Intergenerational Mobility and the Timing of Parental Income

Pedro Carneiro

Department of Economics

University College London, IFS, CEMMAP

p.carneiro@ucl.ac.uk

Italo Lopez Garcia

Department of Economics

University College London

i.lopez@ucl.ac.uk

Kjell G. Salvanes

Department of Economics

Norwegian School of Economics, IZA and CEE

kjell.salvanes@nhh.no

Emma Tominey

University of York, IZA

emma.tominey@york.ac.uk

September 2013

Abstract

We extend the standard intergenerational mobility literature by modelling individual outcomes as a function of the history of parental income, as opposed to a single measure of parental income. Using data for 500,000 individuals in Norway, we present semi-parametric estimates of the effect of the timing of parental income on outcomes measured when an individual is in his early 20s. We find that schooling is maximized when permanent income is high, and income is balanced between the early childhood and middle childhood years. There is however some advantage in shifting income from either the early childhood or the middle childhood period towards the adolescent years of the child. To interpret our findings we simulate models of parental investment in children with more than one period of childhood, under different assumptions about credit markets and the information sets of parents. Simple models emphasizing borrowing constraints do not explain our findings. More promising models feature uncertainty about income shocks, child endowments, and the technology of skill formation.

* We thank participants in a seminar at Johns Hopkins, LSE, the MFI Institute Conference in Honor of James Heckman, and the UCL/3IE conference on Early Child Development, 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, and Orazio Attanasio's 2009 ERC Advanced Grant 249612 "Exiting Long Run

Poverty: The Determinants of Asset Accumulation in Developing Countries". Salvanes thanks the Research Council of Norway for financial support. Tominey acknowledges the Research Council for Norway, the Leibniz Association, Bonn, in the research network 'Non-Cognitive Skills:Acquisition and Economic Consequences' and the British Academy for support.

1 Introduction

There is a large empirical literature examining the intergenerational transmission of economic status (for recent surveys see Solon, 1999, Black and Devereux, 2011, Bjorklund and Salvanes, 2010). It is possible to find estimates of intergenerational mobility for various outcomes for virtually every country in the world where data linking parents and children is available. Most estimates come from simple models linking a measure of child income and a measure of parental income, where incomes at a particular parental age window or life-time earnings are used.

$$y_c = \alpha + \beta y_p + u, \tag{1}$$

where y_c is a measure of the child's income, y_p is a measure of parental income, and u is a residual.

Standard theoretical models of intergenerational transmission justify the use of equation (e.g., Becker and Tomes, 1979, 1986), but they usually collapse the childhood years to a single period of life . More realistic models of parental investments in children distinguish several stages of childhood (Cunha and Heckman, 2007, Cunha, Heckman and Schennach, 2010). They point out that the whole history (in particular, the timing) of parental investments in children may be as or more important that the total amount invested during the childhood years. Therefore, if there is a link between shocks to family income and investments in children, a simple model of parental income at one point in time may be misspecified.

This paper extends the literature on intergenerational transmission by examining the relationship between adult outcomes of children and the timing of parental income during their childhood years. We use data from Norway for children born during the 1970s, which allows us to link an individual's outcomes as a young adult to the whole history of parental income during the childhood and adolescence years. We find that, for a given level of permanent parental income, balanced income profiles lead to higher levels of education of the child than income profiles subject to several fluctuations. This is because it is better to smooth investments in children than to suffer large fluctuations (which are a consequence of income shocks). For other outcomes, such as earnings, IQ, high school dropout, college enrolment, or teenage pregnancy, the picture can be slightly different, indicating differences in the production function for different outcomes. That said, we also find that permanent income (average discounted parental income over the first 17 years of life of the child) is a much more important determinant of human capital than the timing of income, regardless of whether we consider education or any other of the variables we study.

The empirical importance of permanent income relative to the timing of income is likely to be dependent on the country that we study. In a country such as Norway in the 1970s, were the welfare state was starting to develop but already well developed safety nets, it may be much easier to smooth fluctuations in income than in other countries where insurance possibilities are more limited, because the welfare system is not as generous, or capital markets are not as developed.2 The fact that income fluctuations matter at all in Norway, suggests that they may be even more important in poorer countries.

The distinction between early and late investments in human capital is a central feature of the recent literature on skill formation (see Cameron and Heckman, 1998, 2001, Carneiro and Heckman, 2002, 2003, or Cunha and Heckman, 2007, among many others). The importance that is given (today) to early childhood investments comes from the idea that investments in different periods of a child's life may play fundamentally different roles, and that early investments are fundamental for the success of later learning.

A few other authors have explicitly examined the role of the timing of income in the formation of human capital. Some of these focus on survey data from the US and Germany, and rely on relatively small datasets (Duncan and Brooks-Gunn, 1997, Duncan et al, 1998, Levy and Duncan, 2000, Jenkins and Schluter, 2002, Carneiro and Heckman, 2003, Caucutt and Lochner, 2012). Others use much larger register data for Denmark and Norway (Aakvik et al, 2005, Humlum, 2010), but nevertheless they estimate very restrictive models. In particular, all these papers estimate regressions of child outcomes on the income of parents at different ages. Since the levels of income in different periods enter in a linear and additive way in these models, they are assumed to be "substitutes" in the production of human capital. Relative to the papers using US and German survey data our paper relies on much better data (larger samples and richer income histories), which allows us to estimate much more flexible models with considerable precision. This is also true when we contrast our analysis to the ones using register data for Norway and Denmark. The flexible models we estimate allow us to construct a much richer picture of the role of the timing of income than the one presented in previous work. This is important because the complementarity (or other interactions) of investments in human capital across periods (Cunha, Heckman and Schennach, 2010) may translate into complementarity (or other interactions) of income shocks across periods.

Our sample consists of all individuals born in Norway between 1971 and 1980. It is possible to link each individual to his mother and father and their respective annual income for all years in this decade. We use this information to construct maternal and paternal income histories from the birth of the child until the year she was 17.[1] In addition, there are multiple outcomes available for each of these individuals (education, IQ, income early in their careers, a health index, fertility), which can be linked to these family income histories.

Ideally, we would want to estimate flexible functions of outcomes in adulthood on the series of annual incomes between the ages of 0 and 17 of the child. In practice it is difficult to implement such an estimator when the number of regressors is as high as this (18). Therefore we group the childhood years into three periods: ages 0-5, 6-11, and 12-17. We construct the average deflated and discounted income for each of these age groups, as well as a measure of permanent income during childhood which takes the average discounted income over all childhood years. We then estimate non-parametric regressions of each outcome on permanent income and incomes in two out of the three periods of childhood (since the third would be collinear), and semi-parametric models which allow the inclusion of parental characteristics as controls.

We present our results through a series of two dimensional graphs. Take for example the case where we include as regressors permanent income, income at ages 6-11, and income at ages 12-17. We can fix, for example, permanent income and income at ages 12-17, and see how changes in income at ages 6-17 translate into changes in outcomes. This corresponds to the impact of shifting income between ages 0-5 and ages 6-11 on the adult outcomes of children.

We realize that income fluctuations over the life-cycle are not entirely driven by shocks, but they also reflect parental choices. For example, family income during the first years of life of the child may be low because the mother decided to take maternity leave. Therefore, in our main specification we use father's income alone, as opposed to mother's income or total family income. In addition we show that removing ages 0-2 from the data (and redefining the age groups to be 3-7, 8-12, 13-17) leads to similar results as in the main specification. The same happens when we include in the model controls for the proportion of years the mother is not working in each period.

We also realize that income profiles depend on parental human capital, which has an independent impact on child outcomes. Therefore we control for paternal and maternal education, which is allowed to interact with paternal and maternal age at birth. We also include controls for the slope of the income profile calculated using prebirth income and income occurring right after the 17th birthday of the child (outside the periods we use to construct income histories), so we can control for whether the father is on a high or a low income growth trajectory (or even on negative trajectory). Other controls include the birth year and gender of the child.

In summary, we examine the impact of fluctuations in father's income on child outcomes, by comparing families with the same permanent income, education and age, and overall income growth between ages 0 and 17, but different levels of income at each age. The covariates we use allow us to control for different income profiles by age and

[1] In this paper, the 0-17 age interval constitutes childhood.

education, and different income growth rates even after controlling for age and education. Our assumption is that the remaining variation in paternal income, i.e., fluctuations in income around income profiles (as predicted by education, age, and a linear growth trend), is driven by income shocks. Whether they translate into changes in parental investments in children depends on whether the shocks are perceived as permanent or temporary, and on the insurance possibilities available to parents.

One implication of our assumptions is that income fluctuations should not predict pre-birth investments, unless they are related with permanent traits of parents which also would have independent effects on all the outcomes we consider. We test this using an indicator for low birth weight, which is strongly correlated with our permanent income measure. We find that the timing of income fluctuations does not predict whether a child is low birth weight.

To guide our empirical analysis and interpret our results we consider a model of parental investments in children with multiple periods of childhood, as in Cunha and Heckman (2007). In each period, parents decide consumption, savings and investments in children. Human capital is a general function of investments in different periods, so the whole history of investments potentially determines human capital formation (except in the special case where there is perfect substitutability between investments in different periods). Parents are subject to shocks to income, which can be permanent or transitory. Markets are incomplete, so there may be only partial insurance against shocks (as in, for example, Blundell, Pistaferri and Preston, 2010). In sum, we add parental investments in children to a standard life-cycle model of consumption and savings, with imperfect insurance.

The structure of the paper is as follows. In section 2 we describe the data, and in section 3 we present our empirical methods. Section 4 discusses our results, and in section 5 we present simulations from dynamic models of parental investments in children which help us interpret the results. Finally, section 6 concludes.

2 Data

Our data source is the Norwegian Registry data maintained by Statistics Norway for the periods 1971 up to 2006. It is a linked administrative dataset that covers the population of Norwegians and is a collection of different administrative registers providing information about month and year of birth, educational attainment, labour market status, earnings, and a set of demographic variables (age, gender) as well as information on families including parents' marital status. We are able to link individuals to their parents, and it is possible to gather labour market information for both.

For the bulk of the analysis we select all births in the period 1971-1980. In particular, we are able to construct annual paternal taxable earnings data for each year from the three years preceding the child's birth, through to their 20th birthday. An additional child outcome is available for births up to 1986, test scores in high school. Therefore, we map income data and parental characteristics for these additional cohorts of children. This gives us information on 556,999 children.

The earnings values include wages and income from business activity but also unemployment, and sickness benefits.. Therefore, our income measures include some degree of insurance against low income shocks,i.e. when workers temporary out of work but still in the labor force, and consequently, we expect the effect of the timing of taxable earnings to be lower than the effect of labour earnings alone (which we cannot measure).We discount all incomes to the year of birth of the child, using a real interest rate of 4.26% (Aakvik et al, 2005).

In order to construct a measure of income in each of the three periods we take the average of discounted annual paternal incomes within each period (0-5,6-11, 12-17). Permanent income is then defined as the sum of income in the three periods.

We consider a large range of child outcomes. The administrative data includes years of education for each individual, an indicator for dropping out of high school at the age of 16, and college enrolment. 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. Unfortunately, it is not possible to measure whether a college degree was completed. Individuals are at least 26 years of age when we observe their educational achievement, and consequently they can be expected to have exited school.

Military service is compulsory in Norway for males, and between the age of 18-20 males usually take an IQ test. This test is a composite of arithmetic, words,[2] and a figures tests[3], all of which are recognized as tests of IQ. See Sundet *et al* (2004, 2005) and Black *et al* (2008) for more information on the tests.

Then, in a move away from the more traditional outcomes, 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. We measure additionally a health score taken 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 have the top score.

For a set of individuals born predominantly in 1986 (so a much later cohort than the ones we have considered so far), we observe grades achieved at the end of the 10th grade, when individuals are aged 16.[4] Unfortunately, grades in schools are not available for earlier cohorts. We define two main variables: 1) one which includes scores in written exams in Mathematics, Norwegian and English; 2) and another with considers achievement additionally in home science, crafts and art, religion, physical training, music, science and social science. Each exam (for each subject) is scored out of six, and the two measures are the sum across relevant exams. For each exam, around 2.5% of students are awarded either 1 or 6.

Finally, we construct a set of important control variables, which are important for the credibility of our empirical strategy. First, we build a measure of the heterogeneous income profile of households, as the difference between income for child aged 18-20 and in the three years pre birth[5]. This allows us to control directly for the slope of the income profile throughout the periods of childhood. Other controls 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.

3 Methods

3.1 Empirical Strategy

Let Y_i be an outcome of child i (education, earnings, high school drop out, college attendance, IQ, health, teenage pregnancy, grades in high school) in later adolescence or young adulthood. We are interested in Y_i as a function of the history of paternal income I_{it} in each period t ($t = 1, 2, 3$), and permanent income of the parents, PI_i. Since $PI_i = I_{i1} + I_{i2} + I_{i3}$ we drop one of the periods from the model, say I_{i1}. Therefore, we write:

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

We allow $m(PI_i, I_{i2}, I_{i3})$ to be a non-parametric function of its arguments.

It is important to be able to estimate a flexible function, and the reason is the following. Parents are faced with income shocks in each period, and in response, decide how much to invest in children (and how much to consume

[2] The word tests are most similar to the Wechsler Adult Intelligent Scale (WAIS).
[3] The figures tests are similar to the Raven Progressive matrix
[4] See Hægeland et al. (2008) for full detail of grade data.
[5] A robustness check conditions instead for the growth rather than the level of pre- and post- childhood income.

and save). There is a technology that links the adult human capital of an individual to the whole history of parental investments in childhood and adolescence. The link between income shocks and child outcomes, described by equation (2), depends on many factors, including preferences, technology, information, and the structure of credit markets (insurance possibilities). Therefore, this relationship can be quite complex.

We are particularly interested in $m_2(PI_i, I_{i2}, I_{i3}) = \frac{\partial m(PI_i, I_{i2}, I_{i3})}{\partial I_{i2}}$ and $m_3(PI_i, I_{i2}, I_{i3}) = \frac{\partial m(PI_i, I_{i2}, I_{i3})}{\partial I_{i3}}$. $m_2(PI_i, I_{i2}, I_{i3})$ tells us the impact on outcome Y_i of shifting income from period 1 to period 2, since we are keeping PI_i and I_{i3} fixed (and $PI_i = I_{i1} + I_{i2} + I_{i3}$). In our empirical section we will present a series of graphs relating Y and I_2 (for different outcomes Y). The graphs will vary depending on the values of PI_i and I_{i3} on which we evaluate this function. An analogous interpretation and graphical representations of results can be given to $m_3(PI_i, I_{i2}, I_{i3})$.

ε_i should be interpreted as the unobserved heterogeneity that is left after controlling for permanent income in the model. Therefore, we assume that ε_i has a finite conditional variance: $E(\varepsilon_i^2 | PI_i, I_{i2}, I_{i3}) \leq C < \infty$ and that $E(\varepsilon_i | PI_i, I_{i2}, I_{i3}) = 0$. We are interested not in the impact of PI itself on Y, but on the impact of the timing of income (I_2 and I_3) on Y, after conditioning on PI. In other words, we want to compare (the late adolescence or adult) outcomes of children whose parents have the same level of permanent income between the ages of 0 and 17, but differ in the level of income they get in each period.

We would like to interpret I_2 and I_3 as income shocks orthogonal to other determinants of outcomes Y, conditional on PI. It is likely that PI absorbs much of the relevant unobserved heterogeneity across parents (correlated with the overall level of their income), but one may still be concerned that parents facing different income profiles may be also different in many other dimensions.

In order to address this issue we start by excluding maternal income from the model, and rely only on paternal income to construct (PI_i, I_{i2}, I_{i3}). Maternal income in each period could be very much related to decisions of staying at home caring for children instead of work, which is likely to affect child outcomes (e.g., maternity leave; see Carneiro, Loken and Salvanes, 2012). On the other end, paternal income is much less likely to be affected by these choices.

In addition, we condition on paternal education interacted with paternal age at birth (by including dummies for years of education and age at birth interacted with each other). This controls for different age-education profiles across fathers. Moreover, we construct a measure of paternal income growth between the ages of 0 and 17 of the child, based on income 1 to 3 years before birth (pre-birth income), and income 1 to 3 years after age 17 (post-17 income). This means that we explore fluctuations in income around deterministic age-income profiles which are allowed to vary with education, after accounting for heterogeneous income growth (and, of course, keeping fixed permanent income). The remaining controls in the model are maternal age at birth interacted with maternal education, and birth year and gender of the child. Therefore, we extend equation (2) to include a large set of controls (Z):

$$Y_i = m(PI_i, I_{i2}, I_{i3}) + Z_i\delta + \varepsilon_i \tag{3}$$

Our argument is that I_2 and I_3 are uncorrelated with ε_i after conditioning on P_i and all the controls just mentioned. One implication of this argument is that pre-birth investments should be uncorrelated with the timing of income, but may still affect child outcomes. We test this by examining the relationship between having a low birth weight baby and the subsequent timing of parental income. We show below that, although low birth weight is strongly correlated with P_i, it is uncorrelated with I_2 and I_3.

We will also present some sensitivity analysis where we control for marital break up, and number of children. In addition, we calculate income residuals from a regression of income on age-education dummies and father fixed effects. We estimate the role of the timing of income residuals by including them in equation (3), instead of PI_i, I_{i2} and I_{i3}.

3.2 Multivariate Local Linear Regression

Equation (3) is a partially linear regression model. We adopt a two step method for estimating this model. In the first step we estimate δ (the coefficients on Z) by using a series approximation for $m(PI_i, I_{i2}, I_{i3})$.[6] In the second step we estimate a local linear regression of $Y_i - Z\hat{\delta}$ on (PI_i, I_{i2}, I_{i3}).

We follow Ruppert and Wand (1994) and Fan and Gijbels (1996) to define the multivariate local linear regression estimator. Let $I_i = (PI_i, I_{i2}, I_{i3})$. Our goal is 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 minimizes the weighted least squares objective function

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

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

$$K(s) = \begin{cases} 0.5 & if\ |s| < 1 \\ 0 & \text{otherwise} \end{cases}$$

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

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

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

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 uniform 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. We expect that $h \to 0$ as n$\to \infty$.

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

$$h_j = C * 2 * \sigma_{x_j} h^{\frac{-1}{7}} \tag{4}$$

where C denotes a constant and σ_{x_j} the standard error of component j of vector I. 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 and Wand (1994).

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

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 of the outcome. We estimate the conditional density and variance as follows:

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

[6] In particular, we approximate $m(PI_i, I_{i2}, I_{i3})$ as:

$$\begin{aligned} m(PI_i, I_{i2}, I_{i3}) \quad = \quad & \alpha_0 + \alpha_1 PI_i + \alpha_2 I_{2i} + \alpha_3 I_{3i} + \alpha_4 PI_i^2 + \alpha_5 I_{2i}^2 + \alpha_6 I_{3i}^2 \\ & + \alpha_7 PI_i^3 + \alpha_8 I_{2i}^3 + \alpha_9 I_{3i}^3 + \alpha_{10} PI_i I_{2i} + \alpha_{11} PI_i I_{3i} + \alpha_{12} I_{2i} I_{3i} \\ & + \alpha_{13} PI_i^2 I_{2i} + \alpha_{14} PI_i^2 I_{3i} + \alpha_{15} I_{2i}^2 I_{3i} + ... \end{aligned}$$

(include all two-way and three-way interactions between $(PI_i, I_{i2}, I_{i3}, PI_i^2, I_{i2}^2, I_{i3}^2, PI_i^3, I_{i2}^3, I_{i3}^3)$). Then we can estimate equation (3) by least squares.

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

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

4 Results

4.1 Descriptive Statistics

The descriptive statistics for the sample are reported in Table 1. There are 522,616 child level observations, which are essentially all individuals born in Norway between 1970 and 1990 for whom we were able to collect paternal income data, plus those born in 1986. The average permanent income of the father (in the period between the ages of 0 and 17 of the child) is about £306,000. There is substantial income dispersion (the standard deviation is £116900). Income in each period (1, 2, and 3) falls with the age of the child because of discounting (we discount all incomes to age 0).

Mothers have on average 11.14 years of schooling, which is slightly lower than the average years of education of the fathers (11.45). Mothers are much younger than fathers at birth (26 vs 29 years of age).

The average years of education of the children in our sample is 12.73. 21% of children drop out from high school, but 39% attend college. The average annual earnings of these children at age 30 is £19,732. As noted above, IQ is only available for males and takes values on a 9 point scale, with a sample average of 5.25, and a standard deviation of 1.79. The average health score for the males is 8.44, indicating that the majority of children achieve perfect physical health on this scale (which has a maximum score of 9). Teen pregnancies occur for 4% of the females in our sample. Finally, the cohort of children for whom we have 10th grade exam information have an average score of 42.75 (out of 60) in all exams combined, and 14.71 (out of 24) in the core exams of Norwegian, English and Mathematics.

The income process is studied in detail in Carneiro, Salvanes and Tominey (2012). They find that, as in many other countries, the income process for Norwegian fathers can be fairly well a approximated by the sum of a random walk (permanent shock) and a low order MA process (temporary shock).

4.2 Simple Patterns

Before we turn to the semi-parametric estimation of the effect of the timing of paternal income on outcomes we present the basic patterns in our data using very simple models. It is particularly interesting to start with a simple version of equation (2) where we ignore the timing of income, and consider only the relationship between an outcome of the child, Y , and the permanent income of the father, PI. Although it is common to estimate linear models, we will allow the relationship between Y and PI to be more flexible. Instead of including PI linearly in the model, we construct indicator variables, $q^k_{PI,i}$, that take value 1 if the paternal income of individual i is in percentile k of the distribution of PI in the sample, with $k = 1, ..., 100$:

$$Y_i = \sum_{k=1}^{100} \phi^k_{PI} q^k_{PI,i} + \varepsilon_i \quad (5)$$

The empirical results in this paper will be presented through a series of graphs. We start by focusing on years of education as the outcome of interest. Figure 1 plots the relationship between years of education of the child and paternal income constructed from the estimates of equation (5). The estimated function is monotonically increasing (except at the very high end) and concave. Doubling permanent paternal income from £200,000 to £400,000 translates roughly into an additional year of schooling for the child.

Figure 2 has several panels, plotting estimates of equation (5) for each of the remaining outcomes in the paper. Because the sample is so much smaller when the outcome is grades in high school, we divide the distribution of PI in these regressions into 50 (as opposed to 100) quantiles, each corresponding to 2 percentiles. High school dropout rates are declining with PI for values of PI below £400,000, and flat after that (remarkably, not going much below 10%). College attendance rates increase substantial throughout the distribution of PI, and so do IQ scores. Log earnings at age 30 rise steeply with PI for values of PI below £400,000, and much more slowly after that. This pattern is somewhat similar to the one we find for high school dropout rates, and curiously, for teenage pregnancy as well. Estimates for the health index are erratic but roughly display an increasing pattern with PI. Finally, both indices of high school grades are increasing in PI. All these panels show patterns as expected, and the magnitudes of the relationships between the different outcomes and PI are very substantial.

We now introduce in the model income in two periods of childhood (leaving a third out of the model, because of collinearity). Take a version of equation (3) where the function $m(PI_i, I_{i2}, I_{i3})$ is separable in its three arguments: $m(PI_i, I_{i2}, I_{i3}) = m^1(PI_i) + m^2(I_{i2}) + m^3(I_{i3})$. We approximate $m^1(PI_i)$ using dummies for each percentile of the distribution of PI, and we proceed analogously for $m^2(I_{i2})$ and $m^3(I_{i3})$. In other words, we estimate the following model:

$$Y_i = \sum_{k_1=1}^{100} \phi_{PI}^{k_1} q_{PI,i}^{k_1} + \sum_{k_2=1}^{100} \phi_{I_2}^{k_2} q_{I_2,i}^{k_2} + \sum_{k_3=1}^{100} \phi_{I_3}^{k_3} q_{I_3,i}^{k_3} + Z_i\delta + \varepsilon_i \tag{6}$$

where $q_{PI,i}^{k_1}$ is an indicator that takes the value 1 if the father of child i has permanent income in percentile k_1 of the distribution of PI and 0 otherwise. $q_{I_2,i}^{k_2}$ and $q_{I_3,i}^{k_3}$ are defined analogously.

As before, we start by looking at years of education of the child. Figure 3 has two panels, corresponding to $m^2(I_{i2})$, and $m^3(I_{i3})$. We plot $m^2(I_{i2})$ keeping the values of all other variables in the model fixed at their means, and analogously for $m^3(I_{i3})$. Since the model is separable, each of these functions shows us the partial derivative of the outcome with respect to income in each period, keeping all else fixed.

Both $m^2(I_{i2})$, and $m^3(I_{i3})$ are inverse U-shaped. This means that education is maximized when there is some balance between paternal income across periods. It is not desirable (in terms of schooling attainment) to have all father's income concentrated in one period of childhood, regardless of whether it is ages 0-5, 6-11, or 12-17. Below we discuss why this might be the case. Not surprisingly, we have similar findings when we use high school dropout or college attendance as the outcomes. These are measures of educational attainment so the relevant patterns should not be very different from the ones found for years of schooling.

We can test and reject that $m^2(I_{i2})$ ($m^3(I_{i3})$) is flat. In particular, we test whether the coefficients $\phi_{I_2}^{k_2}$ ($\phi_{I_3}^{k_3}$) are all equal to each other (across different values of k_2). We reject this hypothesis even when we drop from the test the coefficients $\phi_{I_2}^{k_2}$ ($\phi_{I_3}^{k_3}$) which are at the extremes, i.e., for very low or very high values of k_2 (k_3).

The IQ graphs also display an inverse-U shape, both for income at 6-11 and at 12-17, although they have a fairly long increasing section. When we look at log earnings at age 30 the shapes of the graphs are quite different. Child earnings are decreasing with income at ages 6-11, which says that shifting money away from the first period and towards the second period of childhood results in lower labor market outcomes for the child. Child earnings are roughly increasing in income at ages 12-17.

With regards to teenage pregnancy, there is not much of a gradient with income at 6-11, and a pronounced and declining relationship with income at 12-17. This suggests that positive income shocks in the last period of childhood may be particularly important to prevent teenage pregnancy. In terms of self-reported adult health it also seems to be beneficial to shift income towards late childhood.

Finally, when we examine grades in high school, it is useful to shift income from ages 6-11 to ages 0-5, indicating that the early years are important. But at the same time it is also important to shift income towards ages 12-17. Notice that, for grades in high school, we increase the size of the bins over which we evaluate (PI_i, I_{i2}, I_{i3}) (we do this in Figures 2 and 3). This is because the sample size is so much smaller for this outcome.

We now turn to our main results, which come from the semi-parametric estimation of $m(PI_i, I_{i2}, I_{i3})$. We will see that the most important patterns to report are already present in figure 2.

4.3 Semi Parametric Estimates

In this section we present semi-parametric estimates of $m(PI, I_2, I_3)$, following the method laid out in section 3.2. In order to implement it we need to first create a grid of evaluation points for $m(PI, I_2, I_3)$, which is tri-dimensional. We take 19 points for each income variable (PI, I_2, I_3), corresponding to the ventiles (1/20) of each variable's distribution. This gives us a tri-dimensional grid with 6,859 points $(= 19 * 19 * 19)$.

It is standard practice to trim the data so to avoid spurious results driven by small cells. Therefore, we drop 2% of observations, corresponding to the cells with the smallest number of observations. In our main results we use a uniform kernel and choose the bandwidth using the formula in equation (4), setting $C = 1$. Below we show that our results are robust to the choice of kernel and bandwidth.

One way to present our estimates of $m(PI, I_2, I_3)$ is through a series of two dimensional graphs, where in the y-axis we have the outcome of interest, and in the x-axis we have one of the income variables. The downside of this type of presentation is that we can only vary one of the incomes being considered at a time, which means that we need to fix the remaining two variables (we also fix the remaining control variables at their mean values). Therefore, we need to use of multiple figures for each outcome. The advantage of such an apparently cumbersome approach is that the graphs are straightforward to read. Furthermore, we will see a remarkably consistent pattern across graphs.

For each outcome, we present three sets of graphs. In the first set, we fix PI and I_3 at three different values each (the third, fifth, and seventh deciles of the distribution of each variable), and vary only I_2, for a total of nine possible combinations. These are presented in nine different panels, which plot $m(PI, I_2, I_3)$ against I_2 (for given values of PI and I_3). At the top of each panel we display the values at which we are keeping PI and I_3 fixed.

Since $PI = I_1 + I_2 + I_3$, if we keep PI and I_3 fixed then it is not possible to vary I_1 and I_2 independently. Therefore, as we move towards the right in the x-axis we see how the outcome varies as we shift income from period 1 to period 2. The support of I_2 over which we can evaluate $m(PI, I_2, I_3)$ is not the same across all panels because there are either infeasible values for I_2, or values of I_2 which are feasible but for which there are no observations in the sample (for given combinations of PI and I_3). The second set of panels keeps PI and I_2 fixed, and varies I_3 (so we are shifting income from period 1 to period 3). The third set of panels keeps PI and I_1 fixed, and varies I_2 (so we are shifting income from period 3 to period 2).

Below each panel we display two other parameters and respective standard errors, α_1 and α_2. For each panel, let H be the highest point of support for the income variable being used in that panel, let L be the lowest point of support, and M be the median point of support (which would correspond to exactly the 50th percentile of the distribution of that income variable if all graphs had full support). Take the case where we fix $PI = \overline{PI}$ and $I_3 = \overline{I_3}$, and we let I_2 vary. Then we define:

$$\begin{aligned} \alpha_1 &= m(\overline{PI}, M, \overline{I_3}) - m(\overline{PI}, L, \overline{I_3}) \\ \alpha_2 &= m(\overline{PI}, H, \overline{I_3}) - m(\overline{PI}, M, \overline{I_3}). \end{aligned} \tag{7}$$

α_1 is the difference between the values the outcome takes in the median and lower extreme of the support of I_2, while α_2 is the difference between the values the outcome takes in the median and upper extreme of the support of I_2. If $m(\overline{PI}, I_2, \overline{I_3})$ did not vary with I_2 (in which case the timing of income is irrelevant, at least when we compare first and second period incomes) we would expect $\alpha_1 = \alpha_2 = 0$, so these parameters help us quantify the importance of the timing of income.

4.3.1 Schooling Attainment

We begin by focusing on years of schooling of the child as the outcome of interest, in Figures 4ai)-4jiii). Figures 4ai)-4ciii) show how years of schooling change with I_2, relative to I_1. At top of each panel we display the values at which we keep PI and I_3 fixed, which are either the third, fifth or seventh deciles of the respective distributions.

Each panel shows two lines. The solid line (with the dashed standard errors) corresponds to $m(\overline{PI}, I_2, \overline{I_3})$, where $\overline{PI}$ and $\overline{I_3}$ are the values of PI and I_3 at which we evaluate $m(PI, I_2, I_3)$. The scale of this line is given on the vertical axis located on the left of the graph. The dotted line which is declining in every panel corresponds to the missing income. In this case, it is equal to $I_1 = \overline{PI} - \overline{I_3} - I_2$. The scale of this line can be read on the vertical axis located at the right of the graph.

It is remarkable that all of the figures in panels 4ai)-4ciii) display an inverse U-shape. This is also the picture we get from the estimation of the parametric model of equation (6), as shown in figure 3. We compute α_1 and α_2 for each panel, and we are able to reject that the slope of these functions is equal to zero. What this says is that across different values of PI and I_3 the years of schooling of the child are maximized when there is some balance between period 1 and period 2 income. If income is too concentrated in either period 1 or period 2, then one can improve education outcomes of children by shifting income towards the other period. The (discounted annual) level of I_2 at which the maximum is achieved is roughly between £8000 and £12000 (a little higher for richer households, and lower for poorer households).

We compute α_1 and α_2 (from equation (7)) for all panels. With the exception of one of them (panel 4aiii)), we have statistically significant upward and downward slopes for each figure. This indicates that these curves are definitely not flat.

These results imply that the timing of income shocks is relevant for human capital formation. If the timing of income was irrelevant then all these graphs would be horizontal lines, with only permanent income being relevant for human capital outcomes. Most likely, the reason why timing matters is that the timing of income shocks affects the timing of investments in human capital. This will happen if parents have imperfect insurance possibilities against income shocks.

It is especially interesting that there is an upward sloping section in each curve. One would think that, for a given level of permanent income, it should not be worse to receive all of the income in the first period than to receive it in spread out payments over different periods of childhood. If permanent income is fully available at time zero then one can allocate it freely across periods just by saving the appropriate amount, regardless of whether or not one can borrow.

This reasoning ignores uncertainty about income. When faced with income shocks, parents change their investments in children, unless they have perfect insurance. Savings alone cannot provide perfect insurance. In a scenario where parental investments will react to income shocks, the shape of the curves in figure 4 will tell us something about the technology of skill formation. So suppose we compare children in families with very volatile incomes, and therefore, volatile investments, with children in families with stable incomes (between periods 1 and 2). Then the latter will do much better, keeping constant total (permanent) income across the childhood years, if the technology exhibits complementarity between period 1 and period 2 investments, since in that case, you will want to maintain a stable flow of investments over the life of the child.

We should compare the upward and downward slopes in the different panels of figure 4, with the slope of the relationship between schooling attainment and permanent income, shown in figure 2. The slopes of the figures in figures 4ai)-ciii) are roughly half of those shown in figure 2. For example, a £100000 increase in permanent earnings leads to about an extra 0.5 years of education, while an increase in period 2's income from £0 to £100000 leads to about an extra 0.25 years of education. This means that, although the impact of the timing of income is smaller than that of permanent income, it is still quite substantial.

Figures 4di)-fiii) examine trade-offs between periods 1 and 3 income (keeping fixed period 2 income and permanent income) and show a similar inverse-U shape, although it is less pronounced that in the previous figures. Some of the graphs display curves that are mainly monotonically increasing such as, for example, figure 4diii). Again, if we take the view that uncertainty and partial insurance cause investments in children to reach somewhat to income shocks, these figures are telling us something about the technology. In particular, they are telling us that investments in the adolescent years are particularly productive (or particularly cheap) relatively to parental investments in the early years, and that investments very early and very late in the life of the child may be quite substitutable.

Alternatively, one could also be uncertain about the technology of skill formation (Badev and Cunha, 2012), or about a central input such as the underlying ability of the child. There can be shocks to the technology every period, which change the productivity of investments, or there can be learning about the technology. In addition, if one is uncertain about the ability of the child one may want to postpone investment until more of this uncertainty is revealed (for a related argument applied to inter-vivo transfers see Altonji, Hayashi and Kotlikoff, 1997).

Another issue we should consider is the addition to the model of time as a parental investment. Time and good investments can be complementary or substitutable, and the elasticity of substitution between these two types of investment may change with age. For example, investments in periods 1 and 2 of the child's life may be complements, but the aggregate of the two could be substitutable with investments in the last period of the child's life.

Finally, there could be issues related to preferences. For example, the parents' objective function may include other arguments beyond child's schooling, so depending on how the marginal rate of substitution between parental consumption and investments in children changes with the child's age, delayed parental income could lead to higher investments in children. There can also exist self-control issues. Parents could be unable or unwilling to save for future investments in children, and delayed income could act as forced savings (especially if there are borrowing constraints). We discuss these ideas in detail in section 5, where we simulate different models of parental investments in children, and examine their implications for the impact of the timing of income shocks on human capital formation.

Figures 4gi)-jiii) examine trade-offs between periods 2 and 3 income (keeping fixed period 3 income and permanent income). Most of the figures indicate that it is better to delay income from period 2 to period 3, although a few of the panels still display an inverse-U shape.

4.3.2 High School Drop Out and College Attendance

Instead of years of schooling, it is useful to consider high school dropout rates and college attendance rates separately, since they correspond to two groups of individuals, one in the lower tail and the other in the upper tail of the education distribution. These are shown in several panels in Figures 5ai)-jiii) (high school dropout) and Figures 6ai)-jiii).

Perhaps not surprisingly, results are quite similar to the ones we showed for years of education. High school dropout rates are minimized, and college attendance rates are maximized, when incomes are balanced between the early and middle childhood years (periods 1 and 2), keeping permanent income and income in adolescence fixed. When we increase income in adolescence (period 3), educational outcomes appear to improve, regardless of whether this is done at the expense of early chilldhood or middle childhood income.

Again, we can clearly reject that these curves are flat, by computing both α_1 and α_2 for each panel. The magnitudes of these impacts are substantial. An increase in permanent income of £100000 is associated with roughly a 10% decline in high school dropout rates and a 10% increase in college attendance rates. In comparison, a £100000 shift in income from period 1 to period 2 leads roughly to a 4% decrease in high school dropout and a 6% increase in college attendance.

4.3.3 Log Earnings at age 30

Next we present our results for the case where the outcome is log annual earnings at age 30. These are shown in Figure 7. Like before, panels 7ai) to 7ciii) are all remarkably similar, although they show a different pattern than the one observed before for education. Keeping PI and I_3 fixed, shifting income away from period 1 and towards period 2 leads to a sharp reduction in log earnings, followed by a flattening of the relationship. However, when we look at figures 7di) to 7fiii), and 7gi) to 7jiii), we observe the same pattern we had for education. Shifting income toward the adolescent years, and away from either the early childhood and the middle childhood years, leads to increases in log earnings at age 30.

The slopes of these curves are remarkably steep. For low values of I_1, a £100000 shift in income from I_1 to I_2 (keeping PI and I_3 fixed) leads to a 5-15% decline in wages. A shift of either £100000 in I_1 or I_2 towards I_3 generates gains in earnings close to 5%. These figures are very large, especially in light of the fact that a £100000 increase in PI is associated with a 10% increase in log earnings at age 30.

4.3.4 IQ and Health (males only)

As mentioned above, from the army records it is possible to extract information about IQ and self-reported health status for males at age 18. These are analyzed in Figures 8 and 9, respectively.

Starting with IQ (Figure 8), and examining the trade-off between I_1 and I_2 (Figures 8ai)-8ciii)), there is no obvious pattern, which is in contrast with the results we have had so far. In the top panels (low PI), and in two of the panels in the second row (PI fixed at its median), the curve is clearly increasing. In the other panels it is flat, decreasing, or U-shaped. However, when we study the trade-offs between I_1 and I_3 (Figures 8di)-8fiii)), and I_2 and I_3 (Figures 8gi)-8jiii)), the results clearly indicate that shifting income towards adolescence is associated with higher levels of IQ. This is a result which is common to all the outcomes we have seen so far.

In what regards health, and in contrast to what we have seen so far, delaying income from I_1 to I_2 seems to lead to poorer health outcomes although the patterns are not incredibly clear, and we cannot reject that about half the curves in Figures 9ai)-9ciii) are flat lines. The curves in panels 9di)-9fiii) are either increasing or flat, but again the pattern are not clear. The results are even less consistent across panels 9gi)-9jiii). The estimates are also relatively more imprecise in this case than for the outcomes studied so far.

4.3.5 Teenage Pregnancy (females only)

The graphs for teenage pregnancy, shown in Figures 10, present patterns similar to those shown for education outcomes. In particular, teenage pregnancy is minimized when there is a balance between I_1 and I_2, and when there is a shift in income from I_1 to I_3, and from I_2 to I_3. This is quite remarkable given that educational attainment and teenage pregnancy are two very different variables.

Nevertheless, because teenage pregnancy is only observed for females, and that it is a relatively infrequent phenomenon, these estimates are more imprecise than the ones presented above for education outcomes.

Once again, the impacts of the timing of income in teenage pregnancy are sizeable.

4.3.6 Grades in School

Unfortunately the nonparametric results for grades in school are too imprecise to be informative. They are shown in the different panels of Figure 11.

The parametric graphs corresponding to this outcome and shown in the last panels of Figure 2 are more precise. They show that grades are increasing in permanent income. They also show that grades decline as income is shifted from period 1 to period 2 of the child's life. And they increase when one shifts income from period 1 to period 3. For the other outcomes we have studied the parametric results were a good first guide to the nonparametric results.

4.3.7 Low Birthweight

As a check to the validity of our procedure it is useful to examine whether the timing of income predicts characteristics of the child that existed before the shocks to income ever happened, i.e., pre-determined characteristics. Under our assumptions, the timing of income should not impact such variables. One example is the probability that a given child is born with low birthweight.

In Figures 12ai)-12ciii) we present results from a regression of a low birthweight dummy on (PI, I_2, I_3). It is not possible to reject that these lines are flat. The same pattern emerges in Figures 12di)-12jiii). suggesting that our methodology is indeed valid.

5 Discussion

5.1 Theoretical framework

The question of how the timing of parental investment drives child outcomes can be addressed by building in theoretical models of parental investments in children.[7]. In these models, parents decide consumption, savings and child investments in each period of the childhood according to a budget constraint which might include permanent and transitory components of income, and borrowing constraints. Investments in every period drive human capital accumulation entering as inputs of a technology of skill formation characterized by self-productivity and dynamic complementarity in inputs.

As we do not observe investments in the data, a useful excercise to validate our findings is to calibrate such a model and simulate the impact of shifting away income shocks between periods on human capital accumulation to see whether we can reproduce the data patterns. In the data we do not observe parental investment directly, but parental income. Simulations will also allow us to analyze whether income shocks affect human capital formation by changing the optimal ratio of investments across periods, which is the underlying channel we propose as a justification of our empirical findings. With complete markets and no uncertainty, there should be no differential effect of the timing of income. Parents can borrow and save, in order to smooth their investment in child human capital. Consequently, for a given level of permanent income, shifting income across periods of childhood should have no effect upon child human capital. In our model, we aim to explore potential complementarities in income across periods by simulating a model in which agents face income uncertainty and borrowing constraints, both of them failures of the permanent income hypothesis, and contrast those patterns with what we find in the data.

Consistently with the empirical strategy, we calibrate a four-period model, three periods for the childhood stages and a terminal period for the realization of the child's human capital when she becomes an adult. An important feature of the model is the inclusion of different sources of uncertainty, which requires a recursive numerical solution using dynamic programming techniques. In principle, we consider temporary income shocks as the only source of

[7]Examples are Cunha (2005), Cunha *et al* (2005), Cuhna *et al* (2006) and Cunha and Heckman (2007, 2008).

uncertainty, but we then move away to more complex specifications in which we also include technology shocks and termporary and permanent income shocks.

We use a flexible specification for the technology of skill formation, a CES production function, where human capital at age (t), (H_{t+1}), is a function of the current human capital stock (H_t) and the investment (X_t)

$$H_{t+1} = \left[(1-\gamma_t)H_t^{\phi} + \gamma_t X_t^{\phi}\right]^{\frac{\rho}{\phi}} \tag{8}$$

and where(γ_t) denote the productivity of investment in (t) and ρ is the subjective discount rate. ϕ denotes the complementarity of investment across periods, which takes the value 1 if investments are perfect substitutes and -∞ if investments are perfect compliments.

Overall productivity of investments in each period depends on two important features: self-productivity of the current human capital stock, captured by $((1-\gamma_t))$, and dynamic complementarity between investments across periods (i) and (j), defined as the change in returns to early (late) investment by increasing the level of later (early) investment, that is, if $\frac{\delta^2 H_t}{\delta X_i \delta Xj} > 0$ and *vice versa.*

Regarding preferences, we impose the assumption that households are indivisible decision-maker units with standard CRRA preferences of the form

$$u(C_t) = \frac{C_t^{1-\sigma}}{1-\sigma} \tag{9}$$

where (C_t) is per-period household consumption, facing a standard budet constraint

$$B_{t+1} = (1+r)B_t + I_t(\varepsilon_t) - pX_t + C_t \tag{10}$$

where (p) is the relative price between invstment and consumption, (B_t) is the asset position, and $(I_t(\varepsilon_t))$ is the per-period income, for which we use a simple specification as a function of iid income shocks (ε_t), a minimum income (b), and a flat wage (w)

$$I_t(\varepsilon_t) = b + w\exp(\varepsilon_t) \tag{11}$$

At each childhood stage parents observe a set of state variables and decide consumption and investments. The state space is given by $(\Omega_t = \{H_t, B_t, \varepsilon_t\})$ and the value function given by $(V(\Omega_t))$. The model is solved by backward recursion using numerical methods, where parents maximize the bellman equation

$$V(\Omega_t) = \max_{C_t, X_t}\{u(C_t) + \beta E\{V(\Omega_{t+1})|\Omega_t\} \tag{12}$$

subject to the budget constraint, the technology of skill formation, and a parametrized terminal value function in $(T = 4)$, in which parents value both the level of human capital acquired by their children when they become adults (H_T), and household assets (B_T).

The solution procedure involves the multidimensional approximation of the value function in three continue state variables. We found that Chebyshev polynomials performed very well in approximating our value functions using a large set of Chebyshev extrema for each state variable. Furthermore, in order to avoid the curse of dimensionality problem by using very large approximation grids, which increase exponentially with the number of state variables, we pick up a reduced grid set of points by applying the Smolyak Algorithm (Smolyak, 1963), strategy suggested for the solution of problems with many continue states variables by Malin, Krueger and Kubler (2009).

5.2 Predictions and Simulations

In a simple two period model, Cunha and Heckman (2006) derive an equation for the optimal dynamic investment into child human capital as

$$\log\left(\frac{X_1}{X_2}\right) = \left(\frac{1}{1-\phi}\right)\log\left(\frac{\gamma}{(1-\gamma)}\right) - \left(\frac{1}{1-\phi}\right)\log\left(1+r\right) \tag{13}$$

where (γ) and $((1-\gamma))$ are the productivities of investments in periods 1 and 2 respectively. Optimal investment shifts towards the period where the investment is most productive, at any given interest rate. Additionally, optimal investment depends upon the degree of complementarity of investment across periods. In the case of perfect compliments $(\phi \longrightarrow -\infty)$, for example, optimal investment is such that $X_1^* = X_2^*$ and consequently an even bundle of investment in each period is optimal, rather than extreme bundles, which is the case when investments are highly substitutes $(\phi \longrightarrow 1)$. We calibrate our model at different values of (γ_t) and (ϕ) using range of values that have been estimated by Cunha, Heckman and Schennach (2010).

To see how borrowing constraints affect optimal investment ratios, we can extend the two-period model solution to the case when parents face borrowing constraint in period 1. In this case there is now an extra term for the marginal rate of substitution of consumption $\left(\frac{u'(c_1)}{u'(c_2)}\right)$.

$$\log\left(\frac{X_1}{X_2}\right) = \frac{1}{1-\phi}\log\left(\frac{\gamma}{(1-\gamma)}\right) - \frac{1}{1-\phi}\log\left(1+r\right) + \frac{1}{1-\phi}\log\frac{u'\left(c_1\right)}{u'\left(c_2\right)} \tag{14}$$

The extra term on the right of equation () is non-zero if the borrowing constraint binds. With a binding borrowing constraint, c_1 is suboptimally low and consequently $\frac{u'(c_1)}{u'(c_2)} > 0$.The results imply that dynamic income fluctuations of credit constrained parents will drive parental investment in child human capital and consequently there will be an effect of differential timing of parental income.

6 Conclusion

The question of whether early or late income is most productive in producing child human capital is important in order to further our understanding of how the stock of adult human capital accumulates. Should policy be targeted towards very young children, or adolescents, in order to reduce child inequalities in achievement later in life? Our dataset consists of the population of children born in Norway in the 1970s. The large scale of this allows us to estimate the relationship between child's education and the income received in their early years from 0-5, the middle period aged 6-11 and during adolescence aged 12-17, in a semi-parametric setting. The benefits of this choice of methodology are evident from the subtleties of the interactions between income in the three periods that can be evaluated. We find that early years income (age 0-5) is as important in general as income aged 6-11 and as income during adolescence. One exception to this rule is that for the outcome college attendance, an increase in adolescent income at the expense of early income will raise participation at college. There are complementarities across adjacent periods, suggesting that an even bundle of income across periods is optimal, compared to extreme levels. Put another way, when income in any period falls below a threshold, it does so to the detriment of child human capital. These results are robust to the choice of bandwidth and to a semiparametric specification where we control for a detailed set of family inputs.

That we do not find a strategically different pattern for the poorer families, likely to face credit constraints is not entirely surprising. In their test of a prediction of the permanent income hypothesis, that contemporary consumption responds only to unpredictable changes in income, Shapiro and Slemrod (1995), Parker (1997) and Souleles (1999) all find the same pattern for credit constrained households as all others.

There are policy implications from the results of our study. No empirical paper to date has explicitly estimated the return to parental investment in each year of a child's lifetime, however papers cited above suggest that productivity is highest in the early years. As parental investment is a harder object for government policy to define and target, it is possible to instead provide income for families during the periods of high productivity.

References

[1] Aakvik, A., Salvanes, K. and Vaage, K. (2005). "Educational attainment and family background". The German Economic Review. Special Issue on the Economics of Education.

[2] Almond, D. and Currie, J. (2010). 'Human capital development before age five', NBER Working Paper 15827.

[3] Black, S. and Paul Devereux. (2011). 'Recent Developments in Intergenerational Mobility, in Handbook of Labor Economics', Orley Ashenfelter and David Card, editors, North Holland Press.

[4] Black, S., Devereux, P. and Salvanes, K. G. (2005). 'Why the apple doesn't fall far: understanding intergenerational transmission of human capital', The American Economic Review, 95(1), pp. 437-449.

[5] Black, S., Devereux, P. and Salvanes, K. (2008) "Too young to leave the nest? The effects of school starting age." IZA DP No. 3452.

[6] Bjørklund, A. and Salvanes, K. G. (2010). 'Education and family background: Mechanisms and policies', in Hanushek, Eric, Stephen Machin and Ludger Woessmann, Handbook in Economics of Education, 201-247, North-Holland.

[7] Bohlmark, A. and Lindquist, M. J. (2006). 'Life-Cycle Variations in the Association between Current and Lifetime Income: Replication and Extension for Sweden', Journal of Labor Economics 24, pp.879–896.

[8] Cameron, S. V. and Heckman, J. J. (2001). 'The dynamics of educational attainment for black, Hispanic, and white males.' Journal of Political Economy, 109(3), pp. 455-499.

[9] Cameron, S. V. and Taber, C. (2004). 'Estimation of educational borrowing constraints using returns to schooling', Journal of Political Economy, 112(1), pp. 132-181.

[10] Card, David E. (1999), 'The causal effect of education on earnings', in O. Ashenfelter and D. Card, eds., The Handbook of Labor Economics Volume III, Amsterdam: Elsevier.

[11] Carneiro, P. and Heckman, J. J. (2002). 'The evidence on credit constraints in post-secondary schooling', Economic Journal, 112(482), pp. 989-1018

[12] Carneiro, P. and Heckman, J. J. (2003). 'Human capital policy', in Heckman, J. J. and Krueger, A. Inequality in America: What Role for Human Capital Policies, MIT Press.

[13] Carneiro, P., Løken, K. and Salvanes, K. G. (2011). 'A Flying Start? Maternity Leave Benefits and Long Run Outcomes of Children', IZA DP No. 5793.

[14] Carneiro, P., Meghir, C. and Parey, M. (2012). 'Maternal education, home environments and the development of children and adolescents', Journal of the European Economic Association

[15] Caucutt, E. M. and Lockner, L. 'Early and Late Human Capital Investments, Borrowing Constraints, and the Family', NBER Working Paper 18493.

[16] Cunha, F. (2005). 'The complementarity and self-productivity of investments in human capital in a stochastic dynamic general equilibrium economy with altruism and lifetime liquidity constraints' PhD thesis, The University of Chicago.

[17] Cunha, F. and Heckman, J. J. (2006). 'Investing in our young people'

[18] Cunha, F. and Heckman, J. J. (2007). "The technology of skill formation", American Economic Review, (Papers and Proceeding) 97(2) 31-47.

[19] Cunha, F. and Heckman, J. J. (2008) "Formulating, identifying and estimating the technology of cognitive and noncognitive skill formation," Journal of Human Resources, University of Wisconsin Press, 43(4), pp.738-782.

[20] Cunha, F., Heckman, J. J., Lochner, L. and Masterov, D. (2005). 'Interpreting the evidence on life cycle skill formation', In Handbook of the Economics of Education. E. Hanushek, F. Welch, editors.

[21] Cunha, F., Heckman, J. J. and Schennach, S. (2010). 'Estimating the technology of cognitive and noncognitive skill formation', Econometrica.

[22] Currie, J. and Moretti, E. (2003). 'Mother's education and the intergenerational transmission of human capital: evidence from college openings', Quarterly Journal of Economics, VCXVIII(4), pp. 1495-1532.

[23] Currie, J., Stabile, M., Manivong, P. and Roos, L. L. (2010). 'Child health and young adult outcomes". Forthcoming in Journal of Human Resources.

[24] Currie, J. and Thomas, D. (1995). 'Does head start make a difference?', The American Economic Review, 85(3), pp. 341-364.

[25] Currie, J. and Thomas, D. (2000). 'School quality and the longer-term effects of head start', Journal of Human Resources, 35(4), pp. 755-774.

[26] Dearden, L, S. Machin and H. Reed. (1997). 'Intergenerational mobility in Britain.', Economic Journal, 107, 47-66.

[27] Doyle, O., Harmon, C. and Walker, I. (2007). "The impact of parental income and education on child health : further evidence for England," The Warwick Economics Research Paper Series (TWERPS) 788.

[28] Fan, J. and Gijbels, I. (1996). 'Local polynomial modelling and its applications'. Chapman and Hall.

[29] Grossman, M. (2004). 'The demand for health, 30 years later: A very personal retrospective and prospective reflection.' Journal of Health Economics, 23(4), pp. 629–636.

[30] Hægeland, T., Raaum, O. and Salvanes, K. (2008). "Pennies from heaven? Using exogenous tax variation to identify effects of school resources on pupil achievement." IZA Working Paper 3561.

[31] Haider, S. and Solon, G. (2006). 'Life-Cycle Variations in the Association between Current and Lifetime Earnings', American Economic Review 96, pp. 1308–1320.

[32] Hall, R (1978) "Stochastic implications of the life-cycle permanent income hypothesis". (1978). Journal of Political Economy, 86(6), pp. 971-987.

[33] Heckman, J. J., Moon, S. H., Pintoa, R., Savelyeva, P. A and Yavitza, A. (1999). 'The rate of return to the high/scope Perry Preschool Program." NBER Working Paper 15471.

[34] Jenkins, S. P. and Schluter, C. (2002). "The effect of family income during childhood on later-life attainment: evidence from Germany", IZA Discussion Paper, 604.

[35] Joshi, H., Cooksey, E. C., Wiggins, R. D., McCulloch, A., Verropoulou, G. and Clarke, L. (1999). "Diverse family living situations and child development: a multi-level analysis comparing longitudinal evidence from Britain and The United States", International Journal of Law, Policy and the Family, 13(3), pp.292-314.

[36] Keane, M. P. and Wolpin, K.I. (2001). "The effect of parental transfers and borrowing constraints on educational attainment". Internal Economic Review, 42 (November), pp. 1051-1103.

[37] Levy, D. M. and Duncan, G. (2000). "Using sibling samples to assess the effect of childhood family income on completed schooling", JCPR Working Paper, 168.

[38] Meyer, S. (1997), 'What money can't buy: family income and children's life chances.' Cambridge: Harvard University Press.

[39] Mogstad, M. and Havnes, T. (2011). 'No Child Left Behind: Subsidized Child Care and Children's Long-Run Outcomes', American Economic Journal: Economic Policy, 3, pp. 97-129.

[40] Nilsen, V., Aakvik, A. and Jacobsen, K. (2011). 'Intergenerational Earnings Mobility Revisited: Estimates Based on Lifetime Earnings'. Scandinavian Journal of Economics, 114(1), pp.1-23.

[41] Parker, J. A. (1997). "The reaction of household consumption to predictable changes in payroll tax rates", Wisconsin Madison Working Paper 9724.

[42] Robinson, P. (1988). 'Root-N-consistent semiparametric regression', Econometrica, 56(4), pp. 931-954.

[43] Ruppert, D. and Wand, M. P. (1994). 'Multivariate locally weighted least squares regression', The Annals of Statistics, 22(3), pp. 1346-1370.

[44] Shapiro, M. D. and Slemrod, J. (1995). "Consumer response to the timing of income: evidence from a change in tax withholding", American Economic Review, 85(1), pp.274-283.

[45] Shea, J. (2000). 'Does parents' money matter?', Journal of Public Economics, 77(2), pp. 155-184

[46] Solon, Gary (1999). 'Intergenerational mobility in the labor market.' In Handbook of Labor Economics, Volume 3. O. Ashenfelter and D. Card, editors. pp.1761-1800.

[47] Souleles, N. S. (1999). "The response of household consumption to income tax refunds". The American Economic Review, 89(4), pp. 947-958.

[48] Sundet, J. M., Barlaug, D. G. and Torjussen, T. M. (2004) "The end of the Flynn effect? A study of secular trends in mean intelligence test scores of Norwegian conscripts during half a century", Intelligence, 32(4), pp. 349-362.

[49] Sundet, J. M., Tambs, K., Harris, J. R. Torjussen, T. M. (2005) "Resolving the genetic and environmental sources of the correlation between height and intelligence: a study of nearly 2600 Norwegian male twin pairs," Twin Research and Human Genetics, 8(4), pp. 1-5.

[50] Tominey, E. (2010). "The Timing of Parental Income and Child Outcomes: The Role of Permanent and Transitory Shocks.". MIMEO.

[51] Van den Berg, G.J., M. Lindeboom and F. Portrait (2006), 'Economic conditions early in life and individual mortality.' American Economic Review 96(1), pp.290-302.

7 Figures and Tables

Figure 1: Parametric Estimates. Paternal Income 0-17 and Years of Schooling.

Paternal Income 0-17 and Schooling

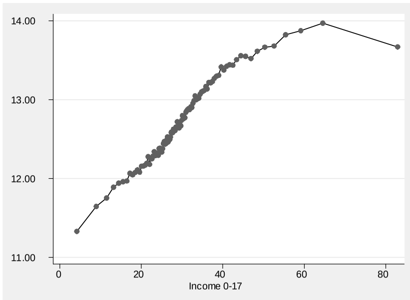
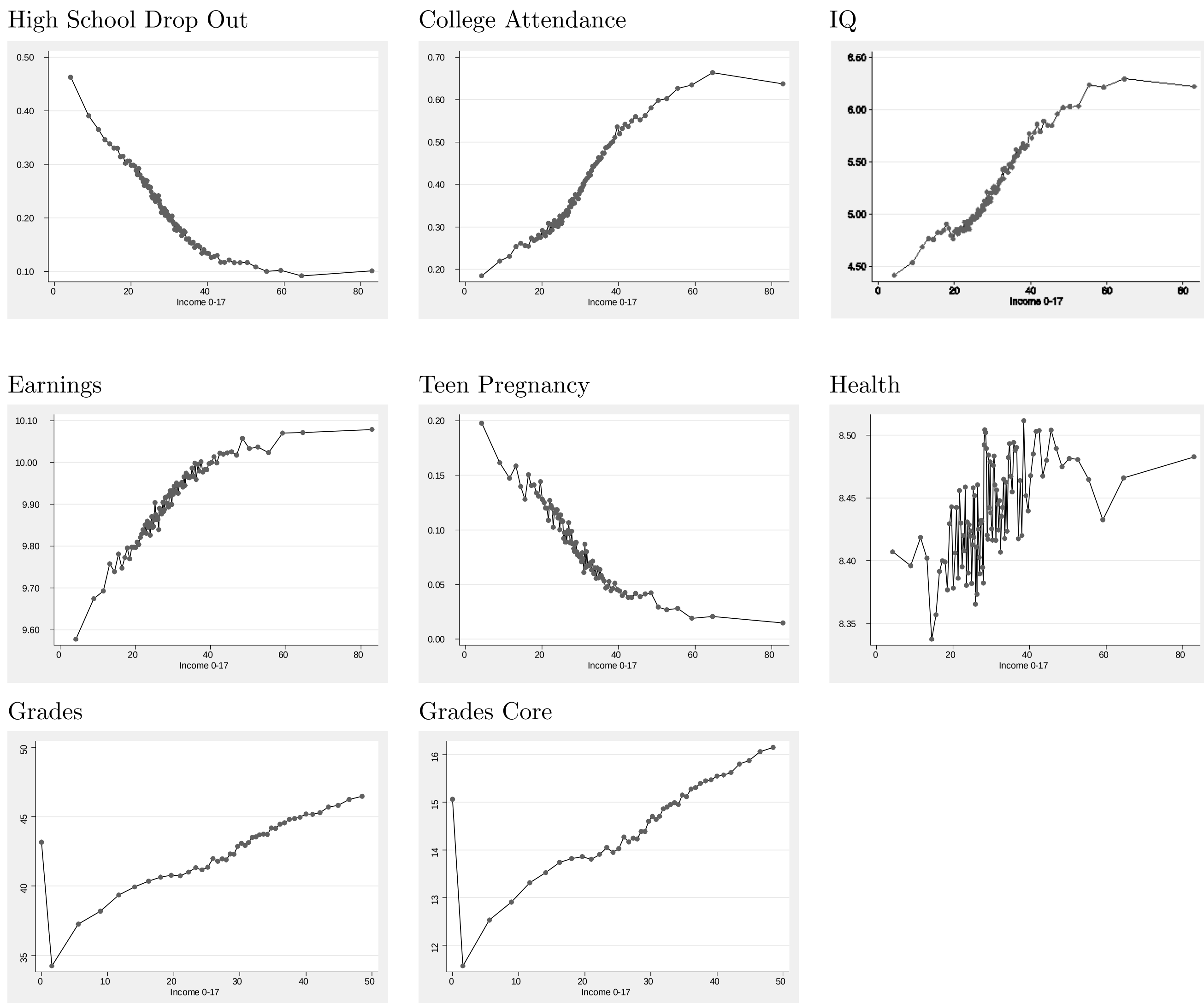


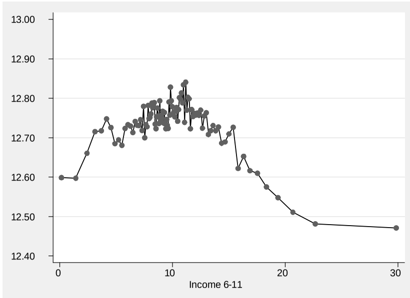
Figure 2: Parametric Estimates. Paternal Income 0-17 and Human Capital Outcomes.



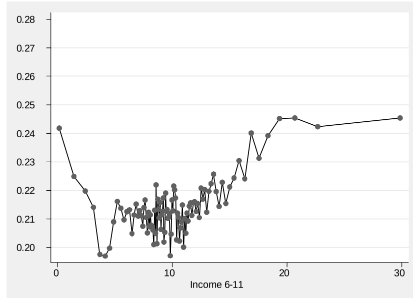
Graphs plot individual coefficients from regression of decile bins for I2, I3, P upon child human capital controlling for heterogeneous income profile and dummy variables for paternal education.. Conditional results control additionally for gender, maternal education and age, paternal age, marital breakup, number of children and child year of birth dummies.

Figure 3a: Parametric Estimates. Paternal Income 6-11 and Human Capital Outcomes

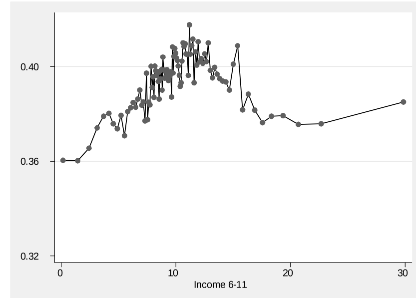
Years of Schooling



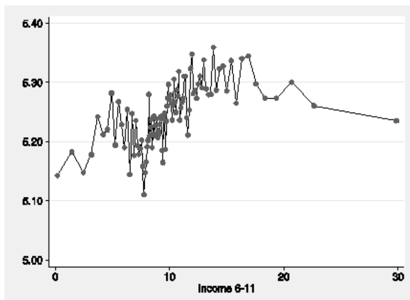
High School Dropout



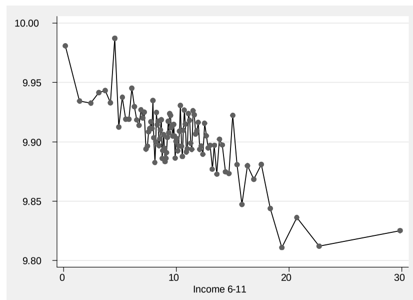
College Attendance



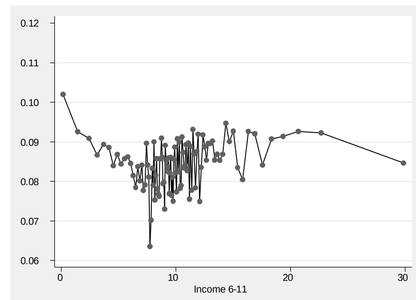
IQ



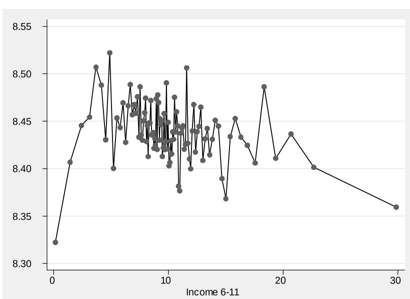
Earnings



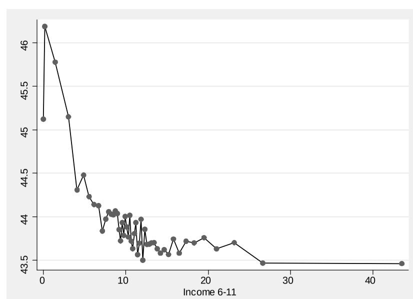
Teen Pregnancy



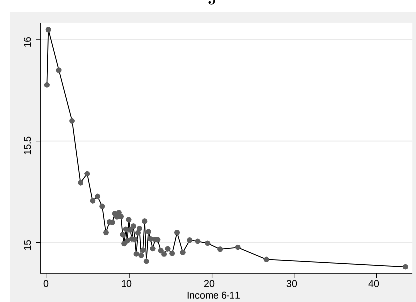
Health



Grades



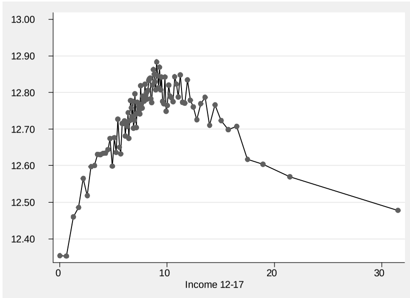
Grades Core Subjects



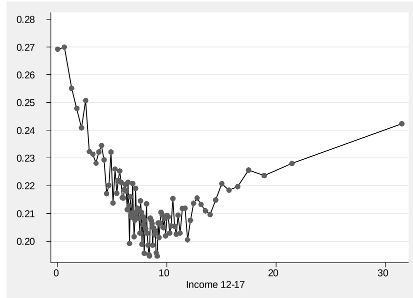
Graphs plot individual coefficients from regression of decile bins for I2, I3, P upon child human capital controlling for heterogeneous income profile and dummy variables for paternal education.. Conditional results control additionally for gender, maternal education and age, paternal age, marital breakup, number of children and child year of birth dummies.

Figure 3b: Parametric Estimates. Paternal Income 12-17 and Human Capital Outcomes

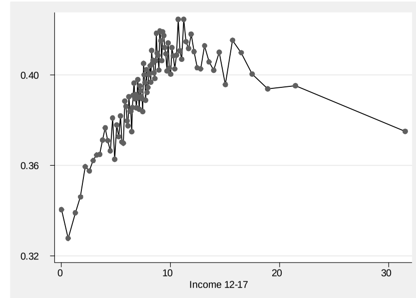
Years of Schooling



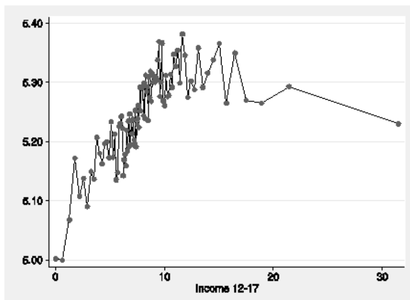
High School Dropout



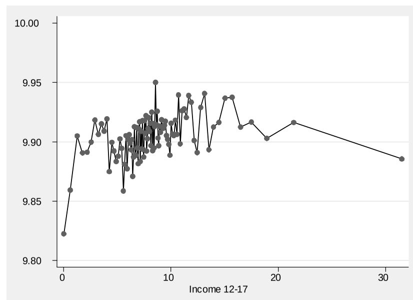
College Attendance



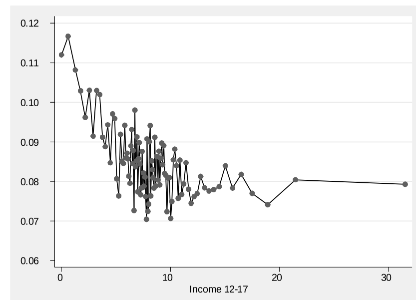
IQ



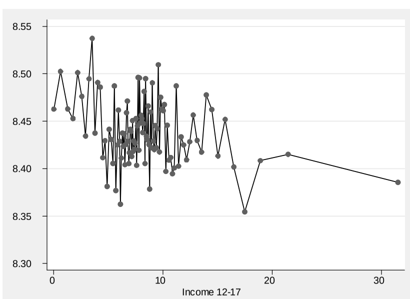
Earnings



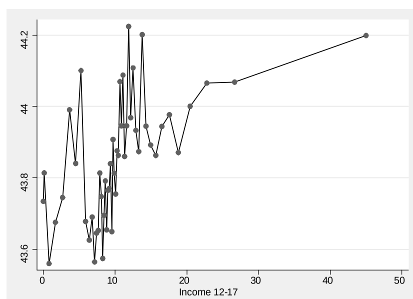
Teen Pregnancy



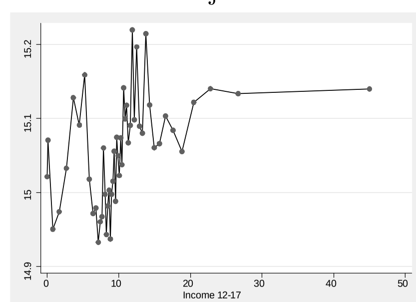
Health



Grades



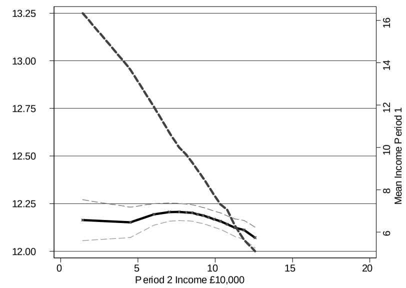
Grades Core Subjects



Graphs plot individual coefficients from regression of decile bins for I2, I3, P upon child human capital controlling for heterogeneous income profile and dummy variables for paternal education.. Conditional results control additionally for gender, maternal education and age, paternal age, marital breakup, number of children and child year of birth dummies.

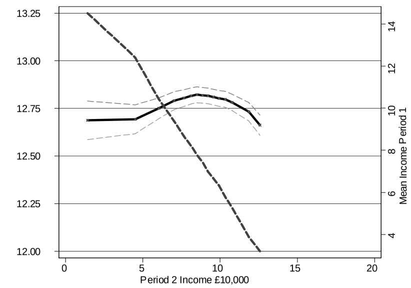
Figure 4: Semi Parametric Estimates. Dependent variable is Years of Schooling.

4ai) I3=6.34, PI=24.18



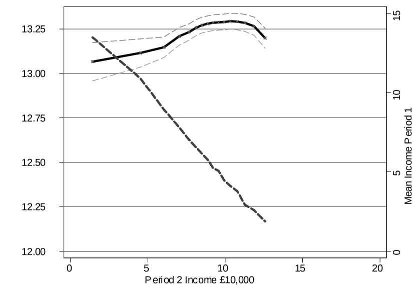
$\hat{\alpha}_1 = \mathbf{0.15}\,(0.09)$ $\hat{\alpha}_2 = -\mathbf{0.24}\,(0.05)$

4aii) I3=7.49, PI=24.18



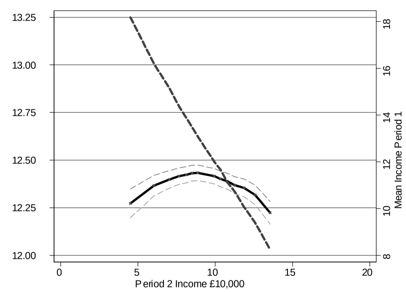
$\hat{\alpha}_1 = \mathbf{0.25}\,(0.08)$ $\hat{\alpha}_2 = -\mathbf{0.21}\,(0.05)$

4aiii) I3=9.32, PI=24.18



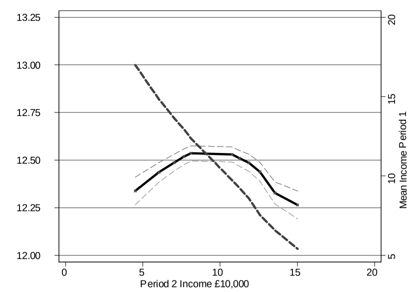
$\hat{\alpha}_1 = \mathbf{0.32}(0.09)$ $\hat{\alpha}_2 = -0.06\,(0.05)$

4bi) I3=6.34, PI=28.24



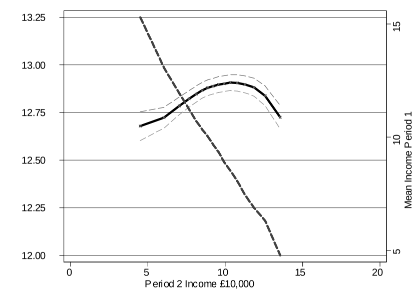
$\hat{\alpha}_1 = \mathbf{0.29}\,(0.06)$ $\hat{\alpha}_2 = -\mathbf{0.23}\,(0.06)$

4bii) I3=7.49, PI=28.24



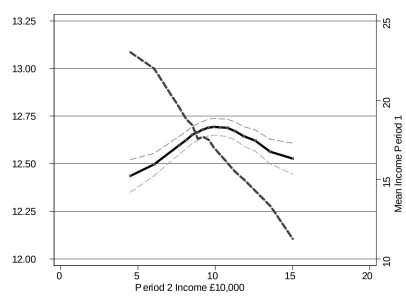
$\hat{\alpha}_1 = \mathbf{0.33}\,(0.08)$ $\hat{\alpha}_2 = -\mathbf{0.25}\,(0.06)$

4biii) I3=9.32, PI=28.24



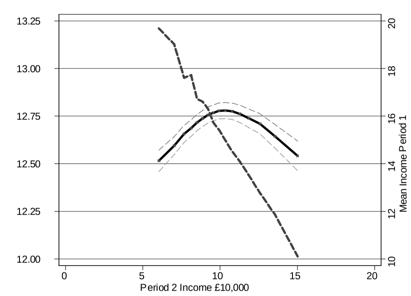
$\hat{\alpha}_1 = \mathbf{0.30}\,(0.09)$ $\hat{\alpha}_2 = -\mathbf{0.15}\,(0.05)$

4ci) I3=6.34, PI=32.93



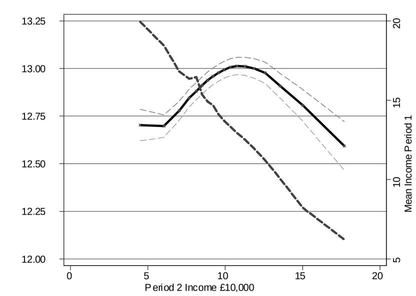
$\hat{\alpha}_1 = \mathbf{0.38}\,(0.07)$ $\hat{\alpha}_2 = -\mathbf{0.15}\,(0.07)$

4cii) I3=7.49, PI=32.93



$\hat{\alpha}_1 = \mathbf{0.36}\,(0.05)$ $\hat{\alpha}_2 = -\mathbf{0.25}\,(0.07)$

4ciii) I3=9.32, PI=32.93

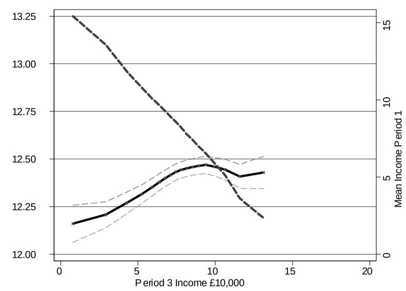


$\hat{\alpha}_1 = \mathbf{0.33}(0.07)$ $\hat{\alpha}_2 = -\mathbf{0.38}\,(0.10)$

Note: 95% confidence intervals shown. Income in 2000 prices, £10,000s.

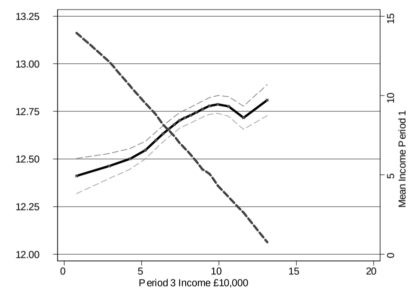
Figure 4: Semi Parametric Estimates. Dependent variable is Years of Schooling.

4di) I2=8.13, PI=24.18



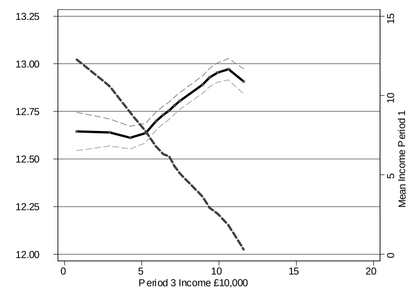
$\hat{\alpha}_1 = \mathbf{0.45}\,(0.08)$ $\hat{\alpha}_2 = -\mathbf{0.27}\,(0.10)$

4dii) I2=12.39, PI=24.18



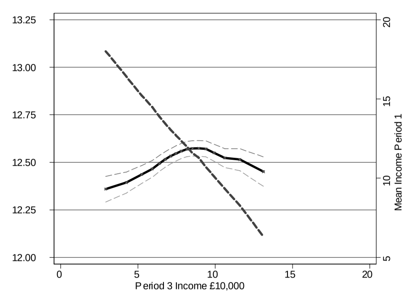
$\hat{\alpha}_1 = \mathbf{0.33}\,(0.08)$ $\hat{\alpha}_2 = -0.07\,(0.06)$

4diii) I2=11.26, PI=24.18



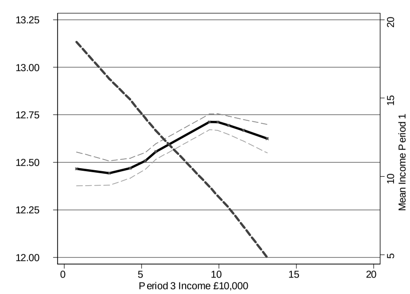
$\hat{\alpha}_1 = 0.13(0.09)$ $\hat{\alpha}_2 = \mathbf{0.27}\,(0.06)$

4ei) I2=8.13, PI=28.24



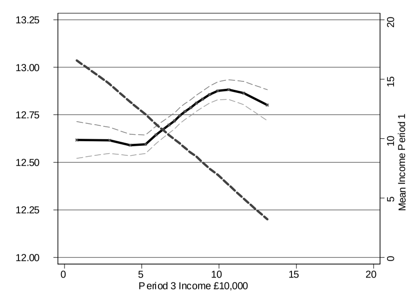
$\hat{\alpha}_1 = \mathbf{0.28}\,(0.07)$ $\hat{\alpha}_2 = -\mathbf{0.11}\,(0.07)$

4eii) I2=12.39, PI=28.24



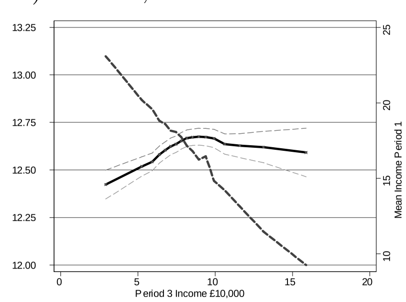
$\hat{\alpha}_1 = \mathbf{0.32}\,(0.07)$ $\hat{\alpha}_2 = -\mathbf{0.32}\,(0.09)$

4eiii) I2=11.26, PI=28.24



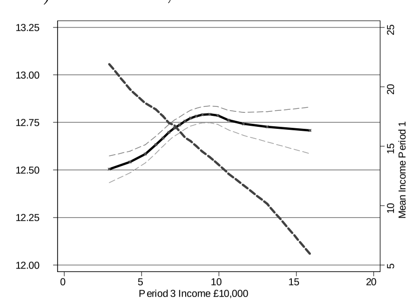
$\hat{\alpha}_1 = \mathbf{0.22}(0.08)$ $\hat{\alpha}_2 = 0.11\,(0.07)$

4fi) I2=8.13, PI=32.93



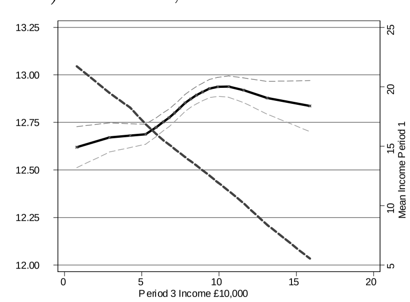
$\hat{\alpha}_1 = -0.12\,(0.08)$ $\hat{\alpha}_2 = -0.14\,(0.10)$

4fii) I2=12.39, PI=32.93



$\hat{\alpha}_1 = \mathbf{0.50}\,(0.06)$ $\hat{\alpha}_2 = -0.13\,(0.10)$

4fiii) I2=11.26, PI=32.93

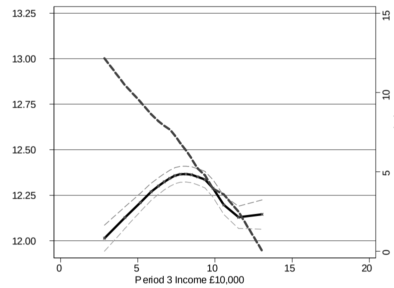


$\hat{\alpha}_1 = \mathbf{0.25}(0.09)$ $\hat{\alpha}_2 = 0.02\,(0.11)$

Note: 95% confidence intervals shown. Income variables are in 2000 prices, in UK sterling in £10,000s.

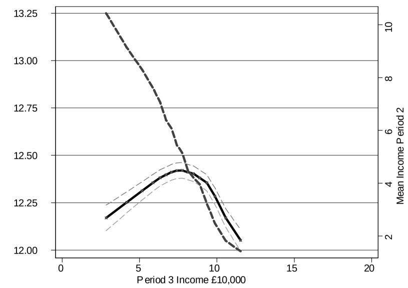
Figure 4: Semi Parametric Estimates. Dependent variable is Years of Schooling.

4gi) I1=10.91, PI=24.18



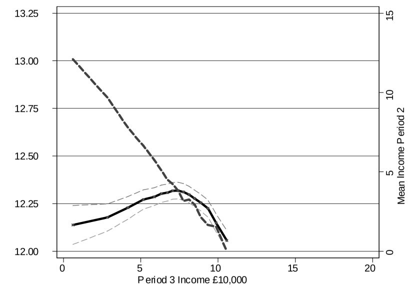
$\hat{\alpha}_1 = 0.08\,(0.06)$ $\hat{\alpha}_2 = -\mathbf{0.26}\,(0.05)$

4gii) I1=13.02, PI=24.18



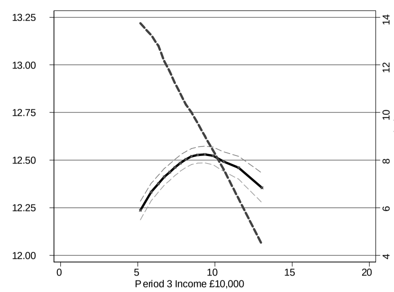
$\hat{\alpha}_1 = \mathbf{0.14}\,(0.05)$ $\hat{\alpha}_2 = -\mathbf{0.33}\,(0.07)$

4giii) I1=15.64, PI=24.18



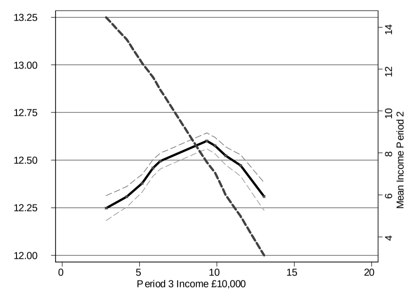
$\hat{\alpha}_1 = 0.07(0.04)$ $\hat{\alpha}_2 = -0.12\,(0.08)$

4hi) I1=10.91, PI=28.24



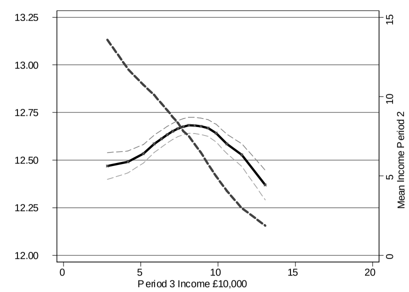
$\hat{\alpha}_1 = -0.02\,(0.10)$ $\hat{\alpha}_2 = -\mathbf{0.29}\,(0.05)$

4hii) I1=13.02, PI=28.24



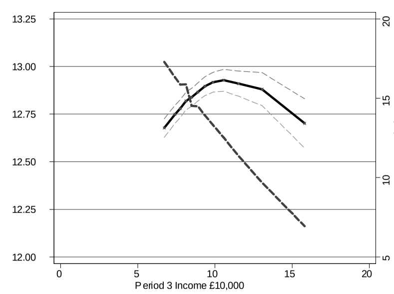
$\hat{\alpha}_1 = \mathbf{0.11}\,(0.05)$ $\hat{\alpha}_2 = -\mathbf{0.30}\,(0.06)$

4hiii) I1=15.64, PI=28.24



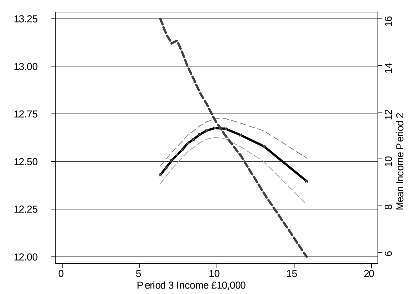
$\hat{\alpha}_1 = \mathbf{0.10}(0.04)$ $\hat{\alpha}_2 = -\mathbf{0.20}\,(0.07)$

4ji) I1=10.91, PI=32.93



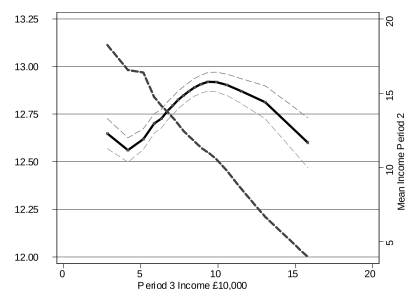
$\hat{\alpha}_1 = -\mathbf{0.19}\,(0.10)$ $\hat{\alpha}_2 = -\mathbf{0.19}\,(0.05)$

4jii) I1=13.02, PI=32.93



$\hat{\alpha}_1 = -\mathbf{0.05}\,(0.06)$ $\hat{\alpha}_2 = -\mathbf{0.33}\,(0.05)$

4jiii) I1=15.64, PI=32.93

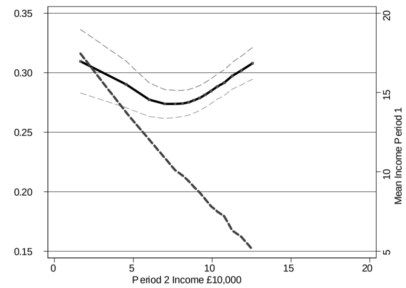


$\hat{\alpha}_1 = \mathbf{0.03}\,(0.06)$ $\hat{\alpha}_2 = -\mathbf{0.27}\,(0.10)$

Note: 95% confidence intervals shown. Income variables are in 2000 prices, in UK sterling in £10,000s.

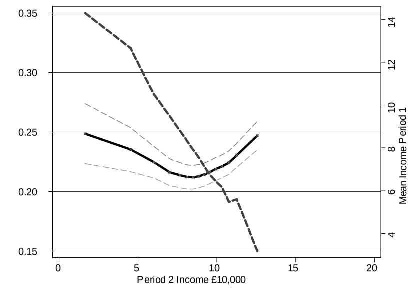
Figure 5: Semi Parametric Estimates. Dependent variable is High School Dropout.

5ai) I3=6.34, PI=24.18



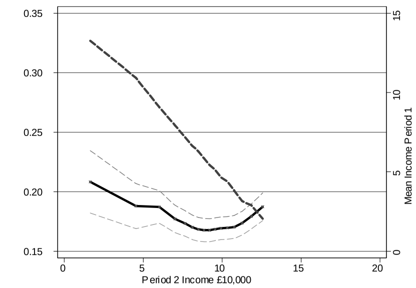
$\hat{\alpha}_1 = -\mathbf{0.03}(0.01)$ $\hat{\alpha}_2 = \mathbf{0.03}(0.01)$

5aii) I3=7.49, PI=24.18



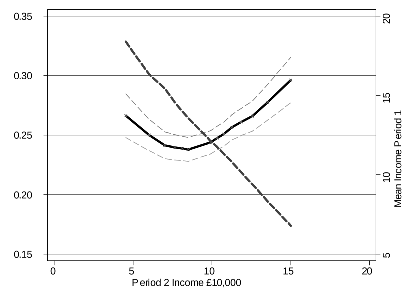
$\hat{\alpha}_1 = -\mathbf{0.04}(0.01)$ $\hat{\alpha}_2 = \mathbf{0.03}(0.01)$

5aiii) I3=9.32, PI=24.18



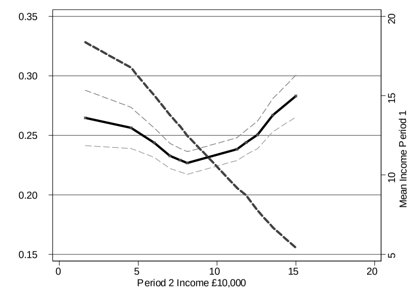
$\hat{\alpha}_1 = -\mathbf{0.04}(0.01)$ $\hat{\alpha}_2 = \mathbf{0.02}(0.01)$

5bi) I3=6.34, PI=28.24



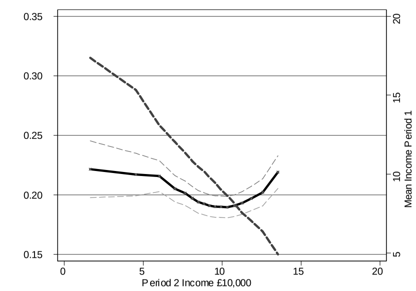
$\hat{\alpha}_1 = -\mathbf{0.03}(0.01)$ $\hat{\alpha}_2 = \mathbf{0.06}(0.01)$

5bii) I3=7.49, PI=28.24



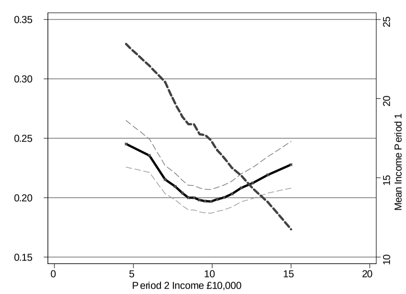
$\hat{\alpha}_1 = -\mathbf{0.04}(0.01)$ $\hat{\alpha}_2 = \mathbf{0.06}(0.01)$

5biii) I3=9.32, PI=28.24



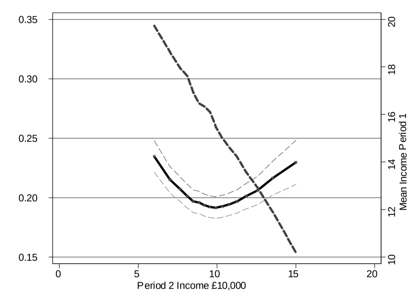
$\hat{\alpha}_1 = -\mathbf{0.03}(0.01)$ $\hat{\alpha}_2 = \mathbf{0.03}(0.01)$

5ci) I3=6.34, PI=32.93



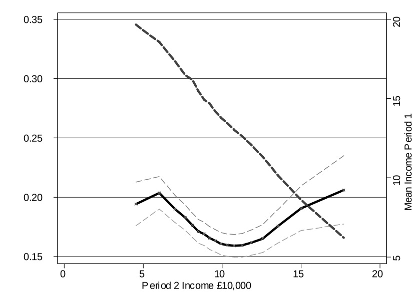
$\hat{\alpha}_1 = -\mathbf{0.05}(0.01)$ $\hat{\alpha}_2 = \mathbf{0.03}(0.01)$

5cii) I3=7.49, PI=32.93



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

5ciii) I3=9.32, PI=32.93

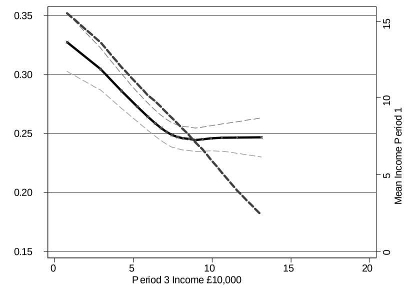


$\hat{\alpha}_1 = -\mathbf{0.03}(0.01)$ $\hat{\alpha}_2 = \mathbf{0.04}(0.02)$

Note: 95% confidence intervals shown. Income in 2000 prices, £10,000s.

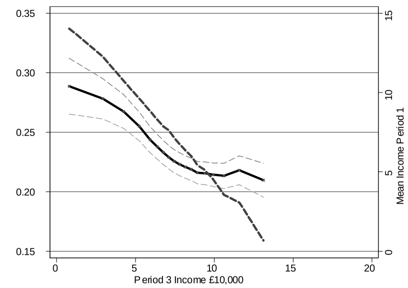
Figure 5: Semi Parametric Estimates. Dependent variable is High School Dropout.

5di) I2=8.13, PI=24.18



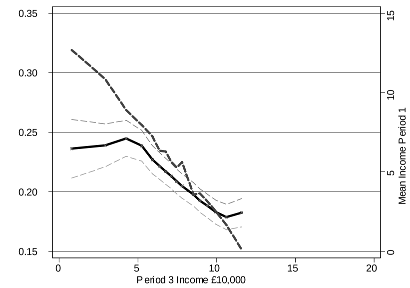
$\hat{\alpha}_1 = -\mathbf{0.08}(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.03}(0.01)$

5dii) I2=12.39, PI=24.18



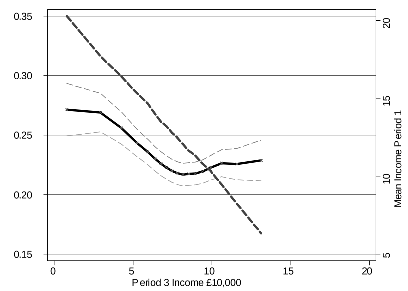
$\hat{\alpha}_1 = -\mathbf{0.06}(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.02}(0.01)$

5diii) I2=11.26, PI=24.18



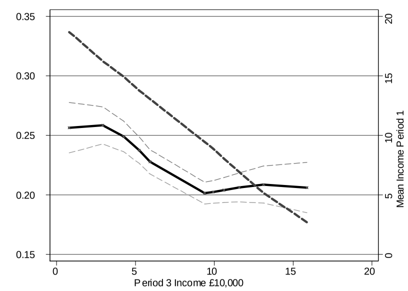
$\hat{\alpha}_1 = -\mathbf{0.02}(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.03}(0.01)$

5ei) I2=8.13, PI=28.24



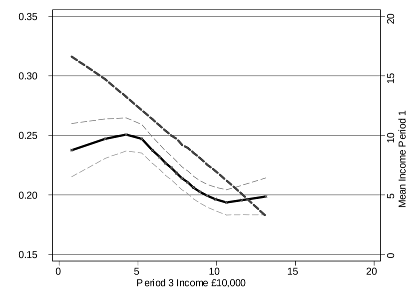
$\hat{\alpha}_1 = -\mathbf{0.05}(0.01)$ $\hat{\alpha}_2 = 0.01(0.01)$

51eii) I2=12.39, PI=28.24



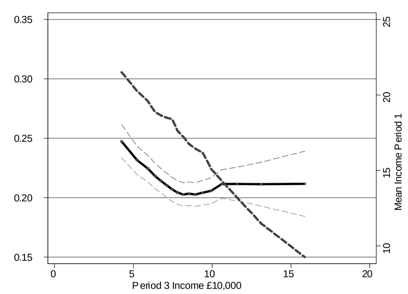
$\hat{\alpha}_1 = -\mathbf{0.05}(0.01)$ $\hat{\alpha}_2 = 0.00(0.01)$

5eiii) I2=11.26, PI=28.24



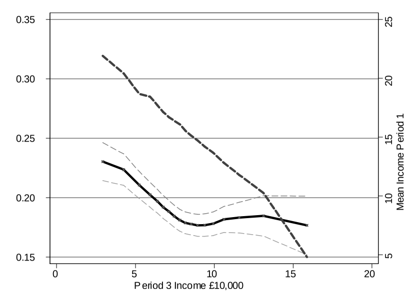
$\hat{\alpha}_1 = -0.02(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.02}(0.01)$

5fi) I2=8.13, PI=32.93



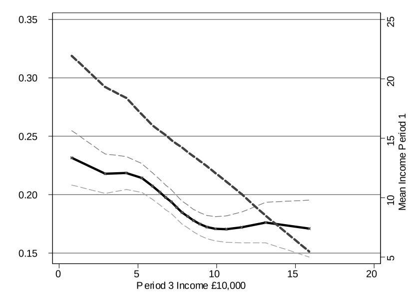
$\hat{\alpha}_1 = -\mathbf{0.06}(0.01)$ $\hat{\alpha}_2 = 0.01(0.01)$

5fii) I2=12.39, PI=32.93



$\hat{\alpha}_1 = -\mathbf{0.05}(0.01)$ $\hat{\alpha}_2 = -0.00(0.01)$

5fiii) I2=11.26, PI=32.93

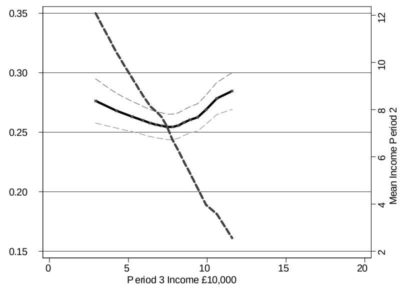


$\hat{\alpha}_1 = -0.05(0.01)$ $\hat{\alpha}_2 = -0.01(0.01)$

Note: 95% confidence intervals shown. Income variables are in 2000 prices, in UK sterling in £10,000s.

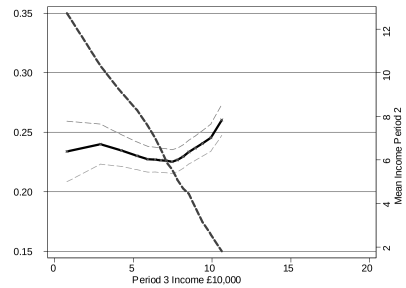
Figure 5: Semi Parametric Estimates. Dependent variable is High School Dropout.

5gi) I1=10.91, PI=24.18



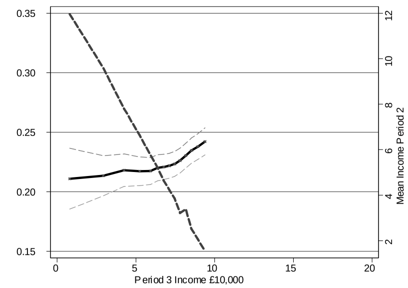
$\hat{\alpha}_1 = -\mathbf{0.02}(0.01)$ $\hat{\alpha}_2 = \mathbf{0.03}(0.01)$

5gii) I1=13.02, PI=24.18



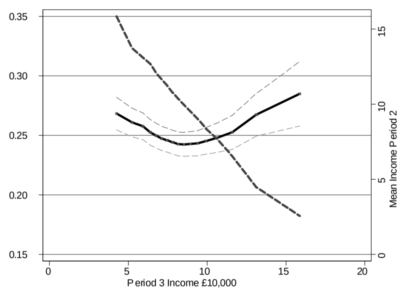
$\hat{\alpha}_1 = -\mathbf{0.03}(0.01)$ $\hat{\alpha}_2 = \mathbf{0.04}(0.01)$

5giii) I1=15.64, PI=24.18



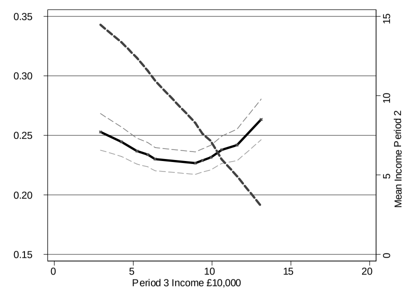
$\hat{\alpha}_1 = -\mathbf{0.02}(0.01)$ $\hat{\alpha}_2 = 0.00(0.02)$

5hi) I1=10.91, PI=28.24



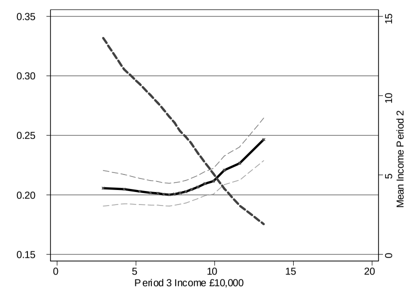
$\hat{\alpha}_1 = -0.01(0.01)$ $\hat{\alpha}_2 = \mathbf{0.03}(0.01)$

5hii) I1=13.02, PI=28.24



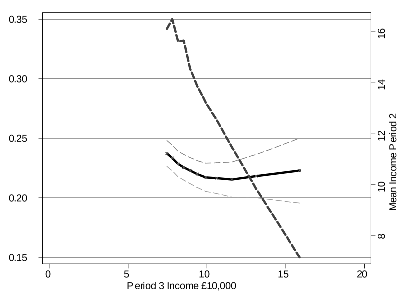
$\hat{\alpha}_1 = -\mathbf{0.03}(0.01)$ $\hat{\alpha}_2 = \mathbf{0.04}(0.01)$

5hiii) I1=15.64, PI=28.24



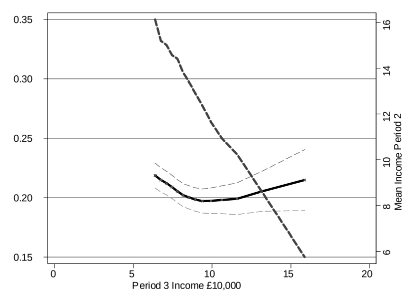
$\hat{\alpha}_1 = -\mathbf{0.02}(0.01)$ $\hat{\alpha}_2 = 0.01(0.01)$

5ji) I1=10.91, PI=32.93



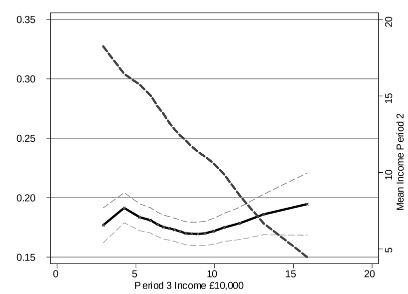
$\hat{\alpha}_1 = 0.01(0.01)$ $\hat{\alpha}_2 = \mathbf{0.02}(0.01)$

5jii) I1=13.02, PI=32.93



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

5jiii) I1=15.64, PI=32.93

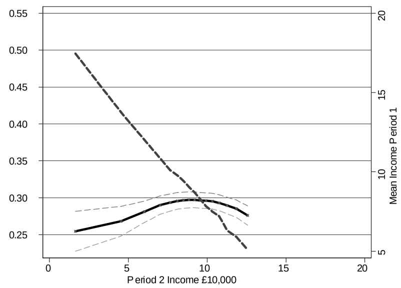


$\hat{\alpha}_1 = -0.01(0.01)$ $\hat{\alpha}_2 = 0.02(0.01)$

Note: 95% confidence intervals shown. Income variables are in 2000 prices, in UK sterling in £10,000s.

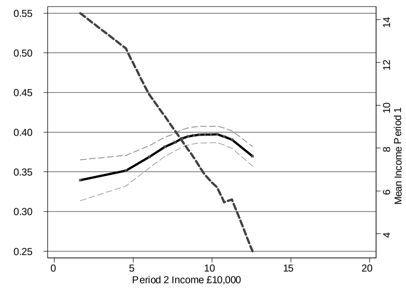
Figure 6: Semi Parametric Estimates. Dependent variable is College.

6ai) I3=6.34, PI=24.18



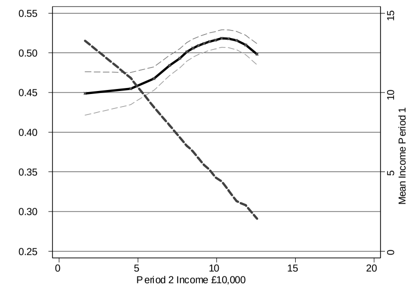
$\hat{\alpha}_1 = \mathbf{0.04}(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.02}(0.01)$

6aii) I3=7.49, PI=24.18



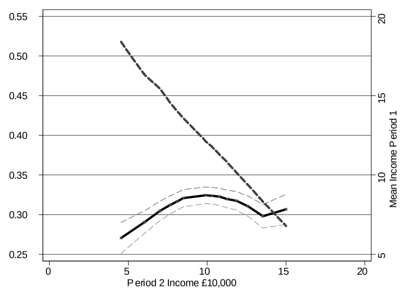
$\hat{\alpha}_1 = \mathbf{0.06}(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.03}(0.01)$

6aiii) I3=9.32, PI=24.18



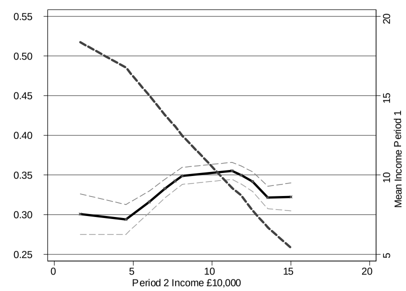
$\hat{\alpha}_1 = \mathbf{0.06}(0.02)$ $\hat{\alpha}_2 = -0.01(0.01)$

6bi) I3=6.34, PI=28.24



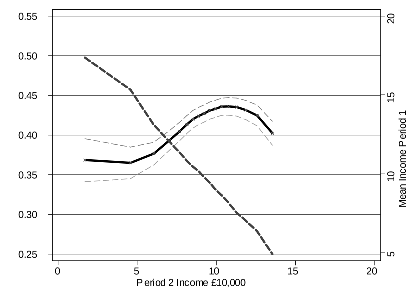
$\hat{\alpha}_1 = \mathbf{0.05}(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.02}(0.01)$

6bii) I3=7.49, PI=28.24



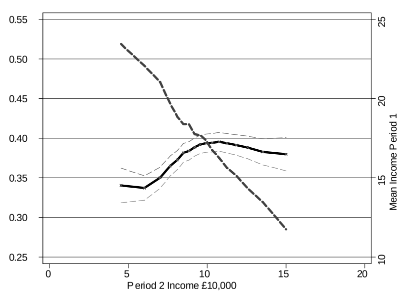
$\hat{\alpha}_1 = \mathbf{0.06}(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.04}(0.01)$

6biii) I3=9.32, PI=28.24



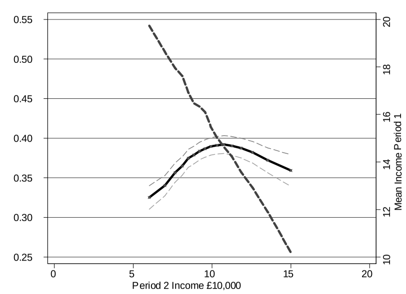
$\hat{\alpha}_1 = \mathbf{0.06}(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.02}(0.01)$

6ci) I3=6.34, PI=32.93



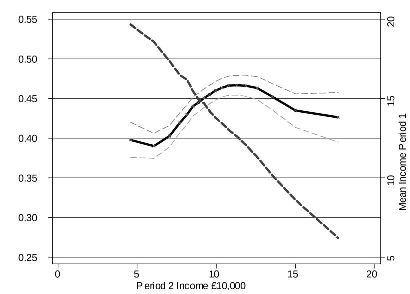
$\hat{\alpha}_1 = \mathbf{0.05}(0.01)$ $\hat{\alpha}_2 = -0.01(0.01)$

6cii) I3=7.49, PI=32.93



$\hat{\alpha}_1 = \mathbf{0.06}(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.03}(0.01)$

6ciii) I3=9.32, PI=32.93

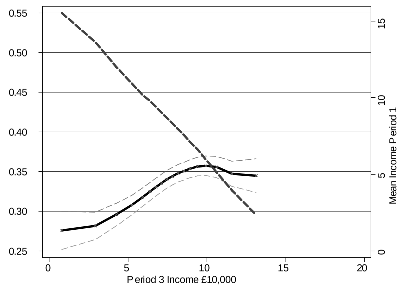


$\hat{\alpha}_1 = \mathbf{0.06}(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.03}(0.02)$

Note: 95% confidence intervals shown. Income in 2000 prices, £10,000s.

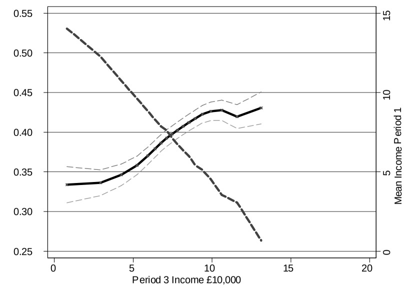
Figure 6: Semi Parametric Estimates. Dependent variable is College.

6di) I2=8.13, PI=24.18



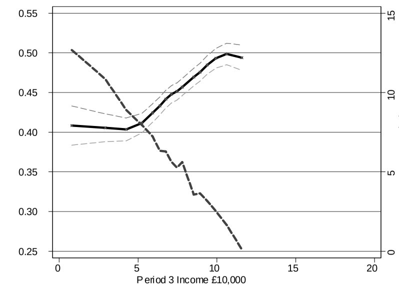
$\hat{\alpha}_1 = \mathbf{0.07}(0.01)$ $\hat{\alpha}_2 = -0.00(0.02)$

6dii) I2=12.39, PI=24.18



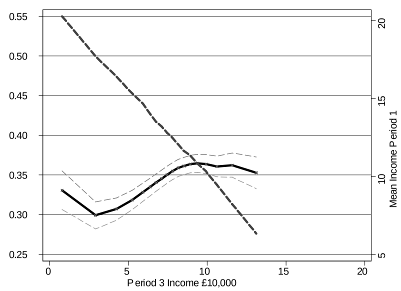
$\hat{\alpha}_1 = \mathbf{0.06}(0.01)$ $\hat{\alpha}_2 = \mathbf{0.03}(0.01)$

6diii) I2=11.26, PI=24.18



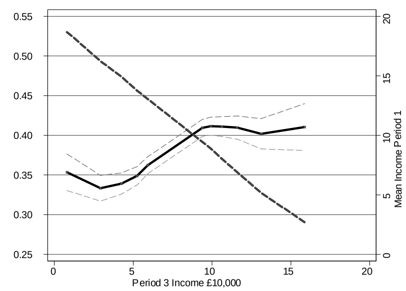
$\hat{\alpha}_1 = \mathbf{0.04}(0.01)$ $\hat{\alpha}_2 = \mathbf{0.05}(0.01)$

6ei) I2=8.13, PI=28.24



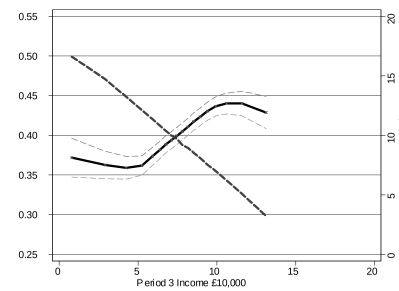
$\hat{\alpha}_1 = 0.02(0.01)$ $\hat{\alpha}_2 = 0.00(0.01)$

6eii) I2=12.39, PI=28.24



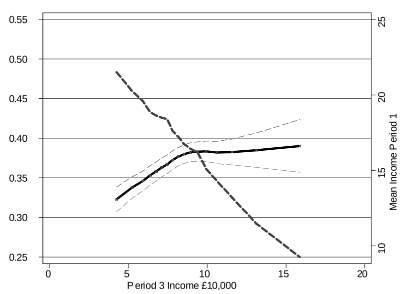
$\hat{\alpha}_1 = \mathbf{0.04}(0.01)$ $\hat{\alpha}_2 = 0.02(0.02)$

6eiii) I2=11.26, PI=28.24



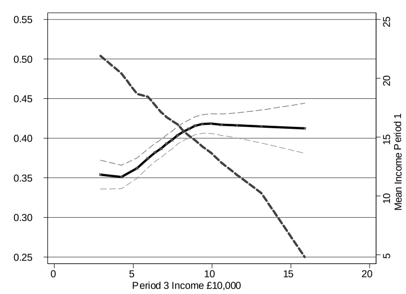
$\hat{\alpha}_1 = \mathbf{0.03}(0.01)$ $\hat{\alpha}_2 = \mathbf{0.03}(0.01)$

6fi) I2=8.13, PI=32.93



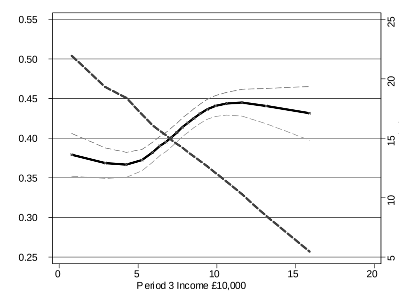
$\hat{\alpha}_1 = 0.02(0.02)$ $\hat{\alpha}_2 = 0.02(0.02)$

6fii) I2=12.39, PI=32.93



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

6fiii) I2=11.26, PI=32.93

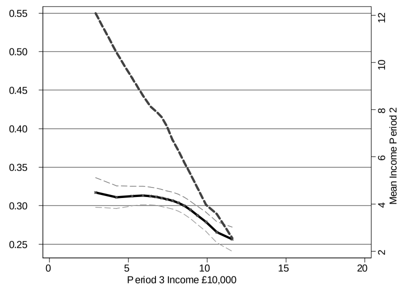


$\hat{\alpha}_1 = \mathbf{0.03}(0.02)$ $\hat{\alpha}_2 = 0.02(0.02)$

Note: 95% confidence intervals shown. Income variables are in 2000 prices, in UK sterling in £10,000s.

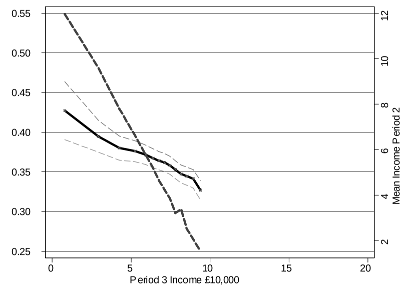
Figure 6: Semi Parametric Estimates. Dependent variable is College.

6gi) I1=10.91, PI=24.18



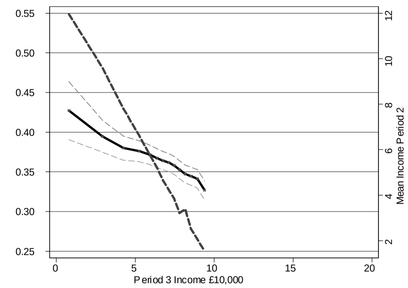
$\hat{\alpha}_1 = -0.01(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.05}(0.01)$

6gii) I1=13.02, PI=24.18



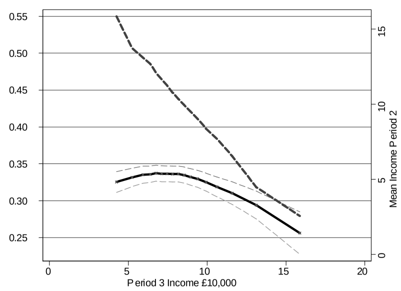
$\hat{\alpha}_1 = 0.01(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.08}(0.02)$

6giii) I1=15.64, PI=24.18



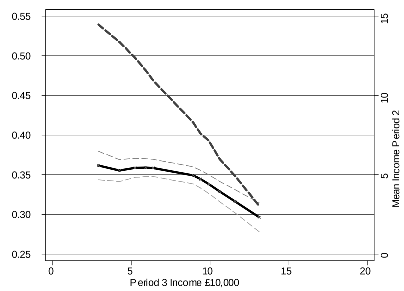
$\hat{\alpha}_1 = 0.01(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.04}(0.02)$

6hi) I1=10.91, PI=28.24



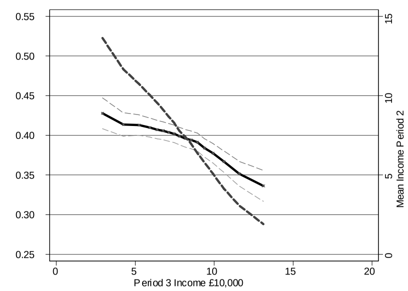
$\hat{\alpha}_1 = -\mathbf{0.04}(0.02)$ $\hat{\alpha}_2 = -\mathbf{0.06}(0.01)$

6hii) I1=13.02, PI=28.24



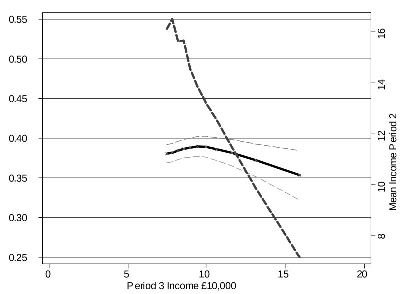
$\hat{\alpha}_1 = -0.01(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.06}(0.01)$

6hiii) I1=15.64, PI=28.24



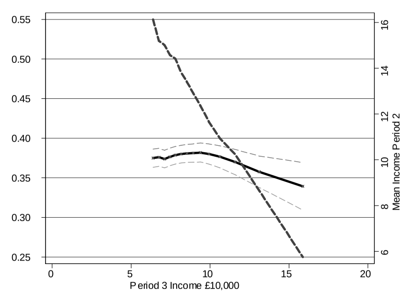
$\hat{\alpha}_1 = 0.01(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.04}(0.02)$

6ji) I1=10.91, PI=32.93



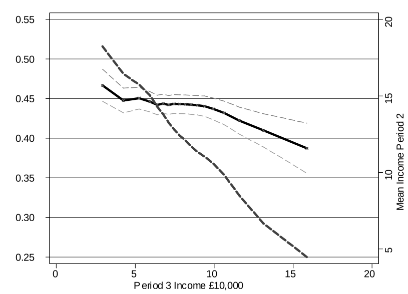
$\hat{\alpha}_1 = -\mathbf{0.06}(0.02)$ $\hat{\alpha}_2 = -\mathbf{0.04}(0.01)$

6jii) I1=13.02, PI=32.93



$\hat{\alpha}_1 = -\mathbf{0.03}(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.06}(0.01)$

6jiii) I1=15.64, PI=32.93

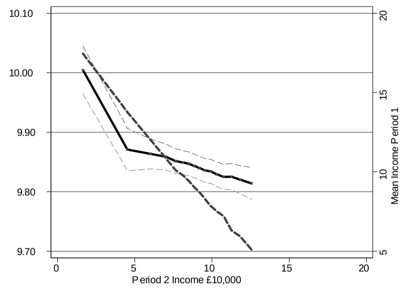


$\hat{\alpha}_1 = -\mathbf{0.02}(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.06}(0.02)$

Note: 95% confidence intervals shown. Income variables are in 2000 prices, in UK sterling in £10,000s.

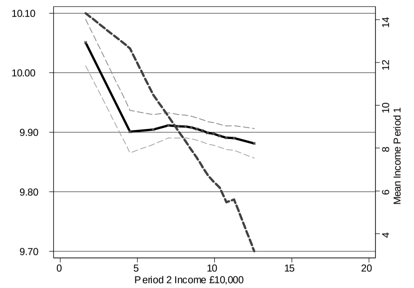
Figure 7: Semi Parametric Estimates. Dependent variable is Log Earnings 30.

7ai) I3=6.34, PI=24.18



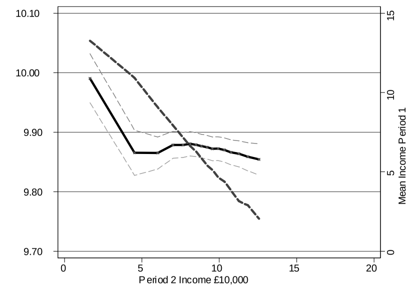
$\hat{\alpha}_1 = -\mathbf{0.16}(0.02)$ $\hat{\alpha}_2 = -\mathbf{0.03}(0.02)$

7aii) I3=7.49, PI=24.18



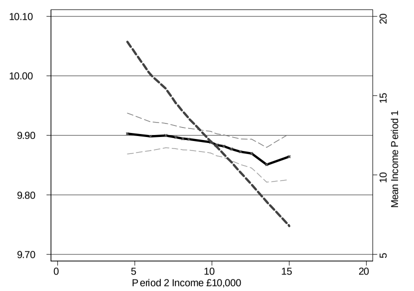
$\hat{\alpha}_1 = -\mathbf{0.15}(0.02)$ $\hat{\alpha}_2 = -0.02(0.02)$

7aiii) I3=9.32, PI=24.18



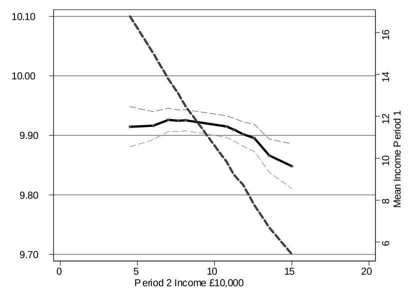
$\hat{\alpha}_1 = -\mathbf{0.11}(0.02)$ $\hat{\alpha}_2 =$ (0.02)

7bi) I3=6.34, PI=28.24



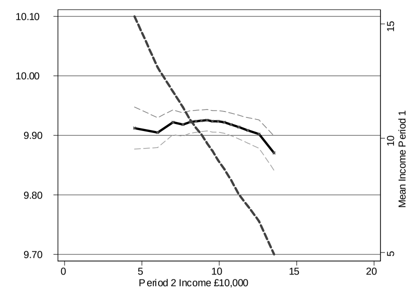
$\hat{\alpha}_1 = -0.01(0.02)$ $\hat{\alpha}_2 = -0.03(0.02)$

7bii) I3=7.49, PI=28.24



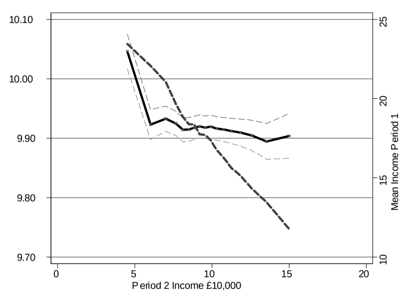
$\hat{\alpha}_1 = -0.17(0.10)$ $\hat{\alpha}_2 = -\mathbf{0.08}(0.02)$

7biii) I3=9.32, PI=28.24



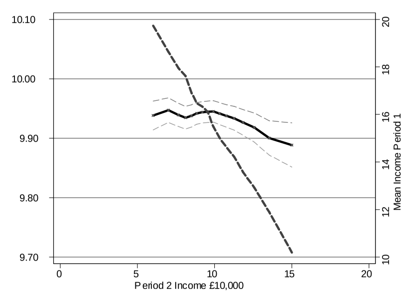
$\hat{\alpha}_1 = -0.18(0.10)$ $\hat{\alpha}_2 = -\mathbf{0.06}(0.02)$

7ci) I3=6.34, PI=32.93



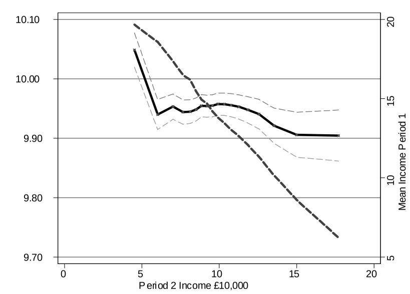
$\hat{\alpha}_1 = -\mathbf{0.13}(0.02)$ $\hat{\alpha}_2 = -0.01(0.02)$

7cii) I3=7.49, PI=32.93



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

7ciii) I3=9.32, PI=32.93

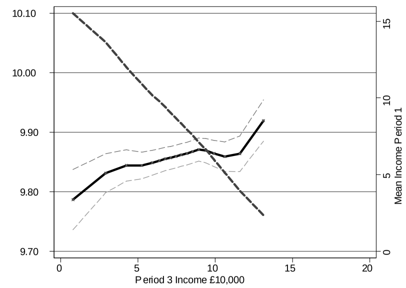


$\hat{\alpha}_1 = -\mathbf{0.09}(0.02)$ $\hat{\alpha}_2 = -\mathbf{0.05}(0.02)$

Note: 95% confidence intervals shown. Income in 2000 prices, £10,000s.

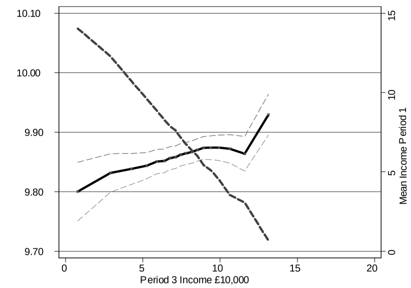
Figure 7: Semi Parametric Estimates. Dependent variable is Log Earnings 30.

7di) I2=8.13, PI=24.18



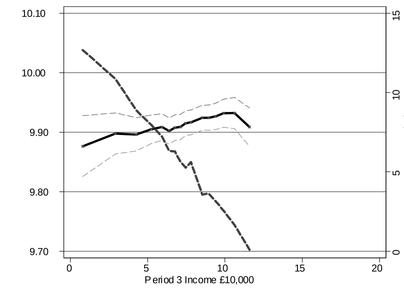
$\hat{\alpha}_1 = \mathbf{0.08}(0.03)$ $\hat{\alpha}_2 = \mathbf{0.16}(0.03)$

7dii) I2=12.39, PI=24.18



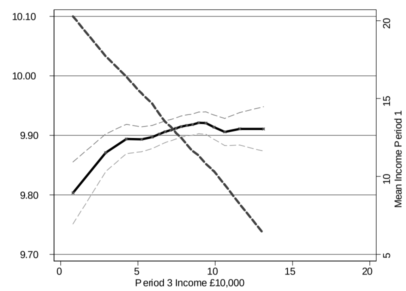
$\hat{\alpha}_1 = \mathbf{0.06}(0.03)$ $\hat{\alpha}_2 = \mathbf{0.07}(0.02)$

7diii) I2=11.26, PI=24.18



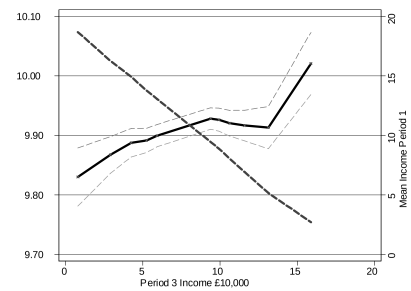
$\hat{\alpha}_1 = 0.03(0.03)$ $\hat{\alpha}_2 = -0.00(0.02)$

7ei) I2=8.13, PI=28.24



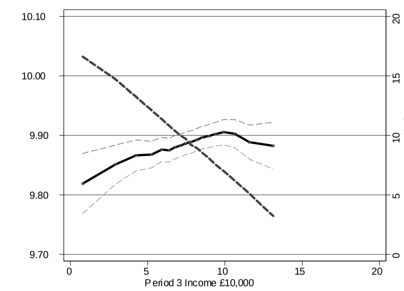
$\hat{\alpha}_1 = \mathbf{0.11}(0.03)$ $\hat{\alpha}_2 = \mathbf{-0.00}(0.02)$

7eii) I2=12.39, PI=28.24



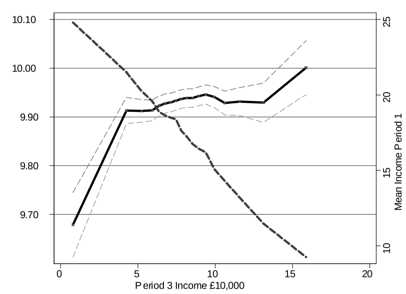
$\hat{\alpha}_1 = \mathbf{0.09}(0.03)$ $\hat{\alpha}_2 = \mathbf{0.10}(0.03)$

7eiii) I2=11.26, PI=28.24



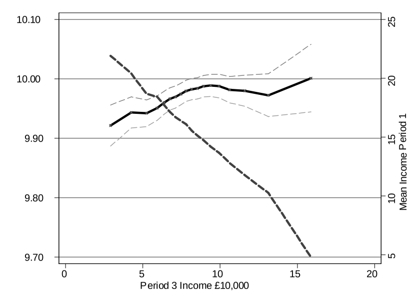
$\hat{\alpha}_1 = \mathbf{0.07}(0.03)$ $\hat{\alpha}_2 = -0.00(0.02)$

7fi) I2=8.13, PI=32.93



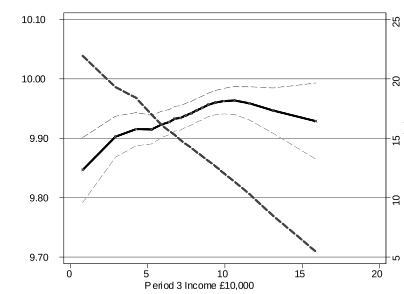
$\hat{\alpha}_1 = \mathbf{0.26}(0.04)$ $\hat{\alpha}_2 = \mathbf{0.06}(0.03)$

7fii) I2=12.39, PI=32.93



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

7fiii) I2=11.26, PI=32.93

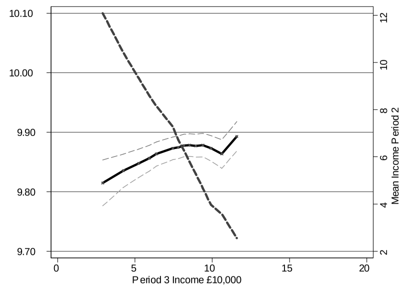


$\hat{\alpha}_1 = \mathbf{0.10}(0.03)$ $\hat{\alpha}_2 = -0.01(0.03)$

Note: 95% confidence intervals shown. Income variables are in 2000 prices, in UK sterling in £10,000s.

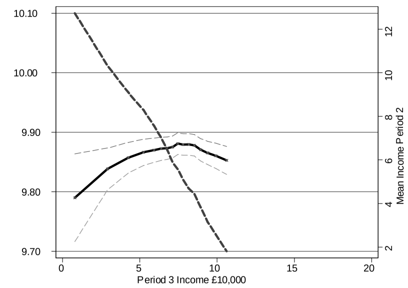
Figure 7: Semi Parametric Estimates. Dependent variable is Log Earnings 30.

7gi) I1=10.91, PI=24.18



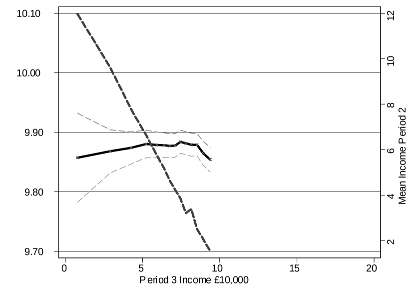
$\hat{\alpha}_1 = \mathbf{0.06}(0.02)$ $\hat{\alpha}_2 = 0.02(0.02)$

7gii) I1=13.02, PI=24.18



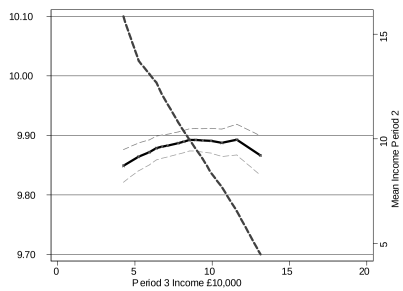
$\hat{\alpha}_1 = \mathbf{0.04}(0.02)$ $\hat{\alpha}_2 = -0.01(0.03)$

7giii) I1=15.64, PI=24.18



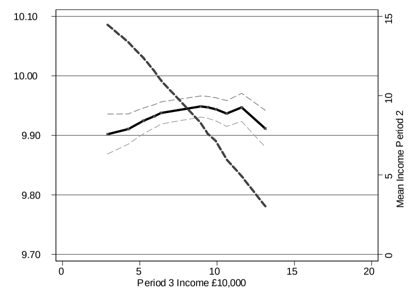
$\hat{\alpha}_1 = 0.01(0.02)$ $\hat{\alpha}_2 = 0.02(0.03)$

7hi) I1=10.91, PI=28.24



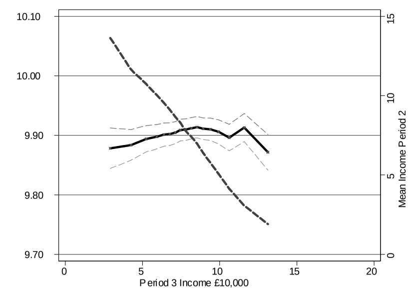
$\hat{\alpha}_1 = \mathbf{0.09}(0.04)$ $\hat{\alpha}_2 = -0.02(0.02)$

7hii) I1=13.02, PI=28.24



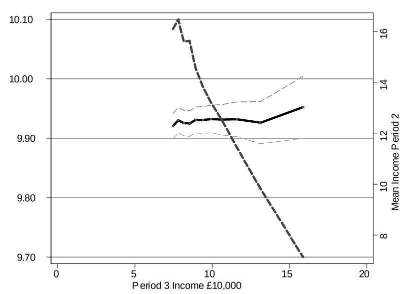
$\hat{\alpha}_1 = \mathbf{0.04}(0.02)$ $\hat{\alpha}_2 = -\mathbf{0.03}(0.02)$

7hiii) I1=15.64, PI=28.24



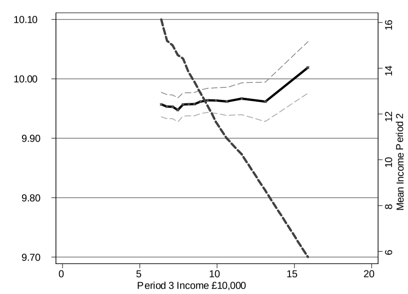
$\hat{\alpha}_1 = 0.00(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.06}(0.02)$

7ji) I1=10.91, PI=32.93



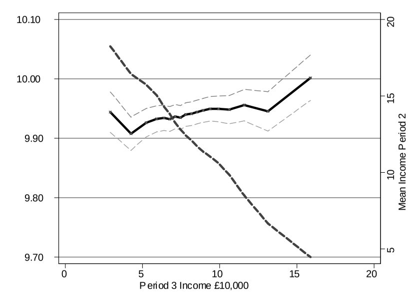
$\hat{\alpha}_1 = 0.02(0.04)$ $\hat{\alpha}_2 = -0.02(0.01)$

7jii) I1=13.02, PI=32.93



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

7jiii) I1=15.64, PI=32.93

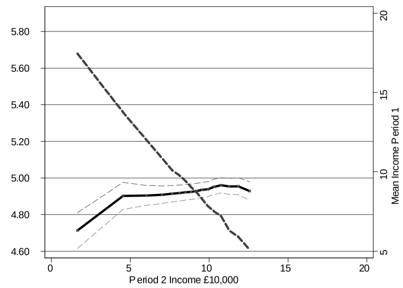


$\hat{\alpha}_1 = -0.00(0.02)$ $\hat{\alpha}_2 = 0.06(0.02)$

Note: 95% confidence intervals shown. Income variables are in 2000 prices, in UK sterling in £10,000s.

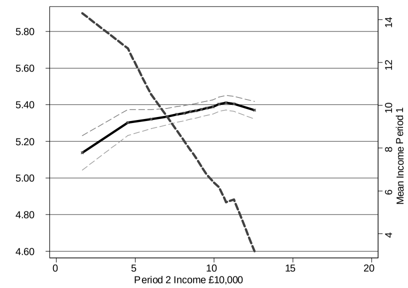
Figure 8: Semi Parametric Estimates. Dependent variable is IQ.

8ai) I3=6.34, PI=24.18



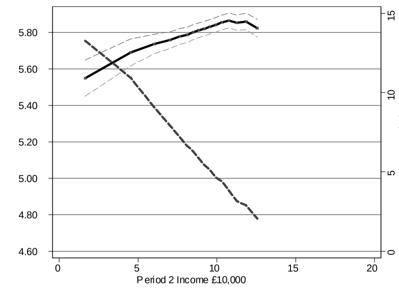
$\hat{\alpha}_1 = \mathbf{0.21}(0.05)$ $\hat{\alpha}_2 = 0.00(0.03)$

8aii) I3=7.49, PI=24.18



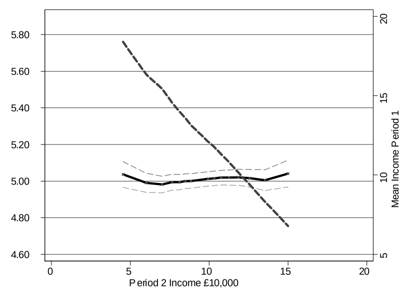
$\hat{\alpha}_1 = \mathbf{0.23}(0.05)$ $\hat{\alpha}_2 = 0.00(0.03)$

8aiii) I3=9.32, PI=24.18



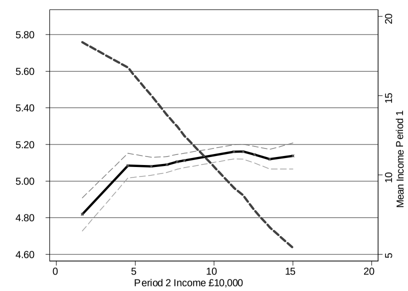
$\hat{\alpha}_1 = \mathbf{0.26}(0.05)$ $\hat{\alpha}_2 = 0.01(0.03)$

8bi) I3=6.34, PI=28.24



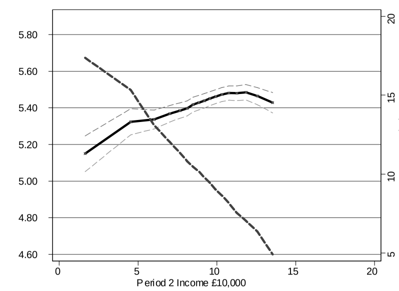
$\hat{\alpha}_1 = -0.03(0.04)$ $\hat{\alpha}_2 = 0.03(0.04)$

8bii) I3=7.49, PI=28.24



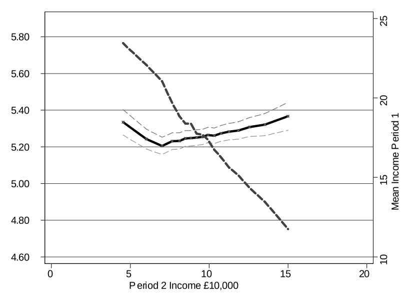
$\hat{\alpha}_1 = \mathbf{0.32}(0.05)$ $\hat{\alpha}_2 = -0.00(0.04)$

8biii) I3=9.32, PI=28.24



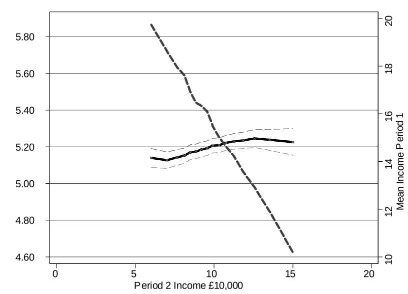
$\hat{\alpha}_1 = \mathbf{0.29}(0.05)$ $\hat{\alpha}_2 = -0.01(0.03)$

8ci) I3=6.34, PI=32.93



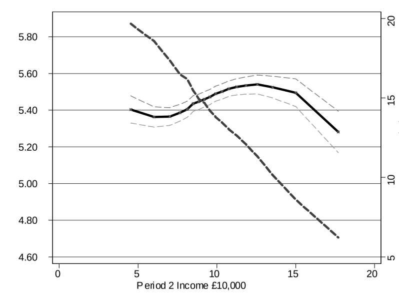
$\hat{\alpha}_1 = -\mathbf{0.08}(0.04)$ $\hat{\alpha}_2 = \mathbf{0.11}(0.04)$

8cii) I3=7.49, PI=32.93



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

8ciii) I3=9.32, PI=32.93

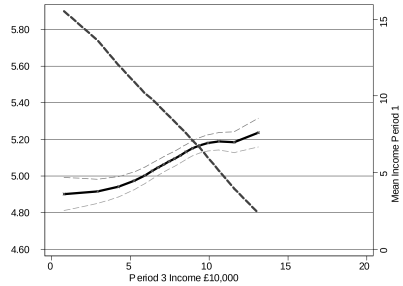


$\hat{\alpha}_1 = 0.07(0.04)$ $\hat{\alpha}_2 = -\mathbf{0.19}(0.06)$

Note: 95% confidence intervals shown. Income in 2000 prices, £10,000s.

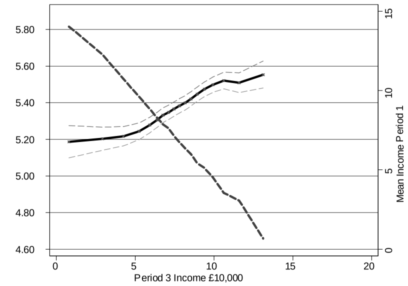
Figure 8: Semi Parametric Estimates. Dependent variable is IQ.

8di) I2=8.13, PI=24.18



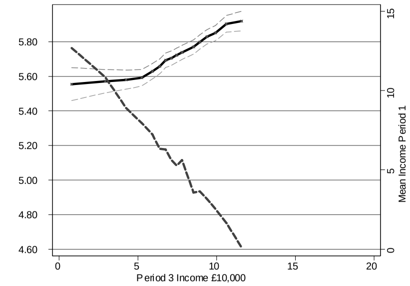
$\hat{\alpha}_1 = \mathbf{0.19}(0.05)$ $\hat{\alpha}_2 = \mathbf{0.42}(0.08)$

8dii) I2=12.39, PI=24.18



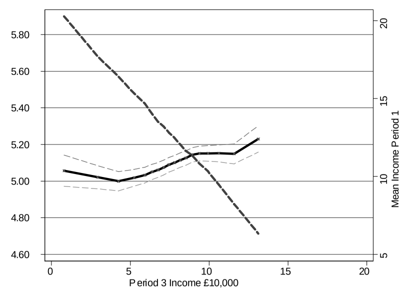
$\hat{\alpha}_1 = \mathbf{0.18}(0.05)$ $\hat{\alpha}_2 = \mathbf{0.19}(0.04)$

8diii) I2=11.26, PI=24.18



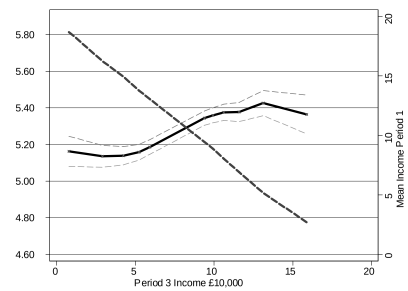
$\hat{\alpha}_1 = \mathbf{0.15}(0.05)$ $\hat{\alpha}_2 = \mathbf{0.22}(0.04)$

8ei) I2=8.13, PI=28.24



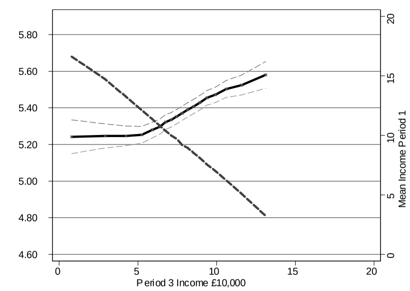
$\hat{\alpha}_1 = 0.03(0.05)$ $\hat{\alpha}_2 = \mathbf{0.14}(0.04)$

8eii) I2=12.39, PI=28.24



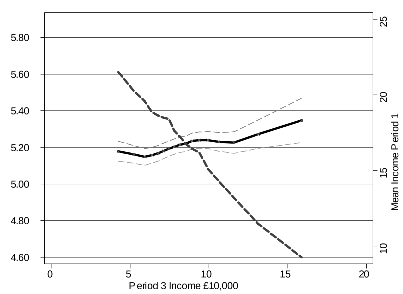
$\hat{\alpha}_1 = \mathbf{0.11}(0.05)$ $\hat{\alpha}_2 = 0.09(0.06)$

8eiii) I2=11.26, PI=28.24



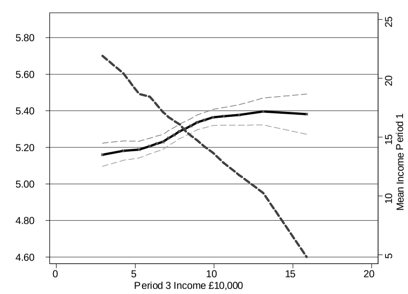
$\hat{\alpha}_1 = \mathbf{0.11}(0.05)$ $\hat{\alpha}_2 = \mathbf{0.23}(0.04)$

8fi) I2=8.13, PI=32.93



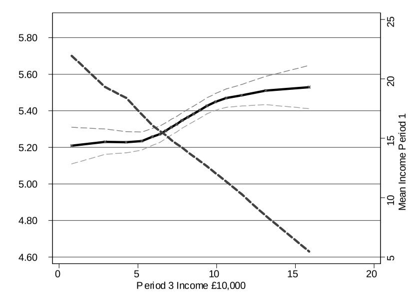
$\hat{\alpha}_1 = -0.03(0.05)$ $\hat{\alpha}_2 = \mathbf{0.14}(0.07)$

8fii) I2=12.39, PI=32.93



$\hat{\alpha}_1 = \mathbf{0.13}(0.04)$ $\hat{\alpha}_2 = 0.09(0.06)$

8fiii) I2=11.26, PI=32.93

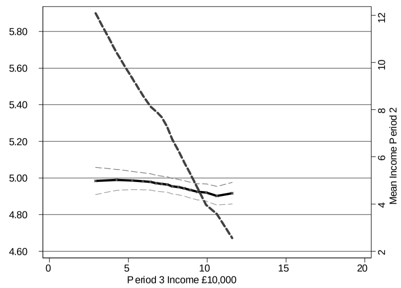


$\hat{\alpha}_1 = \mathbf{0.14}(0.06)$ $\hat{\alpha}_2 = \mathbf{0.18}(0.06)$

Note: 95% confidence intervals shown. Income variables are in 2000 prices, in UK sterling in £10,000s.

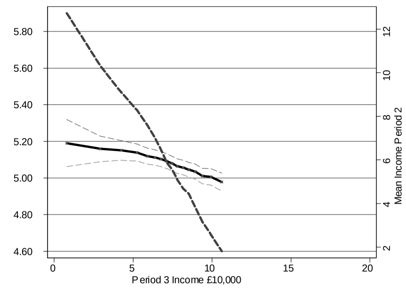
Figure 8: Semi Parametric Estimates. Dependent variable is IQ.

8gi) I1=10.91, PI=24.18



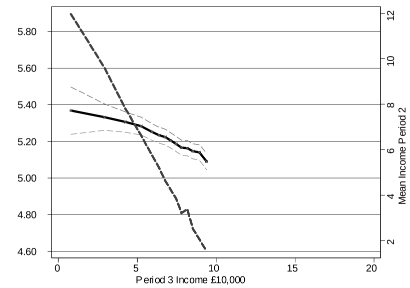
$\hat{\alpha}_1 = -0.02(0.04)$ $\hat{\alpha}_2 = -0.05(0.04)$

8gii) I1=13.02, PI=24.18



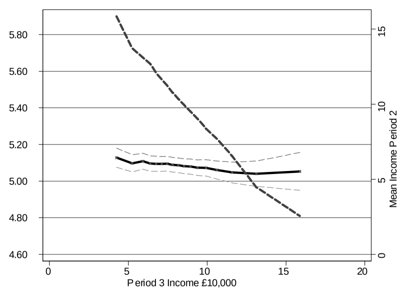
$\hat{\alpha}_1 = -0.04(0.03)$ $\hat{\alpha}_2 = -0.03(0.06)$

8giii) I1=15.64, PI=24.18



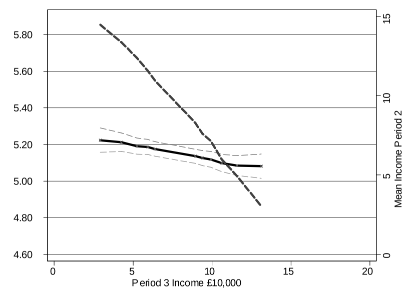
$\hat{\alpha}_1 = -0.01(0.03)$ $\hat{\alpha}_2 = -0.07(0.06)$

8hi) I1=10.91, PI=28.24



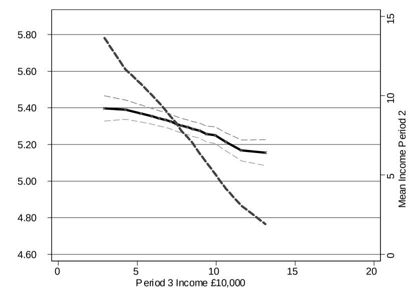
$\hat{\alpha}_1 = -0.10(0.07)$ $\hat{\alpha}_2 = -\mathbf{0.11}(0.03)$

8hii) I1=13.02, PI=28.24



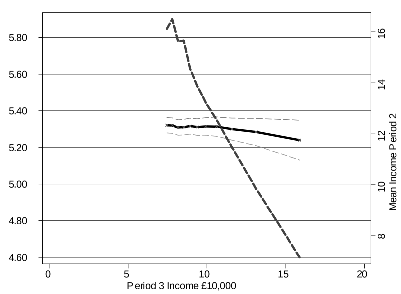
$\hat{\alpha}_1 = -\mathbf{0.07}(0.04)$ $\hat{\alpha}_2 = -\mathbf{0.07}(0.04)$

8hiii) I1=15.64, PI=28.24



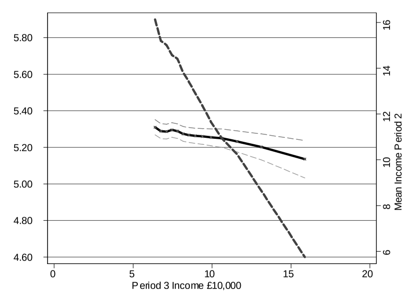
$\hat{\alpha}_1 = 0.04(0.03)$ $\hat{\alpha}_2 = -\mathbf{0.13}(0.06)$

8ji) I1=10.91, PI=32.93



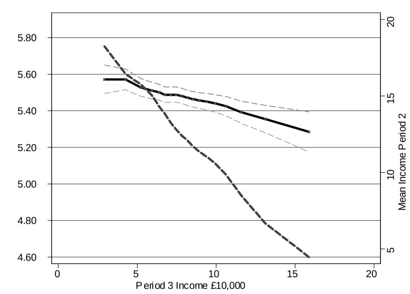
$\hat{\alpha}_1 = -\mathbf{0.14}(0.07)$ $\hat{\alpha}_2 = -\mathbf{0.13}(0.03)$

8jii) I1=13.02, PI=32.93



$\hat{\alpha}_1 = -\mathbf{0.09}(0.04)$ $\hat{\alpha}_2 = -\mathbf{0.15}(0.04)$

8jiii) I1=15.64, PI=32.93

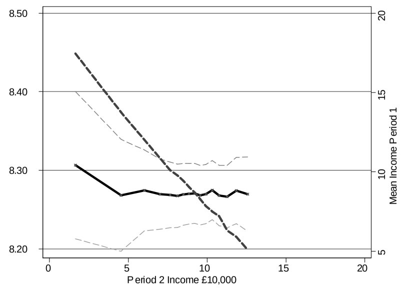


$\hat{\alpha}_1 = -\mathbf{0.09}(0.05)$ $\hat{\alpha}_2 = -\mathbf{0.20}(0.06)$

Note: 95% confidence intervals shown. Income variables are in 2000 prices, in UK sterling in £10,000s.

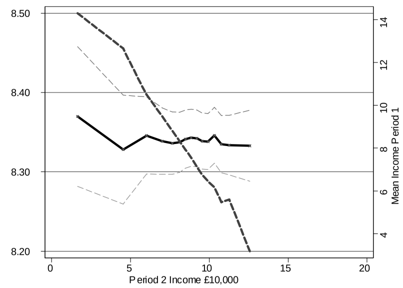
Figure 9: Semi Parametric Estimates. Dependent variable is Health.

9ai) I3=6.34, PI=24.18



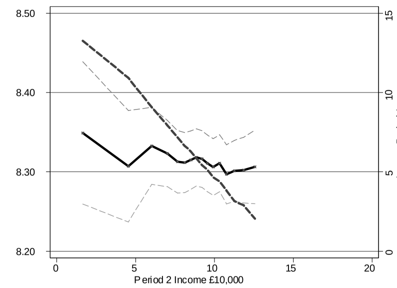
$\hat{\alpha}_1 = -0.04(0.05)$ $\hat{\alpha}_2 = -0.00(0.03)$

9aii) I3=7.49, PI=24.18



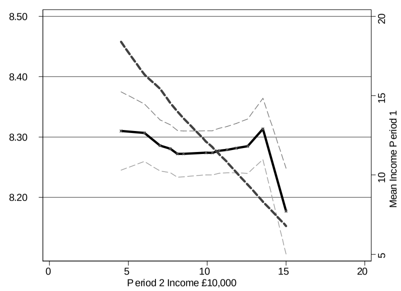
$\hat{\alpha}_1 = -0.03(0.05)$ $\hat{\alpha}_2 = -0.01(0.03)$

9aiii) I3=9.32, PI=24.18



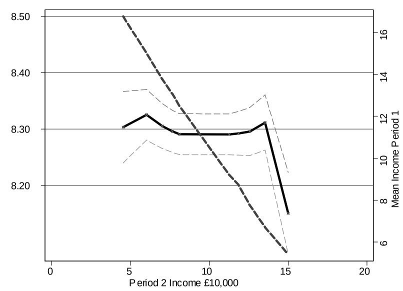
$\hat{\alpha}_1 = -0.03(0.05)$ $\hat{\alpha}_2 = -0.01(0.03)$

9bi) I3=6.34, PI=28.24



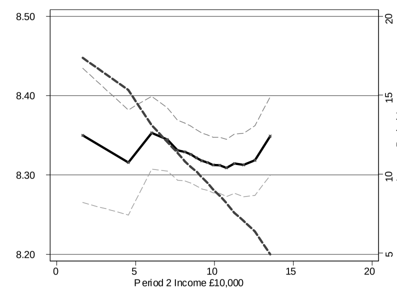
$\hat{\alpha}_1 = -0.04(0.04)$ $\hat{\alpha}_2 = -\mathbf{0.10}(0.04)$

9bii) I3=7.49, PI=28.24



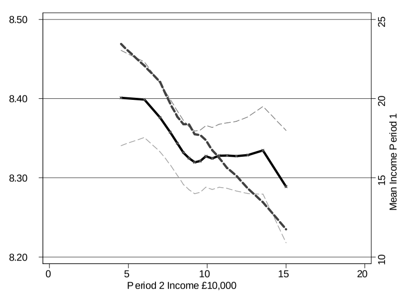
$\hat{\alpha}_1 = -0.04(0.04)$ $\hat{\alpha}_2 = -\mathbf{0.14}(0.04)$

9biii) I3=9.32, PI=28.24



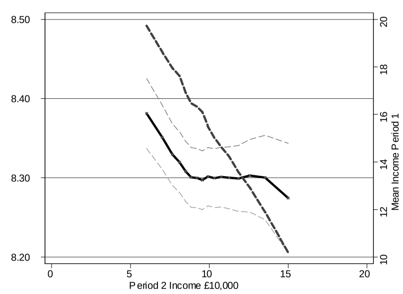
$\hat{\alpha}_1 = -0.03(0.05)$ $\hat{\alpha}_2 = 0.03(0.03)$

9ci) I3=6.34, PI=32.93



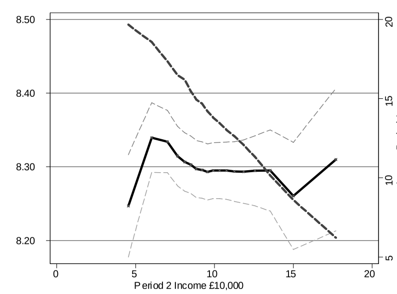
$\hat{\alpha}_1 = -\mathbf{0.08}(0.04)$ $\hat{\alpha}_2 = -0.03(0.04)$

9cii) I3=7.49, PI=32.93



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

9ciii) I3=9.32, PI=32.93

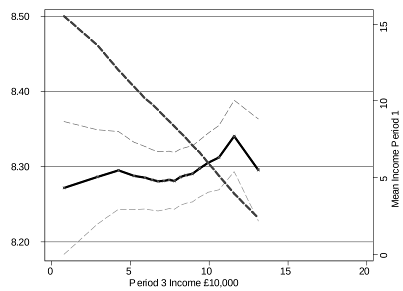


$\hat{\alpha}_1 = -0.05(0.04)$ $\hat{\alpha}_2 = 0.02(0.05)$

Note: 95% confidence intervals shown. Income in 2000 prices, £10,000s.

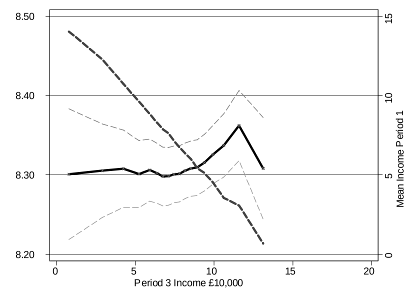
Figure 9: Semi Parametric Estimates. Dependent variable is Health.

9di) I2=8.13, PI=24.18



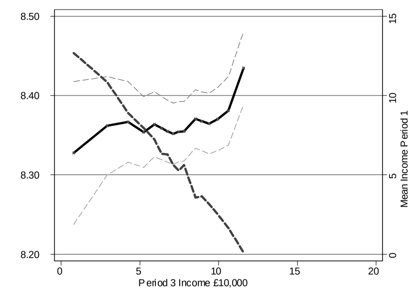
$\hat{\alpha}_1 = 0.01(0.05)$ $\hat{\alpha}_2 = -\mathbf{0.22}(0.06)$

9dii) I2=12.39, PI=24.18



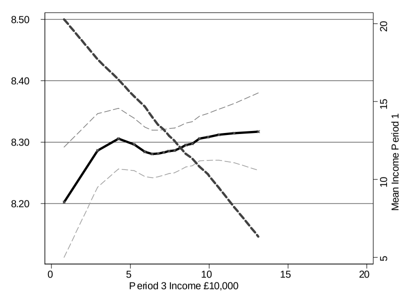
$\hat{\alpha}_1 = -0.00(0.05)$ $\hat{\alpha}_2 = \mathbf{0.01}(0.04)$

9diii) I2=11.26, PI=24.18



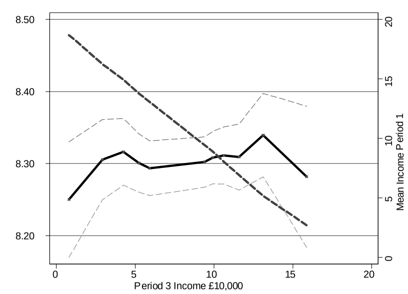
$\hat{\alpha}_1 = 0.02(0.05)$ $\hat{\alpha}_2 = \mathbf{0.08}(0.03)$

9ei) I2=8.13, PI=28.24



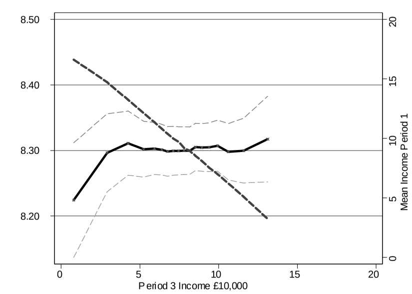
$\hat{\alpha}_1 = \mathbf{0.08}(0.05)$ $\hat{\alpha}_2 = 0.03(0.04)$

9eii) I2=12.39, PI=28.24



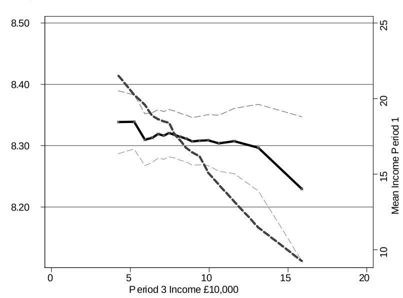
$\hat{\alpha}_1 = 0.04(0.04)$ $\hat{\alpha}_2 = -0.01(0.05)$

9eiii) I2=11.26, PI=28.24



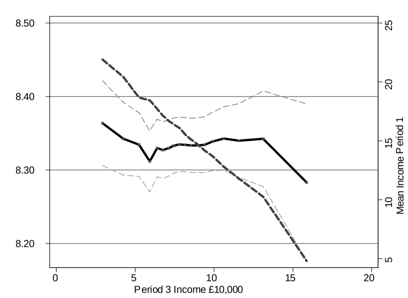
$\hat{\alpha}_1 = 0.08(0.05)$ $\hat{\alpha}_2 = 0.02(0.04)$

9fi) I2=8.13, PI=32.93



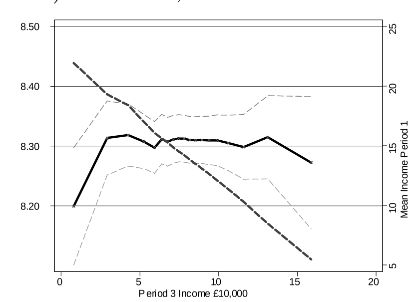
$\hat{\alpha}_1 = \mathbf{0.24}(0.06)$ $\hat{\alpha}_2 = -0.09(0.06)$

9fii) I2=12.39, PI=32.93



$\hat{\alpha}_1 = -0.03(0.04)$ $\hat{\alpha}_2 = -0.05(0.06)$

9fiii) I2=11.26, PI=32.93

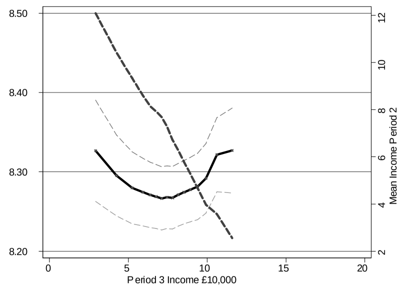


$\hat{\alpha}_1 = \mathbf{0.11}(0.05)$ $\hat{\alpha}_2 = -0.04(0.06)$

Note: 95% confidence intervals shown. Income variables are in 2000 prices, in UK sterling in £10,000s.

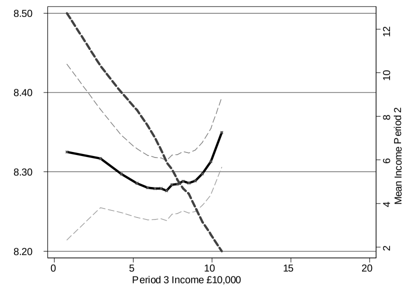
Figure 9: Semi Parametric Estimates. Dependent variable is Health.

9gi) I1=10.91, PI=24.18



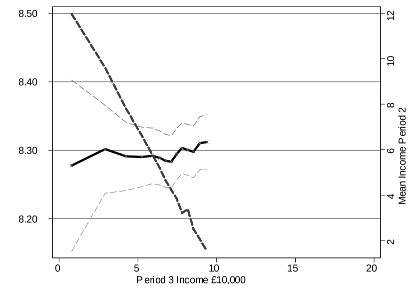
$\hat{\alpha}_1 = -0.06(0.04)$ $\hat{\alpha}_2 = \mathbf{0.06}(0.03)$

9gii) I1=13.02, PI=24.18



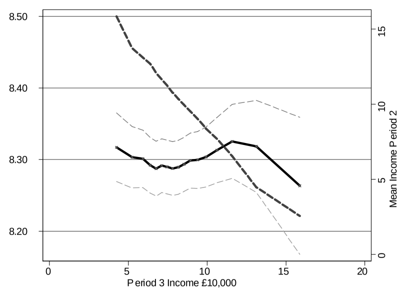
$\hat{\alpha}_1 = -0.03(0.03)$ $\hat{\alpha}_2 = -0.03(0.05)$

9giii) I1=15.64, PI=24.18



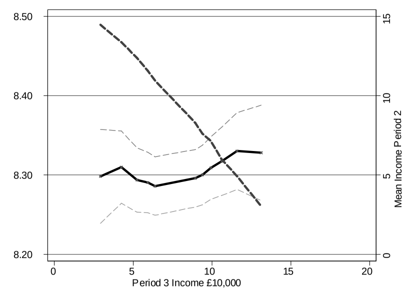
$\hat{\alpha}_1 = -0.02(0.03)$ $\hat{\alpha}_2 = 0.02(0.05)$

9hi) I1=10.91, PI=28.24



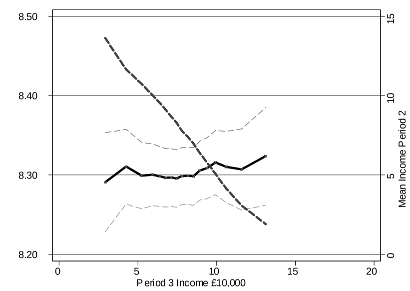
$\hat{\alpha}_1 = -0.05(0.06)$ $\hat{\alpha}_2 = \mathbf{0.07}(0.03)$

9hii) I1=13.02, PI=28.24



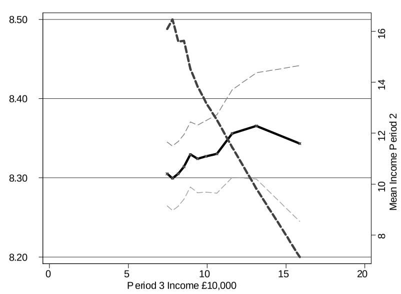
$\hat{\alpha}_1 = -0.01(0.04)$ $\hat{\alpha}_2 = 0.04(0.04)$

9hiii) I1=15.64, PI=28.24



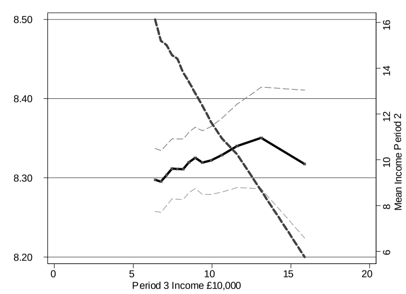
$\hat{\alpha}_1 = -0.02(0.03)$ $\hat{\alpha}_2 = -0.00(0.05)$

9ji) I2=8.13, PI=32.93



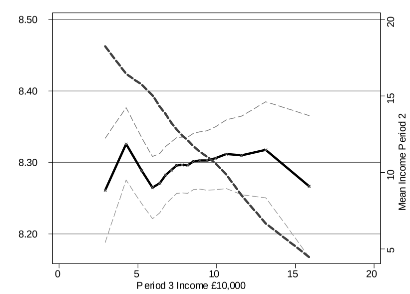
$\hat{\alpha}_1 = 0.01(0.07)$ $\hat{\alpha}_2 = 0.03(0.03)$

9jii) I1=13.02, PI=32.93



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

9jiii) I1=15.64, PI=32.93

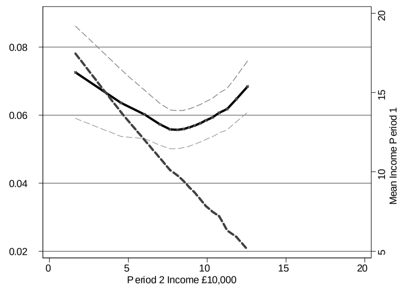


$\hat{\alpha}_1 = 0.04(0.04)$ $\hat{\alpha}_2 = -0.03(0.05)$

Note: 95% confidence intervals shown. Income variables are in 2000 prices, in UK sterling in £10,000s.

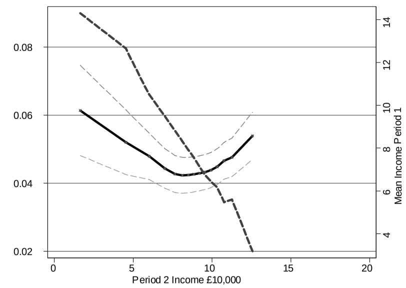
Figure 10: Semi Parametric Estimates. Dependent variable is Teen Pregnancy.

10ai) I3=6.34, PI=24.18



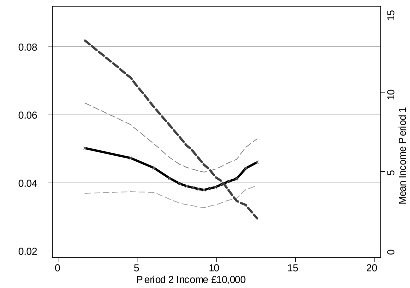
$\hat{\alpha}_1 = -\mathbf{0.02}(0.01)$ $\hat{\alpha}_2 = \mathbf{0.01}(0.00)$

10aii) I3=7.49, PI=24.18



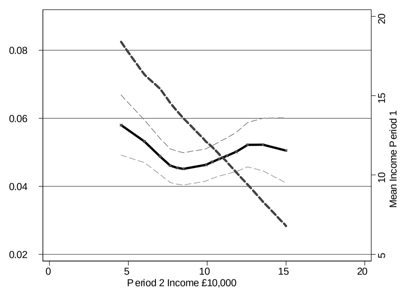
$\hat{\alpha}_1 = -\mathbf{0.02}(0.01)$ $\hat{\alpha}_2 = \mathbf{0.01}(0.00)$

10aiii) I3=9.32, PI=24.18



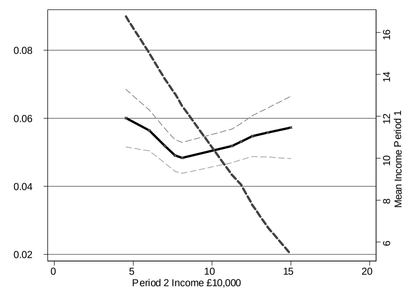
$\hat{\alpha}_1 = -\mathbf{0.01}(0.01)$ $\hat{\alpha}_2 = \mathbf{0.01}(0.00)$

10bi) I3=6.34, PI=28.24



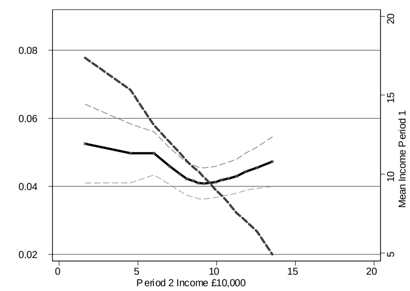
$\hat{\alpha}_1 = -\mathbf{0.01}(0.01)$ $\hat{\alpha}_2 = 0.00(0.01)$

10bii) I3=7.49, PI=28.24



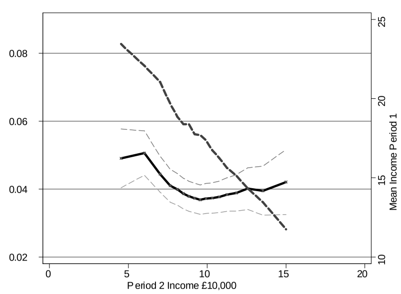
$\hat{\alpha}_1 = -\mathbf{0.02}(0.01)$ $\hat{\alpha}_2 = \mathbf{0.01}(0.00)$

10biii) I3=9.32, PI=28.24



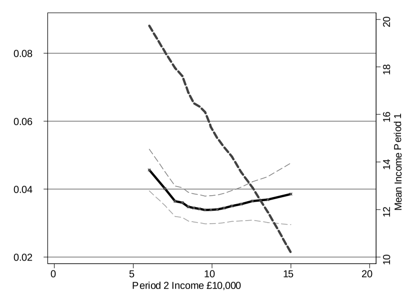
$\hat{\alpha}_1 = -\mathbf{0.01}(0.01)$ $\hat{\alpha}_2 = 0.01(0.00)$

10ci) I3=6.34, PI=32.93



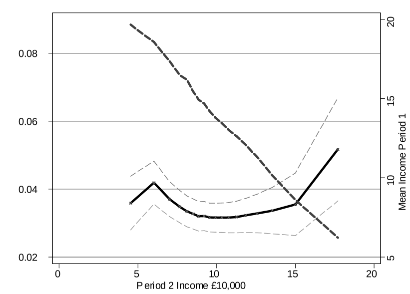
$\hat{\alpha}_1 = -\mathbf{0.01}(0.00)$ $\hat{\alpha}_2 = 0.01(0.01)$

10cii) I3=7.49, PI=32.93



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

10ciii) I3=9.32, PI=32.93

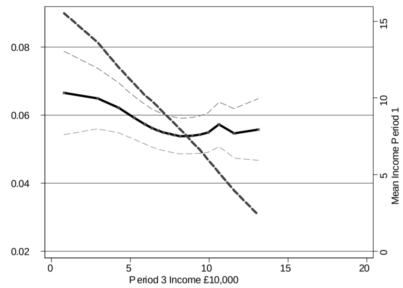


$\hat{\alpha}_1 = -0.00(0.00)$ $\hat{\alpha}_2 = \mathbf{0.02}(0.01)$

Note: 95% confidence intervals shown. Income in 2000 prices, £10,000s.

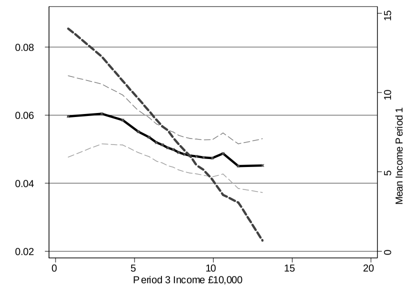
Figure 10: Semi Parametric Estimates. Dependent variable is Teen Pregnancy.

10di) I2=8.13, PI=24.18



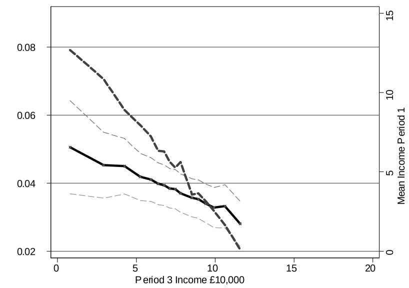
$\hat{\alpha}_1 = -\mathbf{0.01}(0.01)$ $\hat{\alpha}_2 = -0.05(0.04)$

10dii) I2=12.39, PI=24.18



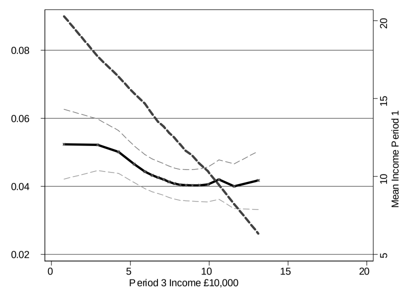
$\hat{\alpha}_1 = -0.01(0.01)$ $\hat{\alpha}_2 = -0.00(0.00)$

10diii) I2=11.26, PI=24.18



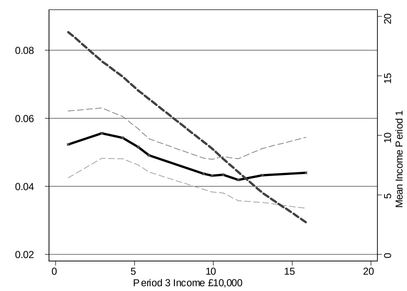
$\hat{\alpha}_1 = -0.01(0.01)$ $\hat{\alpha}_2 = -\mathbf{0.01}(0.00)$

10ei) I2=8.13, PI=28.24



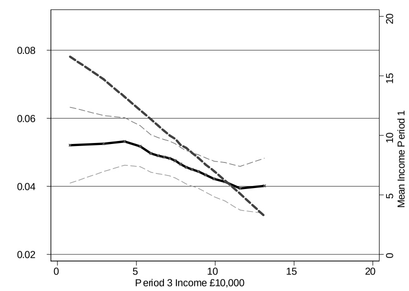
$\hat{\alpha}_1 = -\mathbf{0.01}(0.01)$ $\hat{\alpha}_2 = 0.00(0.00)$

10eii) I2=12.39, PI=28.24



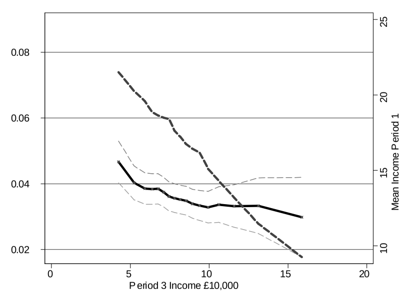
$\hat{\alpha}_1 = -0.01(0.01)$ $\hat{\alpha} = -0.00(0.01)$

10eiii) I2=11.26, PI=28.24



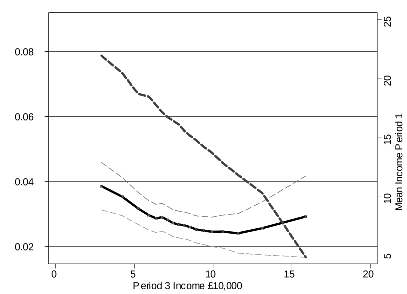
$\hat{\alpha}_1 = -0.00(0.01)$ $\hat{\alpha}_2 = -0.01(0.00)$

10fi) I2=8.13, PI=32.93



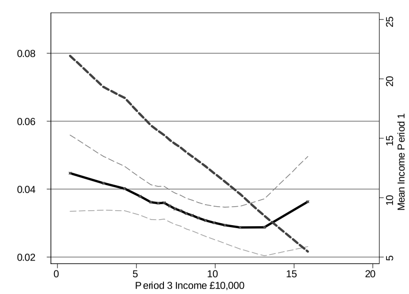
$\hat{\alpha}_1 = -0.01(0.01)$ $\hat{\alpha}_2 = -0.01(0.01)$

10fii) I2=12.39, PI=32.93



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

10fiii) I2=11.26, PI=32.93

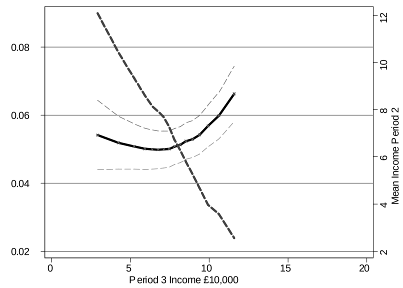


$\hat{\alpha}_1 = \mathbf{0.00}(0.01)$ $\hat{\alpha}_2 = 0.00(0.01)$

Note: 95% confidence intervals shown. Income variables are in 2000 prices, in UK sterling in £10,000s.

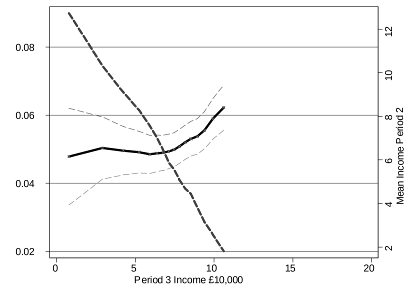
Figure 10: Semi Parametric Estimates. Dependent variable is Teen Pregnancy.

10gi) I1=10.91, PI=24.18



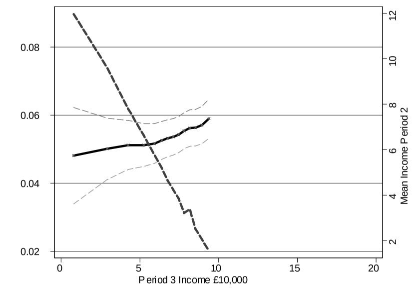
$\hat{\alpha}_1 = -0.00(0.01)$ $\hat{\alpha}_2 = \mathbf{0.02}(0.00)$

10gii) I1=13.02, PI=24.18



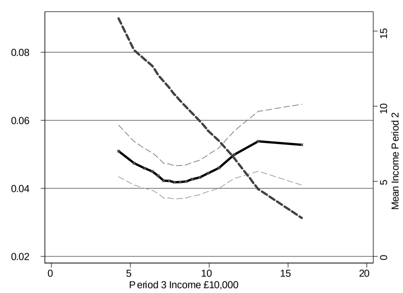
$\hat{\alpha}_1 = -\mathbf{0.01}(0.00)$ $\hat{\alpha}_2 = \mathbf{0.01}(0.01)$

10giii) I1=15.64, PI=24.18



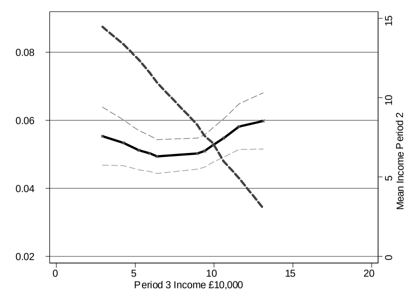
$\hat{\alpha}_1 = -\mathbf{0.01}(0.00)$ $\hat{\alpha}_2 = 0.01(0.01)$

10hi) I1=10.91, PI=28.24



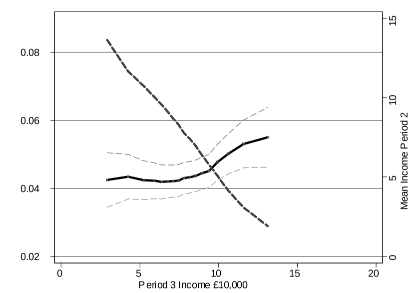
$\hat{\alpha}_1 = 0.00(0.01)$ $\hat{\alpha}_2 = \mathbf{0.01}(0.00)$

10hii) I1=13.02, PI=28.24



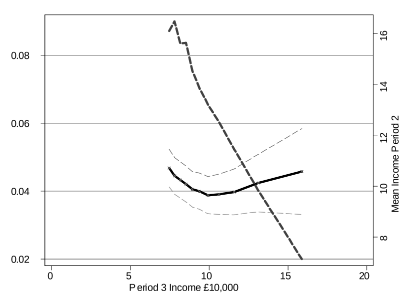
$\hat{\alpha}_1 = -0.01(0.00)$ $\hat{\alpha}_2 = \mathbf{0.01}(0.00)$

10hiii) I1=15.64, PI=28.24



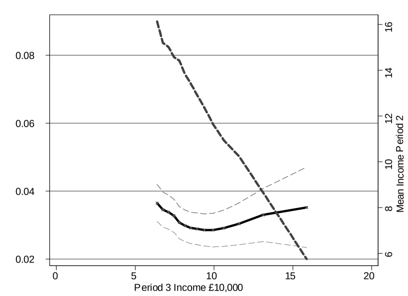
$\hat{\alpha}_1 = -\mathbf{0.01}(0.00)$ $\hat{\alpha}_2 = 0.01(0.01)$

10ji) I1=10.91, PI=32.93



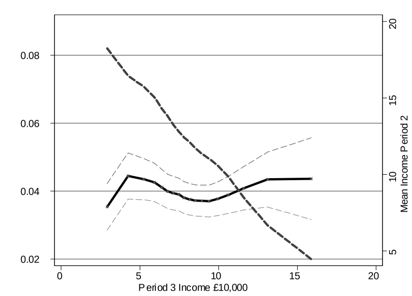
$\hat{\alpha}_1 = 0.01(0.01)$ $\hat{\alpha}_2 = 0.01(0.00)$

10jii) I1=13.02, PI=32.93



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

10jiii) I1=15.64, PI=32.93

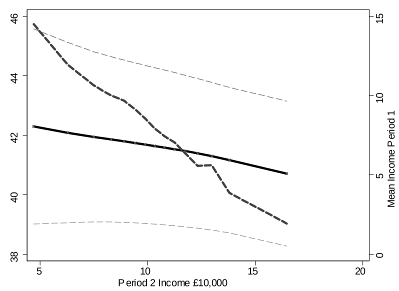


$\hat{\alpha}_1 = 0.00(0.00)$ $\hat{\alpha}_2 = 0.01(0.01)$

Note: 95% confidence intervals shown. Income variables are in 2000 prices, in UK sterling in £10,000s.

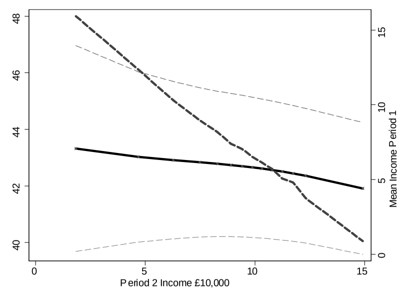
Figure 11: Semi Parametric Estimates. Dependent variable is Grades.

11ai) I3=7.61, PI=25.74



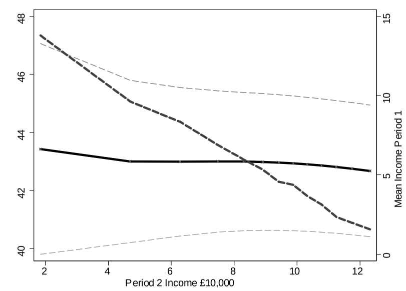
$\hat{\alpha}_1 = -0.66(2.14)$ $\hat{\alpha}_2 = -0.93(1.83)$

11aii) I3=9.33, PI=25.74



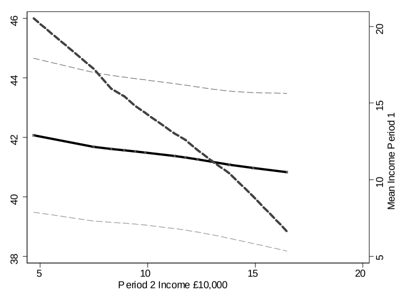
$\hat{\alpha}_1 = -0.63(2.25)$ $\hat{\alpha}_2 = -0.78(1.74)$

11aiii) I3=11.37, PI=25.74



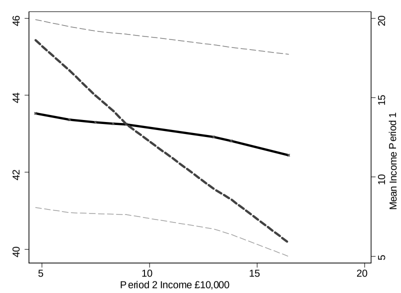
$\hat{\alpha}_1 = -0.47(2.20)$ $\hat{\alpha}_2 = -0.29(1.66)$

11bi) I3=7.61, PI=31.23



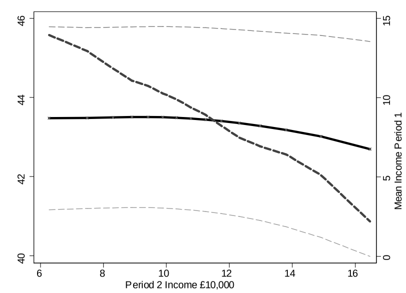
$\hat{\alpha}_1 = -0.65(1.81)$ $\hat{\alpha}_2 = -0.58(1.84)$

11bii) I3=9.33, PI=31.23



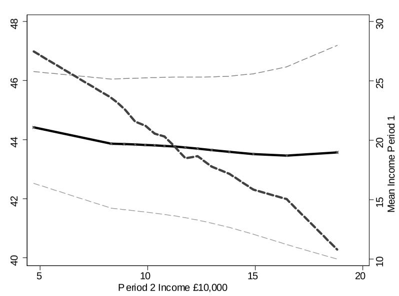
$\hat{\alpha}_1 = -0.35(1.73)$ $\hat{\alpha}_2 = -0.74(1.80)$

11biii) I3=11.37, PI=31.23



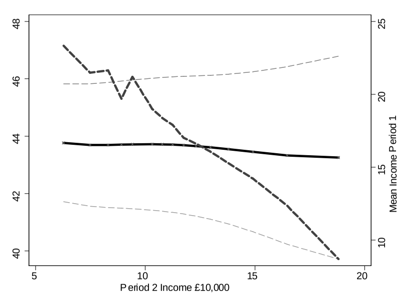
$\hat{\alpha}_1 = -0.01(1.67)$ $\hat{\alpha}_2 = -0.77(1.82)$

11ci) I3=7.61, PI=37.30



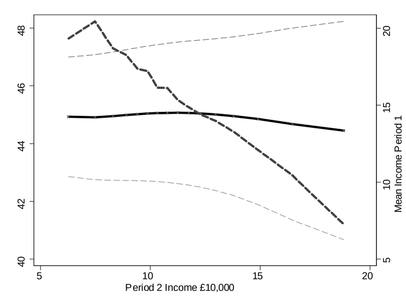
$\hat{\alpha}_1 = -0.65(1.54)$ $\hat{\alpha}_2 = -0.19(2.20)$

11cii) I3=9.33, PI=37.30



$\hat{\alpha}_1 = -0.06(1.60)$ $\hat{\alpha}_2 = -0.46(2.17)$

11ciii) I3=11.37, PI=37.30

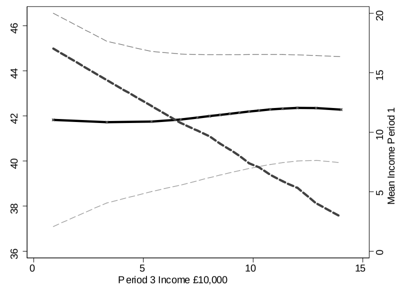


$\hat{\alpha}_1 = 0.14(1.62)$ $\hat{\alpha}_2 = -0.61(2.29)$

Note: 95% confidence intervals shown. Income in 2000 prices, £10,000s.

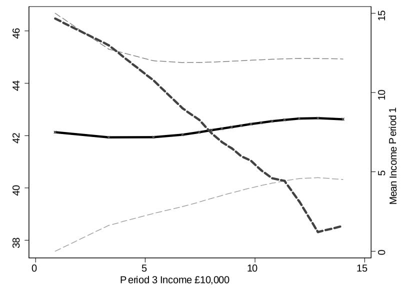
Figure 11: Semi Parametric Estimates. Dependent variable is Grades.

11di) I2=8.53, PI=25.74



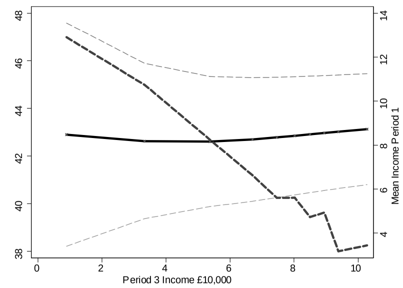
$\hat{\alpha}_1 = 0.27(2.76)$ $\hat{\alpha}_2 = 0.18(1.84)$

11dii) I2=10.31, PI=25.74



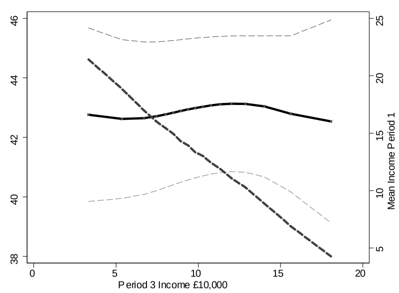
$\hat{\alpha}_1 = 0.20(2.65)$ $\hat{\alpha}_2 = 0.30(1.74)$

11diii) I2=12.37, PI=25.74



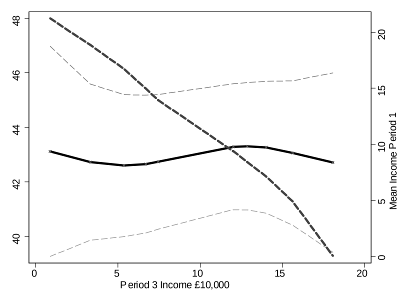
$\hat{\alpha}_1 = -0.05(2.71)$ $\hat{\alpha}_2 = 0.45(1.72)$

11ei) I2=8.53, PI=31.23



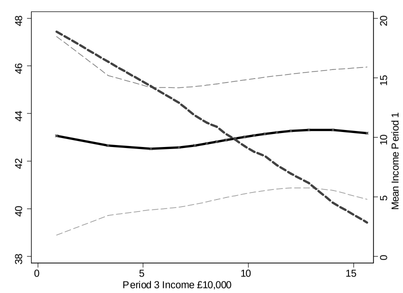
$\hat{\alpha}_1 = 0.22(1.91)$ $\hat{\alpha}_2 = -0.45(2.11)$

11eii) I2=10.31, PI=31.23



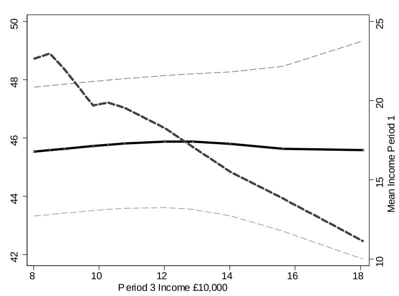
$\hat{\alpha}_1 = -0.10(2.31)$ $\hat{\alpha}_2 = -0.31(2.07)$

11eiii) I2=12.37, PI=31.23



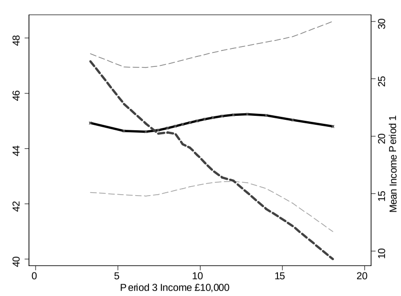
$\hat{\alpha}_1 = -0.11(2.45)$ $\hat{\alpha}_2 = 0.22(1.87)$

11fi) I2=8.53, PI=37.30



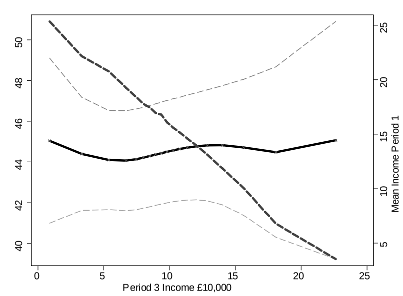
$\hat{\alpha}_1 = 0.28(1.60)$ $\hat{\alpha}_2 = -0.23(2.22)$

11fii) I2=10.31, PI=37.30



$\hat{\alpha}_1 = 0.08(1.75)$ $\hat{\alpha}_2 = 0.42(3.06)$

11fiii) I2=12.37, PI=37.30

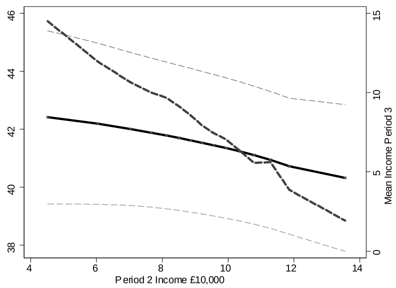


$\hat{\alpha}_1 = -0.54(2.43)$ $\hat{\alpha}_2 = 0.56(3.24)$

Note: 95% confidence intervals shown. Income variables are in 2000 prices, in UK sterling in £10,000s.

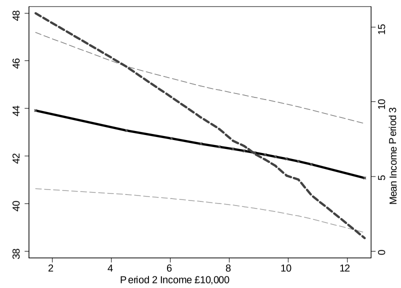
Figure 11: Semi Parametric Estimates. Dependent variable is Grades.

11gi) I2=, PI=25.74



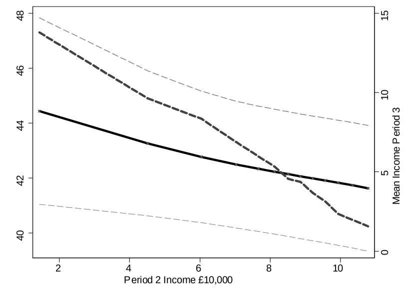
$\hat{\alpha}_1 = -0.88(1.97)$ $\hat{\alpha}_2 = -1.21(1.80)$

11gii) I2=11.87, PI=25.74



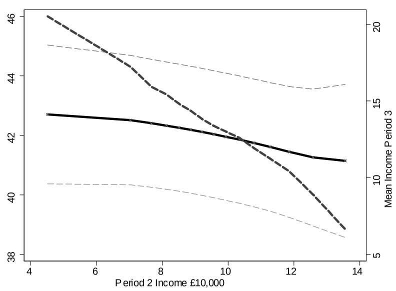
$\hat{\alpha}_1 = -0.66(1.61)$ $\hat{\alpha}_2 = -0.90(1.70)$

11giii) I1=14.15, PI=25.74



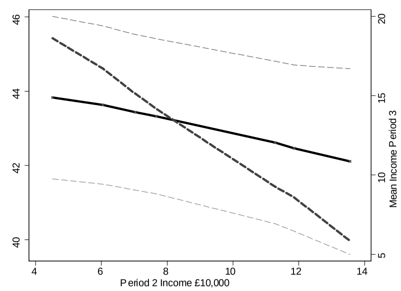
$\hat{\alpha}_1 = -0.54(1.37)$ $\hat{\alpha}_2 = -0.76(2.04)$

11hi) I2=, PI=31.23



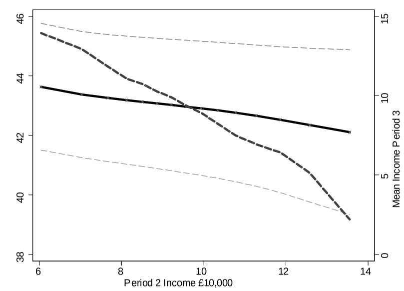
$\hat{\alpha}_1 = -1.70(2.05)$ $\hat{\alpha}_2 = -1.14(1.67)$

11hii) I2=11.87, PI=31.23



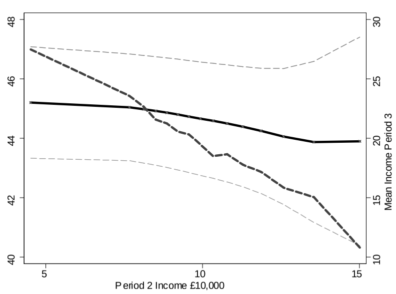
$\hat{\alpha}_1 = -0.77(1.55)$ $\hat{\alpha}_2 = -0.96(1.67)$

11hiii) I1=14.15, PI=31.23



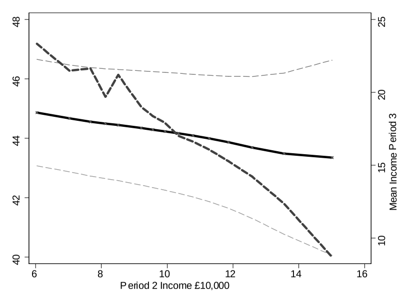
$\hat{\alpha}_1 = -0.63(1.36)$ $\hat{\alpha}_2 = -0.89(1.96)$

11ji) I2=, PI=37.30



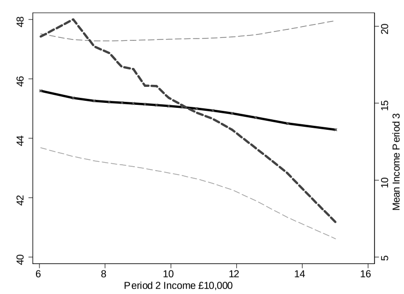
$\hat{\alpha}_1 = -2.29(2.08)$ $\hat{\alpha}_2 = -0.52(1.64)$

11jii) I2=11.87, PI=37.30



$\hat{\alpha}_1 = -0.67(1.57)$ $\hat{\alpha}_2 = -0.86(1.81)$

11jiii) I1=14.15, PI=37.30

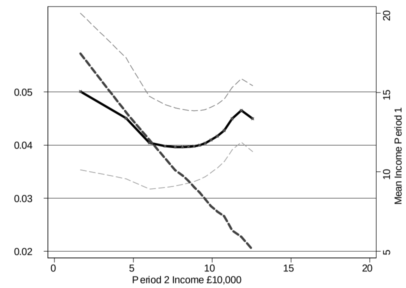


$\hat{\alpha}_1 = -0.49(1.49)$ $\hat{\alpha}_2 = -0.82(2.18)$

Note: 95% confidence intervals shown. Income variables are in 2000 prices, in UK sterling in £10,000s.

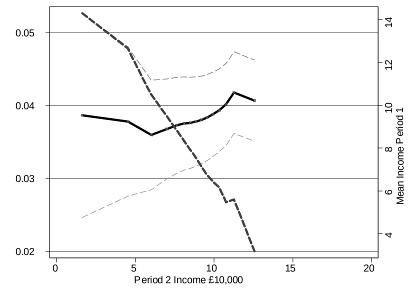
Figure 12: Dependent variable is Child Low Birth Weight.

12ai) I3=9.35, PI=31.01



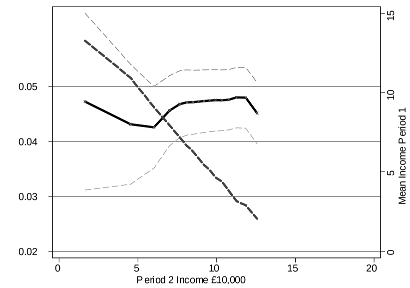
$\hat{\alpha}_1 = -0.01(0.01)$ $\hat{\alpha}_2 = 0.01(0.00)$

12aii) I3=11.67, PI=31.01



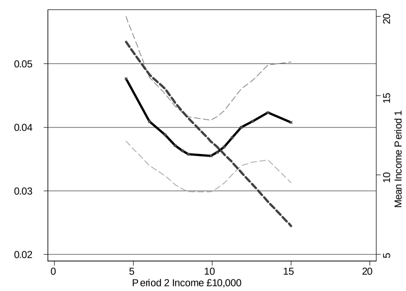
$\hat{\alpha}_1 = -0.00(0.01)$ $\hat{\alpha}_2 = 0.00(0.00)$

12aiii) I3=14.05, PI=31.01



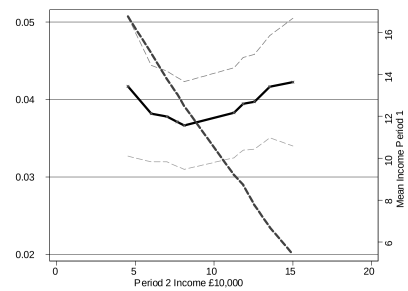
$\hat{\alpha}_1 = -0.00(0.01)$ $\hat{\alpha}_2 = -0.00(0.00)$

12bi) I3=9.35, PI=36.96



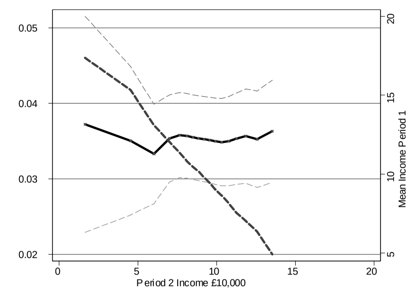
$\hat{\alpha}_1 = -0.01(0.01)$ $\hat{\alpha}_2 = 0.01(0.01)$

12bii) I3=11.67, PI=36.96



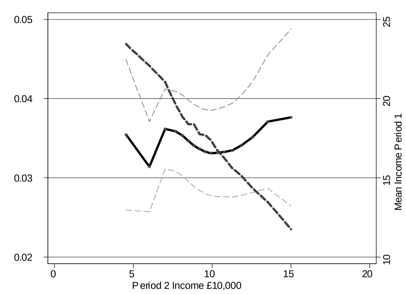
$\hat{\alpha}_1 = -0.01(0.01)$ $\hat{\alpha}_2 = 0.01(0.01)$

12biii) I3=14.05, PI=36.96



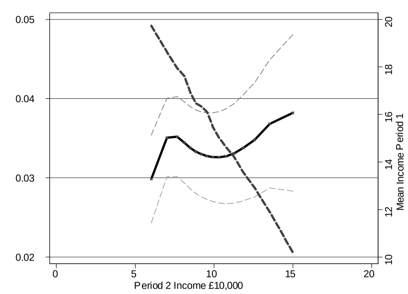
$\hat{\alpha}_1 = -0.00(0.01)$ $\hat{\alpha}_2 = 0.00(0.00)$

12ci) I3=9.35, PI=43.93



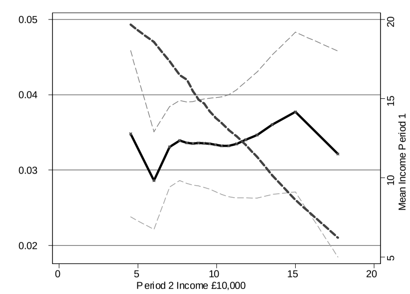
$\hat{\alpha}_1 = -0.00(0.01)$ $\hat{\alpha}_2 = 0.00(0.01)$

12cii) I3=11.67, PI=43.93



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

12ciii) I3=14.05, PI=43.93

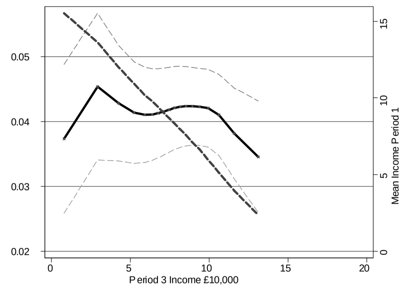


$\hat{\alpha}_1 = -0.00(0.01)$ $\hat{\alpha}_2 = -0.00(0.01)$

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

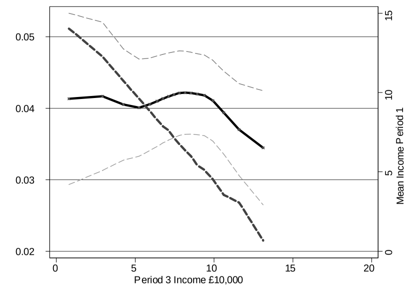
Figure 12: Dependent variable is Child Low Birth Weight.

12di) I2=10.11, PI=31.01



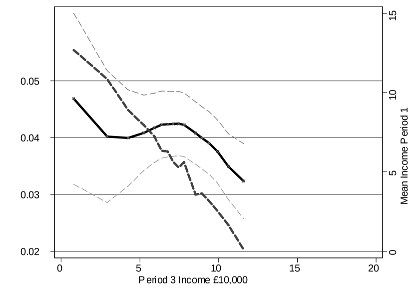
$\hat{\alpha}_1 = 0.00(0.01)$ $\hat{\alpha}_2 = -0.02(0.01)$

12dii) I2=12.39, PI=31.01



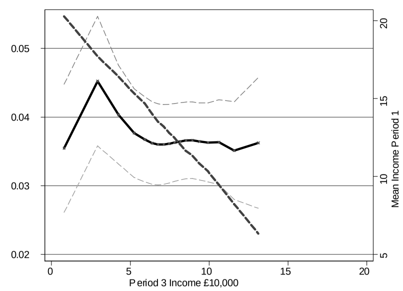
$\hat{\alpha}_1 = 0.00(0.01)$ $\hat{\alpha}_2 = -0.01(0.01)$

12diii) I2=14.98, PI=31.01



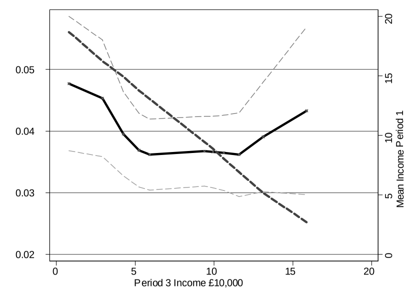
$\hat{\alpha}_1 = -0.00(0.01)$ $\hat{\alpha}_2 = -0.01(0.00)$

12ei) I2=10.11, PI=36.96



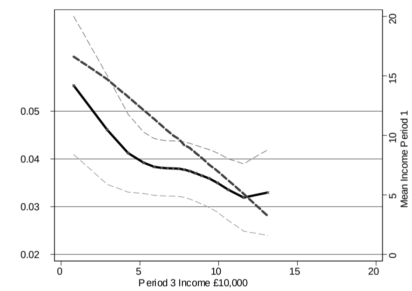
$\hat{\alpha}_1 = 0.00(0.01)$ $\hat{\alpha}_2 = 0.00(0.01)$

12eii) I2=12.39, PI=36.96



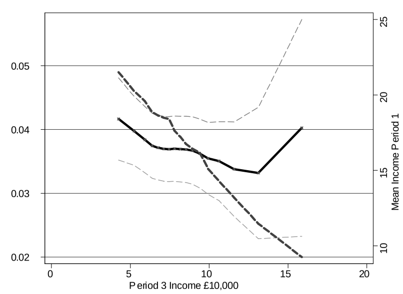
$\hat{\alpha}_1 = -0.01(0.01)$ $\hat{\alpha}_2 = 0.01(0.01)$

12eiii) I2=14.98, PI=36.96



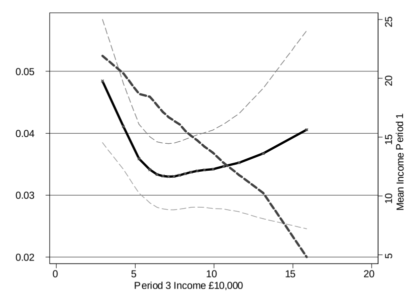
$\hat{\alpha}_1 = -0.02(0.01)$ $\hat{\alpha}_2 = -0.00(0.01)$

12fi) I2=10.11, PI=43.93



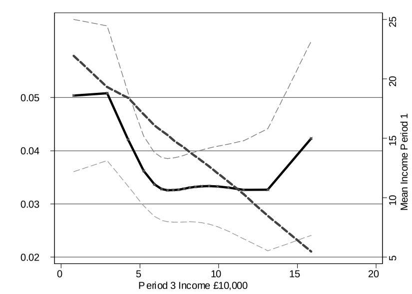
$\hat{\alpha}_1 = 0.01(0.01)$ $\hat{\alpha}_2 = 0.00(0.01)$

12fii) I2=12.39, PI=43.93



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

12fiii) I2=14.98, PI=43.93

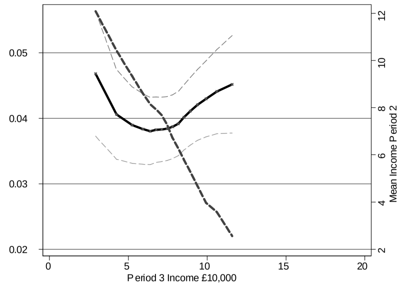


$\hat{\alpha}_1 = -0.02(0.01)$ $\hat{\alpha}_2 = 0.01(0.01)$

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

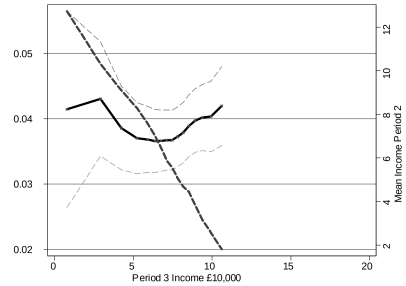
Figure 12: Dependent variable is Child Low Birth Weight.

12gi) I1=10.91, PI=31.01



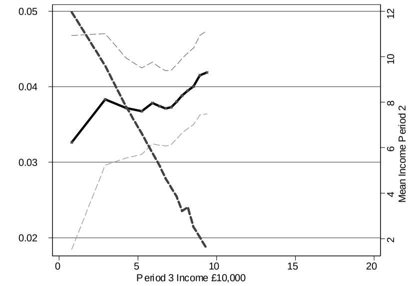
$\hat{\alpha}_1 = -0.01(0.01)$ $\hat{\alpha}_2 = 0.00(0.00)$

12gii) I1=13.02, PI=31.01



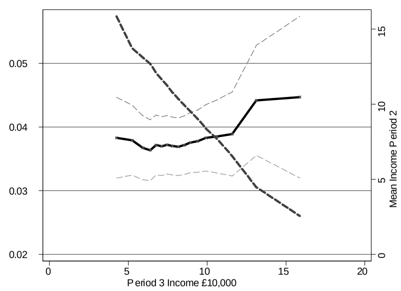
$\hat{\alpha}_1 = 0.01(0.00)$ $\hat{\alpha}_2 = -0.01(0.01)$

12giii) I1=15.64, PI=31.01



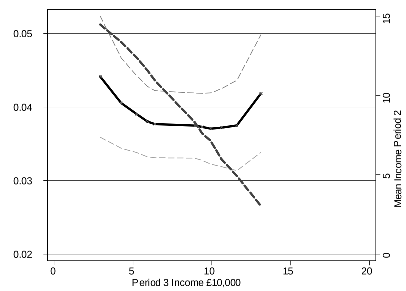
$\hat{\alpha}_1 = -0.01(0.01)$ $\hat{\alpha}_2 = -0.00(0.01)$

12hi) I1=10.91, PI=36.96



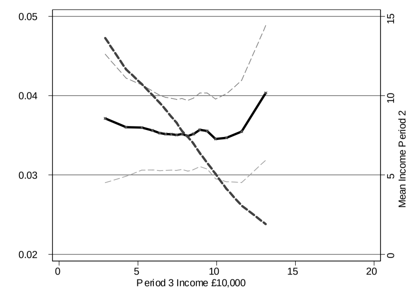
$\hat{\alpha}_1 = -0.00(0.01)$ $\hat{\alpha}_2 = 0.00(0.00)$

12hii) I1=13.02, PI=36.96



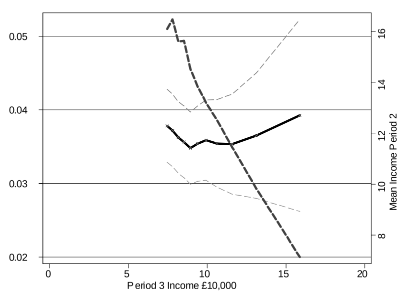
$\hat{\alpha}_1 = -0.01(0.01)$ $\hat{\alpha}_2 = 0.00(0.01)$

12hiii) I1=15.64, PI=36.96



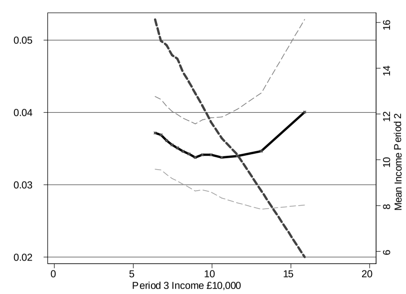
$\hat{\alpha}_1 = -0.00(0.00)$ $\hat{\alpha}_2 = 0.00(0.01)$

12ji) I1=10.91, PI=43.93



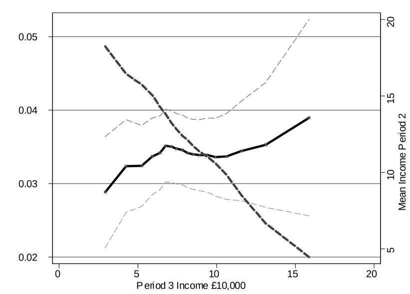
$\hat{\alpha}_1 = -0.00(0.01)$ $\hat{\alpha}_2 = 0.01(0.00)$

12jii) I1=13.02, PI=43.93



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

12jiii) I1=1564, PI=43.93



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

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

	N	Mean	Standard deviation
Paternal Income Period 1, Age 0-5	522490	11.83	4.23
Paternal Income Period 2, Age 6-11	522616	10.25	4.41
Paternal Income Period 3, Age 12-17	522616	8.53	4.68
Paternal Permanent Income, Aged 0-17	522616	30.60	11.69
Mother Years of Schooling	522616	11.14	2.72
Father Years of Schooling	522616	11.45	3.02
Mother Age at Birth	522616	26.26	5.03
Father Age at Birth	522616	29.02	5.74
Child Year of Birth	522616	1975.29	2.88
Years of Schooling	520874	12.73	2.41
High School Drop Out	522616	0.21	0.41
College Attendance	522616	0.39	0.49
IQ	307880	9.90	0.81
Log Earnings age 30	248853	5.25	1.79
Teenage Pregnancy	266014	8.44	1.52
Health	522616	0.04	0.20
Grades	48384	42.75	10.62
Grades Core Subjects	48384	14.71	4.24

Table 2a: Income Mobility of Fathers in Norway: Age 0-5 and 6-11

		6-11	Quartile		
0-5 Quartile	1	2	3	4	Total
1	85,628	32,781	12,769	4,842	136,020
	62.95	24.1	9.39	3.56	100
	58.72	22.71	10.14	4.55	26.03
2	39,947	67,843	28,620	7,082	143,492
	27.84	47.28	19.95	4.94	100
	27.4	46.99	22.73	6.66	27.46
3	13,767	37,306	57,842	22,166	131,081
	10.5	28.46	44.13	16.91	100
	9.44	25.84	45.94	20.83	25.09
4	6,473	6,447	26,664	72,313	111,897
	5.78	5.76	23.83	64.62	100
	4.44	4.47	21.18	67.96	21.42
Total	145,815	144,377	125,895	106,403	522,490
	27.91	27.63	24.1	20.36	100
	100	100	100	100	100

Table 2b: Income Mobility of Fathers in Norway: Age 0-5 and 12-17

		12-17	Quartile		
0-5 Quartile	1	2	3	4	Total
1	77,752	34,967	15,801	7,500	136,020
	57.16	25.71	11.62	5.51	100
	50.49	23.02	12.96	7.92	26.03
2	44,831	61,126	28,078	9,457	143,492
	31.24	42.6	19.57	6.59	100
	29.11	40.24	23.03	9.99	27.46
3	20,523	43,536	45,928	21,094	131,081
	15.66	33.21	35.04	16.09	100
	13.33	28.66	37.67	22.28	25.09
4	10,904	12,259	32,115	56,619	111,897
	9.74	10.96	28.7	50.6	100
	7.08	8.07	26.34	59.81	21.42
Total	154,010	151,888	121,922	94,670	522,490
	29.48	29.07	23.33	18.12	100
	100	100	100	100	100

Table 2c: Income Mobility of Fathers in Norway: Age 6-11 and 12-17

			12-17	Quartile		
6-11	Quartile	1	2	3	4	Total
	1	104,454	30,151	8,263	3,022	145,890
		71.6	20.67	5.66	2.07	100
		67.8	19.85	6.78	3.19	27.92
	2	33,619	83,179	24,116	3,477	144,391
		23.28	57.61	16.7	2.41	100
		21.82	54.76	19.78	3.67	27.63
	3	10,991	33,575	65,062	16,281	125,909
		8.73	26.67	51.67	12.93	100
		7.13	22.1	53.36	17.19	24.09
	4	4,995	4,996	24,499	71,936	106,426
		4.69	4.69	23.02	67.59	100
		3.24	3.29	20.09	75.95	20.36
	Total	154,059	151,901	121,940	94,716	522,616
		29.48	29.07	23.33	18.12	100
		100	100	100	100	100

Table 3a: Parametric Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Years of Schooling			High School Dropout			College Attendance		
Income age 6-11	0.014**	0.001	-0.016***	0.001	0.001***	0.005***	0.004***	0.003***	0.002**
	(0.006)	(0.003)	(0.005)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Income age 12-17	0.015***	0.008***	0.014***	-0.002**	-0.000	-0.000	0.004***	0.003***	0.006***
	(0.006)	(0.003)	(0.005)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Permanent Income	0.033***	0.009***	0.035***	-0.005***	-0.002***	-0.008***	0.006***	0.001*	0.002***
	(0.002)	(0.001)	(0.004)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Income 6-11^2			0.001**			-0.000*			0.000**
			(0.000)			(0.000)			(0.000)
Income 12-17^2			0.001***			-0.000***			0.000***
			(0.000)			(0.000)			(0.000)
Permanent Income^2			-0.000			0.000			0.000
			(0.000)			(0.000)			(0.000)
Income 6-11 * Income 12-17			0.002***			-0.000**			0.000***
			(0.001)			(0.000)			(0.000)
Income 6-11 * Permanent Income			-0.001			0.000			-0.000*
			(0.001)			(0.000)			(0.000)
Income 12-17 * Permanent Income			-0.001**			0.000*			-0.000***
			(0.000)			(0.000)			(0.000)
Observations	507,550	507,550	507,550	507,550	507,550	507,550	507,550	507,550	507,550
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Note: controls include heterogeneous income profile, child gender, family break up dummies in each period, siblings in each period, maternal and paternal years of schooling and age, child year of birth dummies.

Table 3b: Parametric Results

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
		Log Earnings age 30			IQ			Health	
Income age 6-11	-0.010***	-0.007***	-0.021***	0.034***	0.016***	0.012**	0.002	0.001	0.000
	(0.001)	(0.001)	(0.003)	(0.006)	(0.003)	(0.005)	(0.002)	(0.002)	(0.004)
Income age 12-17	0.004***	0.001	-0.006**	0.028***	0.017***	0.043***	-0.000	-0.003	-0.005
	(0.001)	(0.001)	(0.003)	(0.008)	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)
Permanent Income	0.010***	0.008***	0.023***	0.011***	-0.001	0.002	0.001	0.002*	0.005**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)
Income 6-11^2			-0.001**			0.000			-0.000
			(0.000)			(0.000)			(0.000)
Income 12-17^2			-0.000**			0.001***			0.000
			(0.000)			(0.000)			(0.000)
Permanent Income^2			-0.001***			0.000*			-0.000
			(0.000)			(0.000)			(0.000)
Income 6-11 * Income 12-17			-0.001*			0.001***			0.000
			(0.000)			(0.000)			(0.000)
Income 6-11 * Permanent Income			0.001***			-0.000			-0.000
			(0.000)			(0.000)			(0.000)
Income 12-17 * Permanent Income			0.001***			-0.002***			-0.000
			(0.000)			(0.000)			(0.000)
Observations	259,867	259,867	259,867	242,628	242,628	242,628	259,283	259,283	259,283
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Note: controls include heterogeneous income profile, child gender, family break up dummies in each period, siblings in each period, maternal and paternal years of schooling and age, child year of birth dummies.

Table 3c: Parametric Results

	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
	Teen Pregnancy			Grades			Grades Core Subjects		
Income age 6-11	0.001***	0.000	0.001***	-0.204***	-0.107***	-0.199***	-0.078***	-0.036***	-0.067***
	(0.000)	(0.000)	(0.000)	(0.040)	(0.021)	(0.047)	(0.016)	(0.008)	(0.017)
Income age 12-17	0.000	-0.000	-0.000	-0.159***	-0.074***	-0.058*	-0.062***	-0.026***	-0.014
	(0.000)	(0.000)	(0.000)	(0.049)	(0.015)	(0.033)	(0.019)	(0.006)	(0.013)
Permanent Income	-0.002***	-0.001***	-0.002***	0.259***	0.103***	0.180***	0.103***	0.037***	0.063***
	(0.000)	(0.000)	(0.000)	(0.017)	(0.011)	(0.029)	(0.007)	(0.004)	(0.011)
Income 6-11^2			-0.000			-0.001			-0.001
			(0.000)			(0.001)			(0.000)
Income 12-17^2			-0.000***			0.001			0.000
			(0.000)			(0.001)			(0.000)
Permanent Income^2			0.000			-0.001***			-0.001***
			(0.000)			(0.001)			(0.000)
Income 6-11 * Income 12-17			-0.000***			-0.001			-0.000
			(0.000)			(0.001)			(0.001)
Income 6-11 * Permanent Income			-0.000			0.003*			0.001**
			(0.000)			(0.002)			(0.001)
Income 12-17 * Permanent Income			0.000**			0.001			0.000
			(0.000)			(0.001)			(0.000)
Observations	508,874	508,874	508,874	48,384	48,384	48,384	48,384	48,384	48,384
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Note: controls include heterogeneous income profile, child gender, family break up dummies in each period, siblings in each period, maternal and paternal years of schooling and age, child year of birth dummies.

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)

$$Y = \alpha + \beta_1 I_1 + \beta_2 I_2 + u \tag{15}$$

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

$$\begin{aligned} Y &= \delta + \gamma_1 PI + \gamma_2 I_2 + e \\ &= \delta + \gamma_1 (I_1 + I_2) + \gamma_2 I_2 + e \\ &= \delta + \gamma_1 I_1 + (\gamma_1 + \gamma_2) I_2 + e \\ &\therefore \quad \beta_1 = \gamma_1 \\ \beta_2 &= \gamma_1 + \gamma_2 = \beta_1 + \gamma_2 \\ &\therefore \quad \gamma_2 = \beta_2 - \beta_1 \end{aligned} \tag{16}$$

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.

$$Y = \alpha + \beta_1 I_1 + \beta_2 I_2 + \beta_3 I_1 I_2 + u \tag{17}$$

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

$$\begin{aligned} Y &= \delta + \gamma_1 PI + \gamma_2 I_2 + \gamma_3 PI * I_2 + e \\ &= \delta + \gamma_1 (I_1 + I_2) + \gamma_2 I_2 + \gamma_3 (I_1 + I_2) * I_2 + e \\ &= \delta + \gamma_1 I_1 + (\gamma_1 + \gamma_2 + \gamma_3 I_2) I_2 + \gamma_3 I_1 I_2 + e \\ &\therefore \quad \beta_1 = \gamma_1 \\ \beta_2 &= \gamma_1 + \gamma_2 + \gamma_3 I_2 \\ \beta_3 &= \gamma_3 \\ &\therefore \quad \gamma_2 = \beta_2 - \beta_1 - \beta_3 I_2 \end{aligned} \tag{18}$$

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.