9.43	6.37	4.94	3.83	2.93	2.23	1.72	1.26
	2	18.56	22.7	18.3	12.97	9.15	6.46	4.59	3.4	2.26	1.28
	3	9.56	18.16	18.5	16.16	13.04	9.51	6.66	4.35	2.77	1.45
	4	6.23	13.51	16.63	16.53	14.79	12.1	8.95	6.24	3.68	1.62
	5	4.59	9.69	13.08	15.32	15.62	14.31	11.92	8.74	5.05	2.01
	6	3.67	7.16	9.48	12.61	14.55	15.48	14.82	12.03	7.78	2.85
	7	2.96	4.89	6.42	8.97	12.04	14.89	16.51	16.46	12.51	4.85
	8	2.56	3.43	4.12	5.87	8.4	11.95	15.65	18.94	19.82	9.78
	9	2.23	2.55	2.63	3.4	5.05	7.78	11.91	17.31	24.99	22.65
	10	1.52	1.62	1.42	1.79	2.42	3.68	6.06	10.31	19.41	52.26
	Total	100	100	100	100	100	100	100	100	100	100

Table 2e: Household Income Mobility in Norway

		Income Period 2									
		1	2	3	4	5	6	7	8	9	10
Income Period 3	1	59.27	18.53	7.43	4.46	2.99	1.96	1.48	1.03	0.64	0.4
	2	20.22	33.85	20.2	10.53	6.06	3.84	2.48	1.46	0.93	0.45
	3	8.25	21.29	26.19	19.28	11.3	6.39	3.77	2.05	1.1	0.54
	4	5	12	20	22	18	12	6	3.21	1.5	0.64
	5	3	6	13	19	21	18	12	5.43	2.34	0.82
	6	2	4	7	12	18	22	19	11.03	4.03	1.21
	7	1	2	4	7	12	18	23	21.23	9.3	2.16
	8	1	1	2	3	6	11	19	28	23.53	4.99
	9	0.58	0.74	0.94	1.55	2.81	5.25	9.98	20.22	37.53	20.64
	10	0.35	0.34	0.33	0.52	0.8	1.46	2.81	6.34	19.11	68.14
	Total	100	100	100	100	100	100	100	100	100	100

Table 3: Parametric Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Years of Schooling		High School Dropout		College Attendance		Log Earnings age 30	
Income age 6-11	-0.022***	-0.004	0.004***	0.001***	-0.003***	0.001*	-0.011***	-0.007***
	(0.004)	(0.003)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Income age 12-17	0.005	0.016***	-0.001**	-0.003***	0.001	0.004***	0.005***	0.005***
	(0.005)	(0.003)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Permanent Income	0.048***	0.008***	-0.006***	-0.001***	0.009***	0.001***	0.009***	0.006***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Observations	513,278	513,278	514,762	514,762	514,762	507,235	254,402	254,402

	(9)	(10)	(11)	(12)	(13)	(14)
	IQ		Health		Teen Pregnancy	
Income age 6-11	-0.000	0.008***	0.004**	0.003*	0.002***	0.000
	(0.005)	(0.003)	(0.002)	(0.002)	(0.000)	(0.000)
Income age 12-17	0.010	0.016***	0.003	0.001	0.000*	-0.001***
	(0.007)	(0.003)	(0.002)	(0.002)	(0.000)	(0.000)
Permanent Income	0.029***	0.001	-0.001	0.000	-0.002***	-0.000**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Observations	230,569	227,424	261,965	258,380	514,353	506,834

Table 4: Decile Values for the Explanatory Variables: I1, I2, I3 and PI.

Decile Point	Income Period 1	Income Period 2	Income Period 3	Permanent Income
1	7.39	6.57	5.65	21.67
2	9.65	8.79	7.85	27.47
3	10.91	10.11	9.35	31.01
4	11.96	11.26	10.56	34.02
5	13.02	12.39	11.67	36.96
6	14.21	13.59	12.79	40.17
7	15.64	14.98	14.05	43.93
8	17.54	16.77	15.68	48.87
9	20.58	19.60	18.38	56.88

Income values are in 2006 prices, in UK sterling, in £10,000s.

Table 5: Bandwidth Choice

Bandwidth	I2	I3	PI
2 (C=1.0)	1.730	1.755	4.722
3 (C=1.5)	2.595	2.632	7.082
4 (C=2.0)	3.461	3.509	9.443
5 (C=2.5)	4.326	4.387	11.804
6 (C=3.0)	5.191	5.264	14.165
7 (C=3.5)	6.056	6.141	16.526
8 (C=4.0)	6.921	7.019	18.887

Note: Income values are in 2006 prices, in UK sterling, in £10,000s.

Table 6: Control Function First Stage Regressions

VARIABLES	Income period 1	Income period 2	Income period 3
Instrument	2.574***	3.241***	4.398***
	(0.0571)	(0.0709)	(0.0912)
Constant	13.69***	12.96***	12.01***
	(0.0101)	(0.0101)	(0.0100)
Observations	342,009	345,358	357,684

Standard errors in parentheses

Appendix 1: Interpretation of Income Coefficients when Conditioning on Permanent Income

Consider a model estimating the effect of income in period one (X_1) and period 2 (X_2) on child human capital (Y)

$$Y = \alpha + \beta_1 I_1 + \beta_2 I_2 + u \tag{14}$$

If we substitute I_1 for PI, the coefficient on I_2 will be the effect of I_2 relative to I_1

$$\begin{aligned} Y &= \delta + \gamma_1 PI + \gamma_2 I_2 + e \\ &= \delta + \gamma_1 (I_1 + I_2) + \gamma_2 I_2 + e \\ &= \delta + \gamma_1 I_1 + (\gamma_1 + \gamma_2) I_2 + e \\ &\therefore \beta_1 = \gamma_1 \\ \beta_2 &= \gamma_1 + \gamma_2 = \beta_1 + \gamma_2 \\ &\therefore \gamma_2 = \beta_2 - \beta_1 \end{aligned} \tag{15}$$

Appendix 2: Interpretation of Coefficients when Conditioning on Permanent Income, in a model with Interaction Terms

Consider a model estimating the effect of income in period one (I_1) and period 2 (I_2) on child human capital (Y) which allows for complementarity between I_1 and I_2.

$$Y = \alpha + \beta_1 I_1 + \beta_2 I_2 + \beta_3 I_1 I_2 + u \tag{16}$$

Complementarity exists if $\beta_3 > 0$. Substitute I_1 for PI

$$\begin{aligned}
Y &= \delta + \gamma_1 PI + \gamma_2 I_2 + \gamma_3 PI * I_2 + e \\
&= \delta + \gamma_1 \left(I_1 + I_2\right) + \gamma_2 I_2 + \gamma_3 \left(I_1 + I_2\right) * I_2 + e \\
&= \delta + \gamma_1 I_1 + \left(\gamma_1 + \gamma_2 + \gamma_3 I_2\right) I_2 + \gamma_3 I_1 I_2 + e \\
&\therefore \quad \beta_1 = \gamma_1 \\
\beta_2 &= \gamma_1 + \gamma_2 + \gamma_3 I_2 \qquad (17) \\
\beta_3 &= \gamma_3 \\
&\therefore \quad \gamma_2 = \beta_2 - \beta_1 - \beta_3 I_2
\end{aligned}$$

In this model, the coefficient on I_2 is the effect of I_2 relative to I_1 minus the product of the complementarity between I_1 and I_2 and I_2.

Appendix Table 1a: Full Parametric Regression Results for outcomes Years of Schooling, High School Dropout, College Attendance and Log Earnings at age 30.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Years of Schooling		High School Dropout		College Attendance		Log Earnings age 30	
Income age 6-11	-0.022***	-0.004	0.004***	0.001***	-0.003***	0.001*	-0.011***	-0.007***
	(0.004)	(0.003)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Income age 12-17	0.005	0.016***	-0.001**	-0.003***	0.001	0.004***	0.005***	0.005***
	(0.005)	(0.003)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Permanent Income	0.048***	0.008***	-0.006***	-0.001***	0.009***	0.001***	0.009***	0.006***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Mother Education		0.171***		-0.018***		0.034***		0.001
		(0.002)		(0.000)		(0.000)		(0.001)
Father Education		0.150***		-0.015***		0.030***		0.004***
		(0.002)		(0.000)		(0.000)		(0.001)
Mother age at Birth		0.050***		-0.007***		0.010***		0.004***
		(0.001)		(0.000)		(0.000)		(0.001)
Father age at Birth		0.006***		0.000		0.002***		-0.003***
		(0.001)		(0.000)		(0.000)		(0.000)
Marital Breakup age 0-5		-0.298***		0.060***		-0.037***		-0.067***
		(0.015)		(0.003)		(0.003)		(0.009)
Marital Breakup age 6-11		-0.205***		0.036***		-0.026***		-0.044***
		(0.014)		(0.003)		(0.003)		(0.008)
Marital Breakup age 12-17		-0.537***		0.089***		-0.075***		-0.095***
		(0.011)		(0.002)		(0.002)		(0.006)
Number of Children age 0-5		-0.464***		0.051***		-0.083***		-0.026***
		(0.008)		(0.001)		(0.002)		(0.004)
Number of Children age 6-11		0.419***		-0.053***		0.067***		0.030***
		(0.016)		(0.003)		(0.003)		(0.009)
Number of Children age 12-17		-0.196***		0.036***		-0.028***		-0.023***
		(0.013)		(0.002)		(0.003)		(0.007)
Municipality age 0		-0.000*		0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Municipality age 6		-0.000		0.000		0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Municipality age 12		0.000***		-0.000***		0.000***		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Observations	513,278	513,278	514,762	514,762	514,762	507,235	254,402	254,402

Appendix Table 1b: Full Parametric Regression Results for outcomes IQ, Health and Teen Pregnancy.

	(9)	(10)	(11)	(12)	(13)	(14)
	IQ		Health		Teen Pregnancy	
Income age 6-11	-0.000	0.008***	0.004**	0.003*	0.002***	0.000
	(0.005)	(0.003)	(0.002)	(0.002)	(0.000)	(0.000)
Income age 12-17	0.010	0.016***	0.003	0.001	0.000*	-0.001***
	(0.007)	(0.003)	(0.002)	(0.002)	(0.000)	(0.000)
Permanent Income	0.029***	0.001	-0.001	0.000	-0.002***	-0.000**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Mother Education		0.135***		0.006***		-0.003***
		(0.002)		(0.002)		(0.000)
Father Education		0.120***		0.004***		-0.002***
		(0.002)		(0.001)		(0.000)
Mother age at Birth		0.029***		-0.007***		-0.003***
		(0.001)		(0.001)		(0.000)
Father age at Birth		0.007***		-0.001		-0.000
		(0.001)		(0.001)		(0.000)
Marital Breakup age 0-5		-0.074***		0.023		0.014***
		(0.017)		(0.014)		(0.002)
Marital Breakup age 6-11		-0.010		-0.003		0.009***
		(0.016)		(0.014)		(0.002)
Marital Breakup age 12-17		-0.157***		0.008		0.019***
		(0.013)		(0.011)		(0.001)
Number of Children age 0-5		-0.316***		0.019**		0.011***
		(0.009)		(0.008)		(0.001)
Number of Children age 6-11		0.151***		0.004		-0.008***
		(0.018)		(0.015)		(0.002)
Number of Children age 12-17		0.008		0.020		0.011***
		(0.014)		(0.012)		(0.001)
Municipality age 0		0.000		0.000		0.000***
		(0.000)		(0.000)		(0.000)
Municipality age 6		-0.000*		-0.000		0.000**
		(0.000)		(0.000)		(0.000)
Municipality age 12		0.000***		-0.000		0.000***
		(0.000)		(0.000)		(0.000)
Observations	230,569	227,424	261,965	258,380	514,353	506,834