

Insurance against Income Shocks, Parental Investments, and Child Development

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DISCUSSION PAPER

NHH



Institutt for samfunnsøkonomi
Department of Economics

SAM 10/24

ISSN: 0804-6824

June 2024

This series consists of papers with limited circulation, intended to stimulate discussion.

Insurance against Income Shocks, Parental Investments, and Child Development

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Abstract

Faced with income shocks, households may be unable to smooth their consumption, because of limited insurance possibilities. Likewise, it may also be difficult to smooth investments in children. This could have large consequences for their human capital if there are sensitive periods of learning, or if investments are not perfect substitutes over time. In this paper we estimate the impact of transitory and permanent shocks to household income in different periods of childhood on the human capital of their children, using administrative records from Norway. Across outcomes, the impacts of transitory and permanent shocks are largely similar regardless of the age at which they occur, with a few exceptions (small in magnitude). The impact of transitory shocks is larger for college enrolment and obesity if these shocks occur at earlier ages. The impacts of permanent shocks on high school graduation are larger the later in childhood they occur.

Keywords: Child human capital; insurance; income dynamics

JEL codes: D12, J13

Acknowledgements: Carneiro gratefully acknowledges the support of the ERC through grant ERC-2015-CoG-682349. Tominey would like to thank for financial support from the British Academy and the Leibniz Association, Bonn in the research network ‘Non-Cognitive Skills: Acquisition and Economic Consequences’. Salvanes gratefully acknowledges the Research Council of Norway for support for the grants for the Center of Excellence, FAIR, and grant number 275274 ”Childhood Gap”. We thank Richard Blundell and Steve Machin for their comments and participants at the York WOLFE Workshop and seminar participants at CEP, UCL and Bristol. Finally, thanks to Ben Etheridge for help with coding.

1 Introduction

A large literature investigates the transmission of income to consumption inequality, and in particular the response of household consumption to income shocks (for recent surveys see [Attanasio and Pistaferri 2016](#) and [Kaplan and Violante 2022](#)). Faced with unexpected income fluctuations, individuals and households attempt to use a variety of insurance mechanisms, public and private, in order to smooth their consumption. Unsurprisingly, full insurance is not observed in the data. Furthermore, the distinction between permanent and transitory shocks is central, because the former are much harder to insure against than the latter (e.g., [Blundell et al. 2008](#), [Brugiavini and Weber 2014](#), [Jappelli and Pistaferri 2017](#), [Commault 2022](#)). If, as suggested by most of the literature, much of the recent changes in inequality are due to changes in the variance of permanent, not transitory shocks, then rising income inequality will lead to rising consumption inequality (see [Attanasio and Pistaferri 2016](#) and the papers they cite).

Although this literature focuses primarily on the insurability of non-durable consumption, income shocks may affect other important household outcomes, such as durable consumption, or human capital formation of children (see, e.g., the survey by [Page forthcoming](#)), which is the focus of our paper. The households' ability to insure against income shocks affects the current welfare of its members through its effect on consumption smoothing, and the future welfare of its children through its effect on the path of investments in children.¹

The consequences of income shocks for investments in children could however be very different than what would be expected for non-durable consumption. In particular, the timing of shocks, which is essentially ignored when analyzing non-durable consumption, may affect not only the level but also the timing of parental investments (i.e., in which ages of the child do they occur). In turn, as discussed in the literature (e.g., [Knudsen et al. 2006](#), [Cunha et al. 2010](#), [Carneiro et al. 2021](#)), the timing of investments for human capital formation can be as important as their magnitude. This will happen if there are sensitive periods of learning so that investments in some time periods are particularly productive, or if investments are not substitutable over time in the production of human capital.

¹[Schneider et al. \(2018\)](#) document a relationship between income inequality and socioeconomic gaps in investments in children, and [Jackson and Schneider \(2022\)](#) discuss the role of welfare programs in mitigating these gaps.

In this paper we examine the extent to which permanent and transitory shocks to income occurring at different points in childhood affect children’s human capital. Using register data from Norway (for about 580000 children born in the 70s and tracked through 2010), we start by estimating the family income process for the first 16 years of life of the child, allowing us to characterize the magnitude of permanent and transitory shocks to income at different stages of childhood, for households defined by different demographics (education of the mother and father, age of the father at birth, year of birth of the child). We then study the relationship between the age profile of transitory and permanent income shocks and several child outcomes (high school graduation, college enrolment, IQ, teenage parenthood, and obesity).

This is not the first paper to investigate the role of the timing of income shocks for human capital formation (see, e.g., [Carneiro and Heckman 2002](#), [Caucutt and Lochner 2020](#), [Carneiro et al. 2021](#), [Carneiro et al. 2023](#)). It is, however, the first one to distinguish the role of transitory and permanent shocks occurring in different periods, a distinction which is crucial to understanding the consequences of changes in inequality, and the design of social insurance programs, which should be informed by the knowledge of which shocks are particularly hard (or easy) for households to insure against, and whether the timing of particular shocks is especially detrimental for household outcomes, in particular the human capital of children.²

Our empirical strategy draws on the literature studying partial insurance in consumption (e.g., [Blundell et al. 2008](#)), although the relevant framework is one in which there are important non-separabilities over time (see e.g., [Attanasio 1999](#), [Jappelli and Pistaferri 2017](#), and the papers they cite). Intuitively, it works in the following way. We divide the sample into different cells, according to demographic characteristics: mother and father’s education, father’s age at birth, and cohort. For each of these cells, we measure how much income varies at different child ages (variance), and how correlated (persistent) income is across ages (covariance). We use this information to decompose the total variance of income at each age into the variance of a permanent (persistent) component and the variance of a transitory component (in a similar way to [Blundell and Preston 1998](#), [Meghir and Pistaferri 2004](#) and [Blundell et al. 2015](#)). This gives us variances of permanent and transitory shocks to income that are specific to each child age, and to each demographic cell.

²[Carneiro and Ginja \(2016\)](#) are the first to study the impact of transitory and permanent shocks to income on parental investments, however, without analyzing the effect on children’s human capital.

For each demographic cell, we also measure the covariance between human capital in adulthood and income fluctuations experienced at each age during childhood. We can then ask if the covariance between human capital and income shocks at a particular age is especially large if the variance of permanent shocks is large at that same age (indicating that permanent shocks at that age are strongly related to human capital in adulthood), or if it is the variance of transitory shocks that is large (indicating that it is the transitory shock at that age that is important), or neither.

The model is identified from variation in these covariances and variances across demographic cells. We can include in the model controls for demographic group fixed effects (by including indicators for mother and father’s education, father’s age at birth, and cohort), so we only explore variation within these groups. In principle, we can only identify the impact of fluctuations in income at each point in childhood around a long term permanent income or a trend (as in, for example, [Carneiro et al. 2021](#)), so the shocks we consider should average to zero across all periods of childhood, and we can only identify the relative impact of shocks occurring at different ages (i.e., the impact of an income shock at age t on human capital in adulthood relative to the impact of the same shock if it occurred in another benchmark age, say $t-k$). We do not directly observe the reaction of parental investments to income shocks (as in, for example, [Carneiro and Ginja 2016](#)), but a natural conjecture is that income shocks at different ages could affect adult outcomes of children partly by impacting parental investments at each age. Nevertheless, there may also be effects of these shocks on other aspects of the home environment, such as family stress, that go beyond parental investments ([Black et al. 2016](#); [Carneiro et al. 2023](#); [Song 2018](#)), and we show below that these can be important in our setting.

We find that, in Norway, the timing of permanent and transitory shocks to household income has small impacts on the different dimensions of children’s human capital we consider.³ There are however some instances where we can reject that these impacts are similar across all ages.

For example, permanent income shocks have slightly larger impacts on high school graduation if they occur later in childhood, closer to the actual date and final exams and graduation. This could be seen as surprising since permanent shocks affect household income for many more periods of childhood if they occur in the beginning rather than at the end of childhood. Therefore, if

³This is consistent with [Carneiro et al. \(2021\)](#), who argue that the intergenerational transmission of economic status is primarily driven by a more permanent source of inequality ([Huggett et al. 2011](#)), rather than by the particular sequence of (permanent or transitory) shocks affecting a household.

anything, early permanent shocks should have stronger impacts than later permanent shocks. The finding that for outcomes like high school graduation, late permanent shocks have slightly more importance, suggests either that permanent shocks are easier to insure if they occur when the child is younger (it is not clear why this would be the case), or that they may be operating through channels other than just income, such as parental and child stress. High school graduation may be particularly sensitive to the stress induced by permanent shocks to income occurring close to the high school graduation years (as in, for example, [Carneiro et al. 2023](#)).

We also find that transitory shocks to household income have the same impact on high school graduation regardless of the time when they occur, but they have larger impacts on college enrolment if they occur earlier rather than later during the childhood years. The effect of transitory shocks on obesity in late adolescence also appears to differ according to their timing.

As mentioned above we can't tell whether households in our study show a remarkable ability to shield the human capital of their children from shocks to income in childhood, or whether the timing of investments in children does not matter very much. If it was the latter, we recognize that this may be special to Norway, because of its generous welfare system in the 1970s with a well-established social insurance system, including universal and generous unemployment, disability, and other benefits.

For example, in the US, the literature studying the impact of income shocks on children, or the impact of increasing the generosity of welfare benefits, suggests that income shocks may be more important for child development in this and other similar countries, see for instance [Bailey et al. \(2023\)](#); [Dahl and Lochner \(2012\)](#). However, whilst antipoverty programs such as food stamps provision in the US have been effective at improving outcomes for treated children (see for example [Hoynes et al. 2016](#) and [Bailey et al. 2023](#)) in the US, recent well-identified studies assessing conditional or unconditional cash transfers do not find much of an effect on short and long term outcomes for children. For instance, [Hawkins et al. \(2023\)](#) analyse a program where low income families with low birth weight children received additional benefits for the first three years of life, finding that the cash transfer did not improve longer run schooling, earnings or mortality outcomes. In a large RCT in California where families with small children received unconditional cash transfers, no effect was found on household expenditures, labour supply and well-being ([Gennetian et al., 2022](#)). Moreover, a study of Spain, with a more comprehensive welfare state than the US, does not find support for

the effect of an unconditional cash transfer at birth on health and test scores of children ([Borra et al., 2021](#)).

In our study, we detect magnitudes of the impact of shocks that whilst small, are not all zero. In other settings, with less generous welfare systems such as the US, these impacts may be larger. That said, for the context we study, no major redesign of social insurance programs or welfare transfers would be required to take into account the timing of transitory and permanent shocks to income during childhood (if the government wished to promote higher levels of human capital accumulation).

The emphasis of our paper on the timing of income shocks is driven by academic and policy reasons. Multiple recent papers analyze the consequences of incomplete markets for investments in human capital, (see [Abbott 2022](#); [Caucutt and Lochner 2020](#); [Lee and Seshadri 2019](#)). Borrowing constraints or other sources of market incompleteness may prevent parents from insuring investing in their children during especially sensitive periods. In addition, the technology of skill formation may be such that investing in other periods when borrowing constraints are not as severe does not adequately compensate for the lack of investments during the constrained periods.

From the policy point of view, the question for the design of a social insurance program is not only how much insurance households are able to access when they are faced with a shock, and to what extent transitory and permanent shocks can be insured, but also if they are able to get such insurance during specific periods of development for their children. Therefore, we ask if the timing of income shocks matters, which may be especially important in the case of permanent shocks, which are arguably harder to insure than more transitory shocks. We also ask whether (and when) some households have more difficulty in getting such insurance.

This is the first paper to examine the differential response of human capital to temporary and permanent shocks to income. It combines two strands of the literature which are typically separated, the study of consumption inequality (e.g., [Attanasio 1999](#), [Blundell et al. 2008](#), [Attanasio and Pistaferri 2016](#), [Jappelli and Pistaferri 2017](#)) and the study of intergenerational mobility (e.g., [Solon 1999](#), [Björklund and Salvanes 2011](#), [Black and Devereux 2011](#), [Mogstad and Torsvik 2023](#)). It fits into the literature looking at the implications of incomplete markets for human capital development and intergenerational mobility. The earlier literature, such as [Becker and Tomes \(1979\)](#), [Becker and Tomes \(1986\)](#), or [Mulligan \(1997\)](#), considered a single period of childhood, and discussed the

inability to borrow against (parent or child) resources during the adult years of the child. The more recent literature ([Abbott 2022](#); [Caucutt and Lochner 2020](#); [Lee and Seshadri 2019](#)), already referred to above, considers instead borrowing constraints across periods of childhood, and their implication for the consequences of income shocks at different ages.

It is also related to a large literature exploring the effect of specific shocks to income on child outcomes.⁴ For example, [Cameron and Heckman \(2001\)](#) and [Carneiro and Heckman \(2002\)](#) emphasize the primary role of permanent income and other permanent family factors for human capital formation of children, which is a much more important determinant of college attendance than shorter-term borrowing constraints at age 17. More recently, [Caucutt and Lochner \(2020\)](#) and [Carneiro et al. \(2021\)](#) (among others) suggest that the timing of income is important, finding that the determinant of adolescent college enrolment, among other outcomes, is not contemporaneous income alone, but rather the flow of parental income across childhood. In addition [Akee et al. \(2010\)](#) found that the effect of an exogenous and permanent government transfer to households had a larger effect on schooling and crime outcomes for children with six, rather than two years of exposure to these transfers. Relative to these papers (especially [Carneiro et al. 2021](#), which is the closest to this paper), our analysis emphasizes the insurability of different shocks. We focus on the distinction between permanent and transitory shocks at each age, and the differential household insurance possibilities against these two types of shocks (see also [Carneiro and Ginja 2016](#)).⁵ This distinction is central to understand how the dynamics of income inequality affecting a generation of children growing up affects inequality of child outcomes in adulthood - furthering our understanding of the sources of intergenerational income transmission - and to assess the potential role of public insurance against income shocks. Regardless of whether parental investments are in time or money, they are likely to account for a substantial fraction of resources in most households.

The paper is structured as follows. [Section 2](#) describes the institutional setting in Norway, [Section 3](#) discusses the Norwegian data. [Section 4](#) details the empirical strategy, [Section 5](#) discusses the results and [Section 6](#) concludes.

⁴For reviews, see [Mayer and Leone \(1997\)](#), [Solon \(1999\)](#), [Currie and Almond \(2011\)](#), [Page \(forthcoming\)](#).

⁵Because they ignore the distinction between permanent and transitory shocks and aggregate multiple ages of childhood into just three childhood stages, [Carneiro et al. \(2021\)](#) are able to model interactions across incomes at different ages in a more flexible way than we have in this paper.

2 The Norwegian Setting

In this section, we give an overview of the most relevant aspects of the Norwegian welfare state and education system as well social security system and labor relations. Our sample is made up of all children born between 1970-1980 in Norway (and their parents), and this section explains the relevant institutional setting faced by these parents and their children.

Family Policies. Today family policies including maternal job protection and childcare, play a big role in the Nordic welfare states. However, most of these policies were developed to play an important part in the late 1970s and for the most part, do cover the cohorts we are looking at. To give an example, prior to 1977 there was a very low level of maternity leave available and only some fractions of mothers were covered by access to paid maternity leave. Mothers could take up to 12 weeks of leave. In 1977, there was a reform (studied, for example, by [Carneiro et al. 2015](#)) that changed the system to one where mothers were granted up to a year of leave, with the first 18 weeks paid at the full salary. Tying in with this lower level of maternity leave, for most of the 1970s, there were very low levels of formal childcare take up.⁶ There was no free child care prior to compulsory schooling (which is still the situation nowadays). The consequence was that during the early 1970s, the majority of mothers did not go to work, but stayed at home and looked after the children. In the data used in this paper, only 30% of mothers were working two years after they had given birth, compared to 60% of mothers in 1980. Today the situation is different with universal access to subsidized daycare as well as a generous parental leave policy covering the first year of a child's life.

Education System. Schooling in Norway is now compulsory from age 6 to age 16, although the children in this study started school in the year they turned 7. Note that our analysis considers how income shocks experienced up to age 16 drive later outcomes and therefore excludes shocks realized after making the decision to extend schooling beyond the compulsory schooling age. High School has two tracks, vocational and academic. Only the academic track provides direct access to college and university education. The vocational track results in a trade or certificate. The vocational track does not grant the student access to higher education. Enrollment into tracks is

⁶Which was only 10% for 3-6-year-olds in 1975 but almost none for 1-2-year-olds, according to [Havnes and Mogstad \(2011\)](#).

about fifty-fifty, where more boys choose the vocational track. Access to high schools and programs in high schools is very competitive and is based on GPA (a combination of exit exams and teacher evaluations in class) for middle schools. Higher education is for the most part public institutions without tuition fees. Admission is conditional on an academic high school degree and satisfying a minimum grade requirement. Students are assigned exclusively based on high school GPA from a national ranking. There was free access to school-age education and readily available loans to students attending university (Dalla-Zuanna et al., 2023).

Social Security and Employment Law. Norway has a relatively high degree of employment protection and generous unemployment benefits, high compared to the US, although low compared to Southern European countries (Botero et al., 2004; Huttunen et al., 2018). Employment contracts typically require three months' notice of termination, though there are some exceptions related to employment tenure. There is no generalized legal requirement for severance pay. In the event of mass layoffs, there is no rule determining the order in which workers are laid off (Salvanes et al., 2024). Access to unemployment benefits is given when their work hours are reduced by at least 50 percent and they have an income of a certain level. The replacement rate is 62 percent of the income and is given for a period of 186 weeks in our period. Disability pensions are available due to illness or injury. Access to disability pensions can be described as liberal and is a channel through which individuals can permanently exit the labor force prior to old age pensions (Johnsen et al., 2021). The after-tax replacement rate for previously average earners is around 65 percent.

In a setting with so much public insurance it is possible that income shocks have less impact on child development than in other context with less generous welfare systems (see e.g. Aakvik et al. 2005, Blundell et al. 2015). Elsewhere, market incompleteness has been argued to impair investments in children and their development, especially if they are binding during early childhood (Abbott, 2022; Caucutt and Lochner, 2020; Lee and Seshadri, 2019).

3 Data and Variables

Our data is based on the population-wide panel of Norwegian Registry data. A unique personal identifier enables the linking of families across generations, and the linking with registers containing annual observations regarding birth, education, income, social security, and marriage market status.

The chosen sample contains the population of children born in Norway between 1970-1980, matched to their parents' income history, age, education, etc, and also contains school performance, IQ data for men, education, and teen pregnancy outcomes for children. [Table 1](#) displays the summary statistics for the data, containing 586,069 children born to 379,820 families.

Income is measured by pre-tax parental labor earnings (including income from self-employment) excluding some government transfers such as unemployment benefits and sickness leave, measured from 1970 to 2010. Household income is defined as the sum of maternal and paternal income where income measures are deflated to the year 2000. We supplement the data with information on the household's assets - available from 1993 - for the oldest four cohorts, when the children were aged between 12-16. Assets are constructed for each household as the sum of all positive assets (savings, stocks, shares etc) minus any debt (including mortgage debt, bank balance or credit cards).

Important to our analysis is linking parents to children by age which is possible through the family register. We follow these children over time, from birth to early adulthood which allows us to examine the impact of parental labor market shocks on children's short-and long-run education outcomes, as a function of the child's age at the time of the shock. We define a wide range of child human capital outcomes, recorded from their adolescence to early adulthood. Educational status is measured as late as 2015, meaning that the youngest children in the sample are aged 35 by this time and likely to have completed their education. Two education variables are defined for the analysis. First, an indicator variable equal to one if the child graduated from high school and zero if they dropped out before receiving a certificate for vocational or academic education. Without this certificate, students' future paths are restricted and for example, they will not be able to attend university. ⁷ Second, an indicator for university attendance, which takes value one for 39.4% of individuals in our sample.

Military service is compulsory in Norway for males, who take tests including a measure of IQ upon entry to the army at around age 18. The IQ score, available for males only, is a composite score from arithmetic, word similarities, and figures tests. The arithmetic and word tests are most similar to the Wechsler Adult Intelligent Scale (WAIS), and the figures test to the Raven Progressive matrix, which are standard measures of IQ.⁸ The continuous scores are banded into a 9-point scale.

⁷This outcome is referred to as high school graduation.

⁸For more information, see [Sundet et al. \(2004\)](#), [Sundet et al. \(2005\)](#).

In addition, we can use the same army records for males to get information on height and weight, which can then be used to construct a measure of obesity, defined following the World Health Organization as having a BMI greater than 30. Finally, we create an indicator of teenage pregnancy for females.

Among the children in our sample, 78% completed high school or more, and 39% completed a university degree. In addition, 2.9% of males were obese in early adulthood, and 4.3% of females were teenage mothers. With regards to parents, they experience their first birth when they are 26 (mothers) to 29 (fathers) years of age. On average, they have just below 12 years of education.

We construct indicators for low-educated households (those without a college degree) and high-educated households (where at least one parent has a degree or higher). In 34.9% of households (high education household), either the mother or the father has completed higher education.

4 Empirical Strategy

This section sets out the procedure to estimate the effect of transitory and permanent household income shocks on child human capital (a more detailed explanation is provided in [Appendix A](#)).

4.1 Income Process

We begin with the estimation of the income process, for which we mainly follow the literature (see [Blundell and Preston 1998](#), [Meghir and Pistaferri 2004](#), [Blundell et al. 2015](#)). We use administrative data on the population of Norway, between 1970-2000. [Appendix B](#) explains in detail the procedure and our main results, which suggest that transitory income follows a MA(1) process, and that permanent income follows a random walk (again, a standard specification used in the literature referred to above).

We use this income process to decompose shocks to household income into permanent and transitory components. [Blundell et al. \(2015\)](#) note that there is nonstationarity in the income process in Norway by time, age and education. Analogously, we allow for nonstationarity by age of the household male (in the year the child was born), year of birth of the child (which we call cohort below), and parental education (a dummy variable which takes the value of 1 if either the mother or father has a higher education degree, and zero otherwise). We allow heterogeneity by

the age of only the household male rather than considering combinations of ages of both spouses, to avoid creating small cells.

We assume that the natural logarithm of income ($\ln w_{itcfe}$) for observation i , period t , cohort c , father age f and parental education e can be written as the sum of a permanent and a transitory component (denoted P and v respectively), as well as a deterministic component of covariates (Z):

$$\ln w_{itcfe} = Z'_{itcfe}\varphi + P_{itcfe} + v_{itcfe} \quad (1)$$

where $i = 1, \dots, N$; $t = 1970, \dots, 2000$; $c = 1970, \dots, 1980$; $f = 19, \dots, 55$; $e = 0, 1$. Permanent income follows a random walk (Equation 2) and transitory income is a serially correlated MA(1) process (Equation 3), where ζ and ε denote the permanent and transitory income shocks respectively and θ is the first order MA coefficient which varies across cohort, father age and household education.⁹

$$P_{itcfe} = P_{it-1cfe} + \zeta_{itcfe} \quad (2)$$

$$v_{itcfe} = \theta_{cfe}\varepsilon_{it-1cfe} + \varepsilon_{itcfe} \quad (3)$$

Both permanent and transitory shocks are assumed to have a mean of zero and be uncorrelated with each other: $E(\zeta_{itcfe}) = E(\varepsilon_{itcfe}) = E(\zeta_{itcfe}\varepsilon_{itcfe}) = 0$.

Following Meghir and Pistaferri (2004), we define y as log income with the effect of the covariates removed in a first stage, $y_{itcfe} = \ln w_{itcfe} - Z'_{itcfe}\hat{\varphi}_t$. The controls in Z include a quadratic in mother and father age at birth, mother and father's years of schooling, and indicator variables for municipality of residence. This first stage is run separately for each year t .¹⁰

To estimate the effects of permanent and transitory income shocks on child human capital requires two further steps. First, to isolate innovations to income from time invariant household characteristics, we take the first difference in log income residuals, given by $\Delta y_{itcfe} = \zeta_{itcfe} + \Delta v_{itcfe}$. Because transitory income follows a MA(1) process, the first difference in log income residuals can be written in terms of the innovations to permanent and transitory income, as $\Delta y_{itcfe} =$

⁹Appendix B provide evidence that this is a good representation of the true income process for the population of Norwegian parents having a child between 1970-1980.

¹⁰See Table A.1 for the estimates from a subset of years 1970, 1980, 1990 and 2000 for household income.

$\zeta_{itcfe} + \varepsilon_{itcfe} + (\theta - 1)\varepsilon_{it-1cfe} - \theta\varepsilon_{it-2cfe}$. Second, we match the log income residual in each year t to the age of the child, a , defined across years of childhood between 0-16, so instead of indexing the shocks by time t (ζ_{itcfe} and ε_{itcfe}), we index them by age a (ζ_{iacfe} and ε_{iacfe}).

4.2 The Transmission of Income Shocks to Child Human Capital

To estimate the transmission of household income shocks to children’s human capital we consider the following a statistical model of human capital formation, where h_{icfe} is a residualised measure of human capital.¹¹

$$h_{icfe} = \sum_{a=1}^{16} (\beta_a^P \zeta_{iacfe} + \beta_a^V \varepsilon_{iacfe}) + u_{icfe} \quad (4)$$

The reduced form [Equation 4](#) models human capital in adolescence as a linear function of the sequence of permanent and transitory shocks at each age. β_a^P and β_a^V measure (respectively) the transmission of the permanent and transitory shock at each child age a to human capital.

This is analogous to the model specified in [Blundell et al. \(2008\)](#) to measure the transmission of permanent and transitory income shocks to consumption. In the appendix of their paper they present a life-cycle model of (non-durable) consumption which, under some assumptions, is consistent with the statistical model they estimate. In [Section 4.4](#) we discuss simple models of parental investments and human capital formation in childhood and how they help us interpret the estimates from [Equation 4](#).

As we discuss in [Section 4.3](#), it is more interesting to discuss the differences in β_a^P and β_a^V across ages, than the levels of these parameters for each particular age. In fact, by construction, for each given household, income shocks should average out to zero, which implies that differences across parameters is in fact all that we can identify. Below we graph estimates of $\beta_a^P - \beta_1^P$ and $\beta_a^V - \beta_1^V$, for different age a , although we could have used any other age (besides 1) as the benchmark age.

4.3 Identification

In order to identify transmission parameters β_a^P and β_a^V , we ask if the covariance between human capital and the first difference of income (capturing income shocks) at a particular age is especially

¹¹Each human capital measure is also residualised controlling for the set of controls Z used to residualise income.

large when the variance of permanent shocks is large at that age (indicating that permanent shocks at that age are strongly related to human capital in adulthood), or the variance of transitory shocks is large (indicating that it is the transitory shock at that age that is important), or neither. Formally, we explore variation in the second moments (variances and covariances) of income shocks (ζ_{iace} and ε_{iace}), and (residual) human capital (h_{iace}), across child cohort, father's age, and parental education. This method is similar to [Blundell et al. \(2008\)](#) and [Adda et al. \(2009\)](#), both of whom use time (whereas we explore cohort, male age and education) variation in variances and covariances of shocks to identify impacts of income shocks on the outcomes they were interested in.

As it will become clear in this section, the procedure we just described assumes that the variation in age profiles of the variances of permanent and transitory shocks to income is exogenous across child cohort, male age, and education cells. This is a plausible assumption, because variation over time in the variances of permanent and transitory shocks in the population should depend primarily on macroeconomic conditions, unrelated to the child's age. For example, papers including [Lippi and Reichlin \(1993\)](#) characterise the permanent and temporary volatility in the aggregate economy as due to supply and demand disturbances respectively, whilst [Davis and Kahn \(2008\)](#) explain the declining aggregate volatility in the US economy through increased supply-chain efficiency and a shift in production and employment from goods to services. In addition, note that our model can support the addition of fixed effects for child cohort, male age, and education cells, which weakens this assumption of exogeneity in the variation of shocks across the cells of child cohort, male age and household education cells even more. Even if there was any systematic relationship between the variances of these shocks and the education and age of the parent, it could be captured by these variables. In fact, as we show below, our estimates barely change when they are included in the model.

We begin by discussing the income process. [Meghir and Pistaferri \(2004\)](#) identify the moments of the income process using information on income alone. From [Section 4.1](#), the covariance matrix of income at different lags for a cohort, male age and education is given by

$$\begin{aligned} cov(\Delta y_{iacea}, \Delta y_{iacea-s}) &= \sigma_{\zeta_a}^2 + \sigma_{\Delta v_{icea}}^2 && \text{if } s = 0 \\ &cov(\Delta v_a, \Delta v_{a+s}) && \text{if } s \neq 0 \end{aligned} \tag{5}$$

where $\sigma_{(.)}^2$ and $cov(..)$ denote the variance and covariance respectively. Given that in [Ap-](#)

pendix B estimate a MA(1) process for transitory income, the covariance between Δy_{icfea} and $\Delta y_{icfea-s}$ will be non-zero only for $|s| \leq 2$. Equation 5 can be re-written as:

$$\begin{aligned} cov(\Delta y_{icfea}, \Delta y_{icfea-s}) = & \sigma_{\zeta_a}^2 + \sigma_{\varepsilon_{cfea}}^2 + (\theta - 1)\sigma_{\varepsilon_{cfea-1}}^2 - \theta\sigma_{\varepsilon_{cfea-2}}^2 & if \ s = 0 \\ & (\theta - 1)\sigma_{\varepsilon_{cfea}}^2 - (\theta^2 - \theta)\sigma_{\varepsilon_{cfea-1}}^2 & if \ s = 1 \\ & -\theta\sigma_{\varepsilon_{cfea}}^2 & if \ s = 2 \end{aligned} \quad (6)$$

The aggregation to cohort- father age - parental education cells allows identification of all variance terms, with the exception of shocks in the final period T, $\sigma_{\varepsilon_{Tcfe}}^2$ and $\sigma_{\zeta_{Tcfe}}^2$, which cannot be separately identified. For this reason, an additional year of income data is included for age 17.¹² Details of estimation of the variance terms in Equation 5 is given in Appendix B.1.

In practice we estimate the variance terms in Equation 5 using diagonally weighted minimum distance (DWMD).¹³ Following the literature, we choose to use DWMD over other methods (optimal minimum distance, OMD, or equally weighted minimum distance, EWMD). Altonji and Segal (1996) examined the small sample properties of OMD and found significant sample bias from OMD. In comparing measures of the bias using a Monte Carlo procedure, EWMD tended to dominate OMD. However as noted by Blundell et al. (2008), unlike EWMD, DWMD allows for heteroskedasticity, and this is the weighting matrix that we choose employ in this paper. The variance of permanent and transitory shocks across child age along with the MA parameter θ are allowed to vary across cells, *cfe*.¹⁴

Next, we consider the identification of the effect of the permanent and transitory shocks on human capital formation. The covariance matrix between (residual) income in each year of the child's lifetime and (a measure of residual) human capital is given by:

$$cov(\Delta y_{icfea}, h_{icfe}) = \beta_a^P \sigma_{\zeta_{acfe}}^2 + \beta_a^V \sigma_{\varepsilon_{acfe}}^2 + \beta_{a-1}^V (\theta - 1)\theta \sigma_{\varepsilon_{a-1cfe}}^2 - \beta_{a-2}^V \theta \sigma_{\varepsilon_{a-2cfe}}^2 + \sigma_{\mu_0, \zeta_a + \Delta v_a} \quad (7)$$

where $\sigma_{\mu_0, \zeta_a + \Delta v_a}$ denotes the correlation between μ_{0cfe} and the innovation in income Δy . From

¹²This means that $\sigma_{\varepsilon_{17cfe}}^2$ and $\sigma_{\zeta_{17cfe}}^2$ cannot be distinguished.

¹³The estimation procedure is described in detail in Section B.1

¹⁴This is in line with Blundell et al. 2015 who recommend allowing for variation by age, skill level and time in the estimation of the variance of transitory and permanent shocks.

this system of equations we can estimate β_a^P and β_a^V for all ages.

As discussed above, it is assumed that the variances of permanent and transitory shocks to income are uncorrelated with any residual term in [Equation 7](#), either $\sigma_{\mu_0, \zeta_a + \Delta v_a}$ or any other terms related, for example, to measurement error, which we have not included explicitly in the equation. Notice that permanent and transitory income shocks are net of household fixed effects and several controls. Furthermore, as we also mentioned below, we can enrich [Equation 7](#) with cohort, age of the father, and education of the parent fixed effects (which barely affect our estimates).

[Equation 7](#) describes the relationship between the covariance between human capital and the first difference of (residual) income at each age of the child (i.e., the income *shock*), and the variances of permanent and transitory income shocks at different ages. All these variances and covariances vary across cohort- father age - parental education cells. Our procedure then asks whether the covariance between human capital and income shocks is particularly large in ages for which the permanent shock has a particularly large variance (suggesting that the permanent shock at that age was difficult to insure, and/or that it was especially important for child development), or in ages for which it is the transitory shock that has a large variance. Variation across demographic cells allows us to estimate age specific coefficients for the impact of permanent and transitory shocks on human capital.

For a long enough time horizon, permanent (ζ_{iacfe}) and transitory (ε_{iacfe}) shocks should average to zero. Therefore, in principle it is not possible to separately identify all the coefficients (β_a^P and β_a^V) in [Equation 4](#).¹⁵ The intuition is that, if income shocks represent fluctuations around a more *permanent* income (or even an income trend), with this strategy we cannot identify the impact of that *permanent* income since it will be absorbed into the time invariant effect that is differenced out (or in the trend). It is only possible to identify impacts of shocks in one age relative to another (as in [Carneiro et al. 2021](#)).

The model of [Equation 7](#) allows for any relationship between the estimated coefficients and the

¹⁵Take, for example, permanent shocks, and assume that $\sum_{a=1}^{16} \zeta_{iacfe} = 0$. Then $\zeta_{iacfe} = -\sum_{b=1, b \neq a}^{16} \zeta_{ibcfe}$, and $\sigma_{\zeta_a}^2 = \sum_{b=1, b \neq a}^{16} \sigma_{\zeta_b}^2$. For simplicity, take the special case where $\beta_a^P = 0$ for all ages (i.e., consider only permanent shocks), which means that $cov(\Delta y_{icfea}, h_{icfe}) = \beta_a^P \sigma_{\zeta_a}^2$. Then, noting that $\Delta y_{itcfe} = \zeta_{itcfe} + \Delta v_{itcfe}$, from [Equation 7](#) it follows that, $\beta_a^P = \frac{cov(\Delta y_{icfea}, h_{icfe})}{\sigma_{\zeta_a}^2} = -\sum_{b=1, b \neq a}^{16} \beta_b^P \frac{\sigma_{\zeta_b}^2}{\sum_{b=1, b \neq a}^{16} \sigma_{\zeta_b}^2}$.

corresponding age of the income shock. This may give rise to unrealistic patterns, where these coefficients vary substantially from one age to the subsequent one. Therefore, in addition to these raw estimates, we also estimate an alternative version where we impose that these coefficients are a smooth (quadratic) function of age of the shock.¹⁶ Our analysis is focused on the latter (smoothed) coefficients but we graphically plot the smoothed coefficients together with the coefficients from Equation 7.

Equation 7 assumes that, although the second order moments of the permanent and transitory income process differ across cohorts, father age, education and time, the effect of these shocks upon child outcomes (the β_a^P and β_a^V coefficients) differs only across child age. We relax this assumption in a heterogeneity analysis which allows the coefficients to vary first across household education and fathers' age at birth.

Measurement error is omitted from the model. Meghir and Pistaferri (2004) estimate that between a quarter and a third of the transitory income shock variation is due to measurement error in the Panel Study of Income Dynamics (PSID). However, the bias is likely to be smaller in the current sample, as income is recorded from administrative data. The variance of permanent shocks is unaffected by the presence of measurement error. If the importance of measurement error is similar across ages it is unlikely to affect our estimates of the transmission of transitory shocks to income to human capital formation.

4.4 Interpreting β_a^P and β_a^V

β_a^P and β_a^V measure the transmission of permanent and transitory shocks to income at different ages to the child's human capital. But how should we interpret them in light of an economic model of parental investments in children?

The stock of child human capital (h) accumulates from parental investments taking place during the entire childhood. We can then model human capital in adolescence as a function of income in each period of life, where a different coefficient is allowed for permanent and transitory components of income, a set of parental traits X , a child level idiosyncratic error u_i and initial endowment, μ_{i0}

¹⁶For each child age, estimation of Equation 7 produces one estimate of the transitory shock and one of the permanent shock in the corresponding age. Minimum distance estimation uses these estimates to fit a quadratic function across child age fitting the equation $\beta_a^K = \omega_1 age_a + \omega_2 age_a^2$, where $K = P, V$ denotes the permanent and transitory shocks.

(for example genes or parental unobservable characteristics).¹⁷ Implicitly, parents optimise levels of parental investment and consumption to maximise their utility, which is a function of the child's stock of human capital after childhood, hence human capital has a subscript i relating to the child and parent pair.¹⁸

We start from the simplest model, where human capital is a linear function of parental investments, and parental investments are a linear function of contemporaneous permanent and transitory shocks to income. In this case, human capital is a linear function of income in each period.

$$h_{icfe} = \delta X_{icfe} + \sum_{a=1}^{16} \gamma_a^P P_{iacfe} + \sum_{a=1}^{16} \gamma_a^V v_{iacfe} + \mu_{i0cfe} + u_{icfe} \quad (8)$$

γ_a^P and γ_a^V denote the effect of permanent and transitory shocks at age a .

Repeatedly substituting for P_{iacfe} and substituting for v_{iacfe} gives

$$h_{icfe} = \delta X_{icfe} + \sum_{a=1}^{16} \gamma_a^P \left(P_{i0cfe} + \sum_{s=1}^a \zeta_{iscfe} \right) + \sum_{a=1}^{16} \gamma_a^V (\theta_{cfe,r} \varepsilon_{ia-1cfe} + \varepsilon_{iacfe}) + \mu_{i0cfe} + u_{icfe} \quad (9)$$

We remove the effect of covariates X on human capital and define $\tilde{h}_{icfe} = h_{icfe} - X'_{icfe} \hat{\delta}$ for each measure of human capital. Income shocks are assumed to be uncorrelated with u and u has mean zero; $E(u_{icfe} \varepsilon_{iacfe}) = E(u_{icfe} \zeta_{iacfe}) = E(u_{icfe}) = 0$; $a = 1, \dots, 16$, $i = 1, \dots, N$; $c = 1, \dots, C$.

In this setting one can interpret β_a^P and β_a^V as:

$$\beta_a^P = \sum_{k=a}^{16} \gamma_k^P \quad (10)$$

$$\beta_a^V = \gamma_a^V + \theta \gamma_{a+1}^V \quad (11)$$

where θ is the average taken across cells cfe .

We do not observe investments, which means that we cannot separate the impact of income

¹⁷ X includes mother and father education and age at birth. The estimated income shocks control for Z and it is assumed that whilst other unobserved factors are uncorrelated with shocks, the shocks may be correlated with μ_{i0} (a time invariant factor).

¹⁸In this paper we do not present an explicit dynamic model of parental investments in children. Some examples that discuss such models can be seen in, e.g., [Cunha \(2005\)](#), [Cunha et al. \(2010\)](#), [Carneiro and Ginja \(2016\)](#), [Caucutt and Lochner \(2020\)](#), [Carneiro et al. \(2021\)](#).

shocks on investments (insurance), from the impact of investments on human capital (technology). Therefore, our estimates conflate the two. These data limitations constrain the interpretability of our estimates. Suppose, for example, that one finds that income shocks at a particular age do not affect the child's human capital. Is this because investments do not react to shocks (insurance) or because human capital does not react to investments (technology)? If it is the former, then whatever insurance is available (say from social insurance programs) may be enough, while if it is the latter, whatever insurance is available is unnecessary (at least in what concerns human capital formation).

Furthermore, as is clear from the recent literature on intergenerational mobility (see for example [Cunha et al. 2013](#), [Caucutt and Lochner 2020](#), [Abbott 2022](#)), insurance and technology are likely to interact. Taking another example, if there is strong complementarity between early and late investments, and if, for example, borrowing constraints prevented someone from investing at early ages, then the availability or not of insurance may be irrelevant for late investments because they would be so unproductive that parents would not want to take them. We realize this is an extreme and unrealistic scenario but it makes our point.

Moreover, a general lifecycle model of parental investments in children may be characterized by intertemporal non-separabilities, as models of lifecycle consumption with durables, or with habits, as discussed, for example, in [Carneiro and Ginja \(2016\)](#). Some of the recent literature on intergenerational mobility ([Restuccia and Urrutia 2004](#), [Cunha and Heckman 2007](#), [Cunha et al. 2013](#), [Heckman and Mosso 2014](#), [Daruich 2018](#), [Lee and Seshadri 2019](#), [Caucutt and Lochner 2020](#), [Carneiro et al. 2021](#)) emphasizes that, in that case, the timing of income shocks may be as important as their magnitude, and the income shocks in different time periods interact. That said, the question of whether and at what ages strong non-separabilities are important empirically is an active research topic on which a consensus has not emerged yet (e.g., [Cunha et al. 2010](#), [Agostinelli and Wiswall 2023](#), [Johnson and Jackson 2019](#), [Goff et al. 2023](#), [Campos et al. 2024](#), [Carneiro et al. 2024](#)).

In sum, it would be ideal to estimate a model where human capital in adolescence would be a flexible function of the entire series of permanent and transitory shocks to family income. Unfortunately, estimating such a model is impractical, even with large sample sizes, so some simplifications

need to be done.¹⁹ We recognize that the model we estimate is simplistic, ignoring interactions across periods (more on this below). It can however be interpreted as a first order linear approximation to the more realistic model described above.

That said, we also present estimates of a model with limited non-separabilities between income shocks in different periods. More precisely, we present a set of results where we allow the response of human capital to income shocks in early childhood to depend on the level of income in late childhood, and vice versa, described in more detail in [Section 5.3](#). Such a model allows us a first test of whether such limited non-separabilities are important.

One last point we wish to make here is that the interpretation of β_a^P and β_a^V in [Equation 10](#) and [Equation 11](#) assumes that all the impact of shocks operate solely through their impact on income (and presumably, investments). It is however possible that there are other impacts of shocks that go beyond their impacts on income, for example, on the levels of stress or anxiety experienced in the household (or related variables).

One can easily incorporate these non-income effects of income shocks in our empirical model, namely by rewriting [Equation 9](#):

$$h_{icfe} = \delta X_{icfe} + \sum_{a=1}^{16} \gamma_a^P \left(P_{i0cfe} + \sum_{s=1}^a \zeta_{iscfe} \right) + \sum_{a=1}^{16} \gamma_a^V \left(\theta_{cfe,r} \varepsilon_{ia-1cfe} + \varepsilon_{iacfe} \right) + \sum_{a=1}^{16} \psi_a^P \zeta_{iacfe} + \sum_{a=1}^{16} \psi_a^V \varepsilon_{iacfe} + \mu_{i0cfe} + u_{icfe} \quad (12)$$

Here, ψ_a^P and ψ_a^V measure the non-income impacts of permanent and transitory income shocks, which, for simplicity, we assume not to be persistent (although such persistence could be accommodated). This leads to straightforward modifications of [Equation 10](#) and [Equation 11](#). It is clear that, with our empirical strategy (and data limitations), it is not possible to separate income and non-income impacts of income shocks.

¹⁹Using similar data as us, [Carneiro et al. \(2021\)](#) estimate a model where human capital is a flexible function of family income in different time periods. However, they ignore the distinction between permanent and transitory shocks, and group childhood income into only three large periods.

5 Results

5.1 Distribution of income shocks

Percentiles of the distribution of the variances of the age specific transitory and permanent income shocks (estimated using diagonally weighted minimum distance) are reported in [Table 2](#). The income process assumes a random walk for permanent income and an MA(1) process for transitory income. Details were described above in [Section B.1](#).

There are two things to notice about this table. First, the distribution of the variances of shocks is remarkably similar across child ages. Indeed, panels a) and b) of [Figure 1](#) shows the distribution of the variance of transitory and permanent shocks to vary across the child’s cohort, but confirms little change across the distribution of transitory or permanent shocks across child age (panels c and d respectively) or across fathers’ age (see [Figure A.2](#)). This is perhaps as expected if the distribution of shocks depends primarily on macroeconomic conditions independent of the child’s age at the time of the shock. Reassuringly, this is one of our identifying assumptions, as discussed in the previous section.

Second, the variance of permanent shocks is much higher than the variance of transitory shocks. Therefore, permanent shocks are not only more persistent, they are also more likely to be consequential for household earnings.

Furthermore, the magnitude of these shocks is substantial. The median standard deviation is about 0.17 for transitory shocks and 0.28 for permanent shocks. Since the standard deviation of log income is in the range of 0.6-0.7 for household income, transitory shocks represent around 25% of a standard deviation in annual income, whilst the permanent shocks are of the magnitude of around 50% of a standard deviation in annual income.

5.2 Effect of shocks on adolescent outcomes

The main innovation of this paper is its focus on the transmission of household permanent and transitory income shocks to child outcomes measured in adolescence and adulthood. As argued above, we can only identify the relative impact of income shocks across ages, namely estimates of $\beta_a^P - \beta_1^P$ and $\beta_a^V - \beta_1^V$, corresponding to the coefficients on $\sigma_{\zeta_{acfe}}^2$ and $\sigma_{\varepsilon_{acfe}}^2$ from the model in

Equation 4. We estimate impacts on high school graduation and college enrolment (two schooling variables), IQ and obesity (only for males, because they rely on army data), and teenage pregnancy (only for females). Together they reveal different important aspects of the life of the child as an adult.

We represent these results graphically in [Figure 2a-Figure 2e](#) and [Figure 3a-Figure 3e](#), which show β_a^P and β_a^V (the transmission of transitory and permanent shocks to household income) at different ages (relative to age 1) for high school graduation, college attendance, IQ, obesity and teen pregnancy respectively (see also [Table A.3-Table A.6](#)). The figures also display a smoothed estimate of these age-varying coefficients, which uses a quadratic function of age as described above (labelled as "Smoothed estimates" and "Raw estimates" in the figures, respectively). A bootstrap procedure is used to calculate the standard errors associated with the smoothed estimates.²⁰

Beginning with high school completion and college enrolment, the estimates are quite small. They correspond to the impact of a shock of 1 log point, which in light of the estimated variances of transitory and permanent shocks shown above, is a very large shock. With regards to high school graduation ([Figure 2a](#) and column (1) of [Table A.3](#)), we cannot reject that the impact of transitory shocks is the same across different ages. For example, a transitory shock at age 16 (the approximate age for high school completion) corresponding to roughly 10% of income (0.1 log points) leads to an impact on high school graduation that is 0.15 percentage points smaller than if the shock occurred at age 1. This is a small effect (high school graduation rates are about 78% in our sample), and we cannot reject that this estimate is equal to zero.

In terms of college enrolment ([Figure 2b](#) and column (2) of [Table A.3](#)), the impact of a transitory shock is slightly larger if it occurs at age 1 than if it occurs at much later ages. For example, a transitory shock at age 1 corresponding to 10% of income leads to an impact on college enrolment that is 0.3 percentage points larger than if the shock occurred at age 10. On average, about 39% of our sample enrolls in college, so again this is a small (but non-negligible) effect, which nevertheless is statistically different from zero.

We now turn to the IQ variable, that is only available for males. From [Figure 2c](#) and column (1) of [Table A.4](#) we find no difference in the impact of transitory shocks across age. Again, impacts

²⁰Specifically, we use the bootstrap (500 repetitions) to create the variance-covariance matrix of the age specific estimate of the permanent and transitory shocks. We can then use minimum distance to get the smoothed estimates, by fitting a quadratic in age to the raw estimates along with the standard errors.

are very small (recall that the standard deviation of IQ is about 1.8): a 10% increase in income due to a transitory shock has a 0.004 larger impact on IQ if it occurs at age 10 than at age 1.

Obesity is another variable that is only available for males, and which has a standard deviation of 0.169. In [Figure 2d](#) (column (2) of [Table A.4](#)), early transitory shocks are more effective at lowering obesity, as a positive transitory shock has a more positive impact on obesity if the shock occurs at age 16 than if it takes place at age 1. This difference is however very small (0.001 larger impact on obesity if a transitory income shock worth 10% of income occurs at age 16 rather than age 1), even if statistically different from zero.

The final outcome we consider in [Figure 2e](#) (column (3) of [Table A.4](#)) is teenage pregnancy, an outcome only defined for females. 4.3% of females in the sample were teenage mothers. Relative to age 1, a transitory shock corresponding to 10% of income and occurring at ages 7 to 10, has a more positive (less negative) impact on this outcome, by about 0.1 percentage points. For the remaining ages this relative effect is smaller and statistically insignificant.

Even when statistically significant, the impact of the timing of transitory shocks does not appear to be quantitatively very important. It is possible that transitory shocks are well insured, as argued by [Blundell et al. \(2008\)](#) (although their findings have been partially disputed by [Commault 2022](#)). Therefore, it does not matter in what year they occur. However, it could also happen that investments are close substitutes over time, and not much more productive in one age relative to another.

On the other hand, permanent (persistent) shocks are potentially harder to insure than transitory shocks. Therefore, it is possible that their timing is more important for human capital than the timing of transitory shocks. We now turn to the discussion of a parallel set of figures for permanent shocks.

Across ages, permanent shocks have a variance which is higher than the variance of transitory shocks (see [Table 2](#)), of about 0.08, or a standard deviation of about 0.28. This means that the impact of a permanent shock with a magnitude of one log point corresponds roughly to a shock that is three to four standard deviations above the mean, which is very large. Therefore, as above, we will benchmark our estimates to shocks corresponding to about a 10% (0.1 log points) fluctuation in income.

As in the case of transitory shocks, the timing of permanent shocks does not substantially affect

the development of children. This is true across all outcomes we consider, shown in [Figure 3](#) and [Table A.5-Table A.6](#). Starting with high school graduation in [Figure 3a](#) (column (1) of [Table A.5](#)), a permanent income shock at age 16 has a larger impact on this outcome than a permanent income shock of the same size at age 1, and the difference is statistically significant. For a shock corresponding to 10% of income (0.1 log points), having the shock at age 16 rather than at age 1 leads to an increase in high school graduation of 0.2 percentage points.

It is interesting that it's the later shock that has the largest impact, even though early shocks affect many more years of childhood because they are so persistent. [Equation 10](#) suggests that the impact of permanent shocks should be larger for early than for late shocks, because they affect many more periods of childhood. One explanation for this result is that non-income aspects of permanent shocks may vary across ages, for this specific outcome, be more salient at later ages. These findings are analogous to those of [Carneiro et al. \(2023\)](#), who show that parental job loss episodes affect the mental health of children at the time they occur even if they do not have lasting impacts on this outcome. In addition, parental job loss episodes occurring close to the time of high school graduation have larger impacts on this outcome than similar episodes occurring earlier in the lives of children, even if early job loss affects family income for many more periods of childhood than job loss occurring closer to adulthood.

Permanent shocks have a larger impact on college completion if they occur in the earlier or later years of childhood, than if they occur in the middle, and the exact opposite is true for obesity (see [Figure 3b and d](#); column (2) of [Table A.5](#) and column (2) of [Table A.6](#) for college and obesity respectively). Again these are not large effects, even if statistically significant. Impacts of permanent shocks on the IQ of males ([Figure 3c](#) and column (1) of [Table A.6](#)) or teenage pregnancy of females ([Figure 3e](#) and columns (3) of [Table A.6](#)) are not different for shocks occurring at early or at late periods of childhood.

[Figure A.3-Figure A.4](#) show that the results reported in [Figure 2](#) and [Figure 3](#) are nearly identical when we include fixed effects for cohort, father's age and parental education. Although the arguments and suggestive evidence presented above strongly support the validity of the assumption underlying our results (that the age profile of the variances of transitory and permanent shocks is exogenous across demographic groups), the inclusion of these fixed effects helps bolster our case.

In sum, there are some lessons to take from these results. To start with, whether they are

transitory or permanent, the timing of the shocks does not appear to be a central determinant of human capital development of children in our setting. Across outcomes, even when differences in the impact of shocks across ages are statistically different from zero, their magnitude is not large. This echoes earlier results by [Carneiro et al. \(2021\)](#). The human capital of children is primarily driven by the permanent income of their parents during their childhood, rather than by the timing of parental income fluctuations during that period.

It is possible that this happens because in our setting, parents are either able to insure their investments in children against income fluctuations, or they are reluctant to change their investments in children in response to shocks (for example, because of dynamic complementarity) and adjust on other margins instead (e.g., [Carneiro and Ginja 2016](#)). It is also possible that the timing of investments does not matter if the elasticity of substitution between investments in different time periods is high.

That said, the timing of shocks is not irrelevant for all outcomes, especially for education. If is not irrelevant in a country such as Norway, with a very generous welfare system, it is bound to be more important in other countries where insurance against shocks is more difficult.

5.3 Non-separabilities and Dynamic complementarity

As mentioned above, in order to investigate the potential importance of dynamic complementarity (e.g., [Carneiro et al. 2021](#); [Cunha 2005](#); [Cunha and Heckman 2008](#)), we require a more flexible model. However, it is very difficult to adapt our framework to consider a fully flexible (reduced form) production function of learning (analogous to [Equation 4](#)).

Therefore, we consider a simpler framework. We begin by dividing the childhood period into early years (age 1-8) and late years (age 9-16), and measure permanent income in each period as the sum of the present value of household income in each year. Early permanent income then is the sum of household income at ages 1-8; whilst late permanent income is the sum of household income at ages 9-16.

The estimation model [Equation 7](#) is augmented with an interaction term between each transitory (permanent) income shock between ages 1-8 and an indicator for permanent income between 9-16 being above the mean; each transitory (permanent) income shock between ages 9-16 and an indicator for permanent income at ages 1-8 being above the mean and the two indicators (one for

high early permanent income and the other for high late permanent income).²¹

As a consequence, we estimate double the number of parameters relative to our benchmark model considered above. In particular, we now estimate 15 coefficients for each transitory and permanent income shocks given permanent income in the adjacent period is low and a further 15 estimates for each transitory and permanent given permanent income in the adjacent period is high. Our results will suggest that dynamic non-separabilities in the impact of income shocks are important if the effect of an income shock is different for those with high (above average) permanent income in the adjacent period, compared to those with low (below average) permanent income in the adjacent period.

The results are reported in [Figure A.5](#) for transitory income shocks and [Figure A.6](#) for permanent income shocks. Note that the raw estimates are smoothed using a quadratic spline with knot at age 8.

There are some examples consistent with some dynamic non-separabilities, for example when considering the effect of transitory income shocks on IQ and teen pregnancy in [Figure A.5c and e](#). However, when plotting the confidence intervals, the two lines within each graph lie within the confidence interval of each other and we cannot reject that the curves are the same. Note also that for the outcome high school graduation, at points the effect of transitory shocks is larger for those with low permanent income in the adjacent period, although again we can reject that this relationship is statistically significant.

²¹ Again we estimate a system of equations, one for each year of childhood, where in this case the equation in early childhood (age 1-8) is given by

$$\begin{aligned} cov(\Delta y_{icfea}, h_{icfe}) = & \alpha_a^P \sigma_{\zeta_{acfe}}^2 + \alpha_a^V \sigma_{\varepsilon_{acfe}}^2 + \alpha_{a-1}^V (\theta - 1) \theta \sigma_{\varepsilon_{a-1cfe}}^2 - \alpha_{a-2}^V \theta \sigma_{\varepsilon_{a-2cfe}}^2 \\ & + \alpha_{HL}^P HIGH_{9-16} + \alpha_a^{PH} \sigma_{\zeta_{acfe}}^2 * HIGH_{9-16} + \\ & \alpha_a^{VH} \sigma_{\varepsilon_{acfe}}^2 * HIGH_{9-16} + \alpha_{a-1}^{VH} (\theta - 1) \theta \sigma_{\varepsilon_{a-1cfe}}^2 * HIGH_{9-16} - \alpha_{a-2}^{VH} \theta \sigma_{\varepsilon_{a-2cfe}}^2 * HIGH_{9-16} \\ & + \sigma_{\mu_0, \zeta_a + \Delta v_a} \end{aligned} \quad (13)$$

for ages $a = 1, \dots, 8$ where $HIGH_{9-16}$ is an indicator variable that takes the value 1 when permanent income in ages 9-16 is high and 0 otherwise. In late childhood the equations estimated are given by

$$\begin{aligned} cov(\Delta y_{icfea}, h_{icfe}) = & \alpha_a^P \sigma_{\zeta_{acfe}}^2 + \alpha_a^V \sigma_{\varepsilon_{acfe}}^2 + \alpha_{a-1}^V (\theta - 1) \theta \sigma_{\varepsilon_{a-1cfe}}^2 - \alpha_{a-2}^V \theta \sigma_{\varepsilon_{a-2cfe}}^2 \\ & + \alpha_{HE}^P HIGH_{1-8} + \alpha_a^{PH} \sigma_{\zeta_{acfe}}^2 * HIGH_{1-8} + \\ & \alpha_a^{VH} \sigma_{\varepsilon_{acfe}}^2 * HIGH_{1-8} + \alpha_{a-1}^{VH} (\theta - 1) \theta \sigma_{\varepsilon_{a-1cfe}}^2 * HIGH_{1-8} - \alpha_{a-2}^{VH} \theta \sigma_{\varepsilon_{a-2cfe}}^2 * HIGH_{1-8} \\ & + \sigma_{\mu_0, \zeta_a + \Delta v_a} \end{aligned} \quad (14)$$

for ages $a = 9, \dots, 16$ where $HIGH_{1-8}$ is an indicator variable that takes the value 1 when permanent income in ages 1-8 is high and 0 otherwise.

5.4 Heterogeneity

The conclusions from the paper that the effect of transitory or permanent income shocks is relatively constant regardless of when they occur remain true when considering households with different demographics or by child gender. [Figure A.7-Figure A.11](#) plot the effects of income shocks separately for households where parents have low levels of education compared to households where they have high levels of education (this compares households where neither parents has a college degree to households where at least one parent has a degree). In very few cases, the estimates of the income shock relative to age 1 are statistically different to zero. For example, the permanent income shocks in middle childhood are more productive for college and obesity than early or late childhood in low education households. However in these cases the magnitude of the effect is very small. The same is true when stratifying the sample by the fathers' age into the younger fathers (below the mean of 27) and older fathers (above the mean), in [Figure A.12-Figure A.16](#).

It is also interesting to study the effect of income shocks in households more likely to be credit constrained. [Figure A.17](#) plots for the two educational outcomes the effect of transitory and permanent income shocks in households with low permanent income, measured as the income between ages 1-8 and between 9-16 being below the mean. Again the estimates are imprecisely estimated and the results suggest no substantial differential effect of the income shocks across child age. Finally, when dividing the sample by gender (focusing just on the outcomes measured for both males and females - high school graduation and college) there is no evidence that the income shocks are more productive at any particular age compared to another. These can be seen in [Figure A.18-Figure A.19](#).

5.5 Asset accumulation

Given that the magnitudes of the estimates reported above are so small, one might wonder whether income shocks matter for any other outcome in Norway (given the generosity of its welfare system). Unfortunately, there is no consumption panel in Norway which we can use to study how consumption reacts to permanent and transitory income shocks. There is, however, information on assets, although it is only available for recent years, which do not correspond to the years we use in our analysis. Nevertheless, it is still instructive to check how transitory and permanent income shocks affect asset holdings, using a procedure analogous to that in [Blundell et al. \(2008\)](#), and which we

adapted to the outcomes of our paper.

More precisely, from 1993 onwards, it is possible to measure assets data for Norwegian households. Therefore, for our asset analysis we create a sample of cohorts born from 1977-1980, for whom we can link asset data when the children are aged 12-16. Using this panel we will investigate whether household assets adjust to permanent or transitory income shocks. [Table A.7](#) reports the summary statistics for this sub-sample of our benchmark sample, showing that the child human capital outcomes and parent demographics are broadly similar in the sub-sample as compared to the benchmark in [Table 1](#). We measure the log of net assets, where net assets are defined as household assets (including savings in the bank, stocks and shares etc) minus debt (mortgage debt, bank balance, credit card debt etc) and estimate the effect of transitory and permanent income shocks on (log of) net assets; household assets and debt.

From one period to the next, households may adjust their log assets A between periods $t - 1$ to t (ΔA) in response to innovations to permanent income and transitory income according to the following model:

$$\Delta A_{icfe} = \rho_0 + \rho_1 \zeta_{icfe} + \rho_2 \epsilon_{icfe} + u'_{icfe} \quad (15)$$

In practice we follow [Blundell and Preston \(1998\)](#) who estimate the innovations to consumption as a function of the innovations to permanent and transitory components to income, estimating the equation

$$cov(\Delta y_{cfe}, \Delta A_{cfe}) = \lambda_0 + \lambda_1 \sigma_{\zeta_{cfe}}^2 + \lambda_2 \sigma_{\epsilon_{cfe}}^2 + u''_{cfe} \quad (16)$$

[Table 3](#) reports the effect of permanent and transitory shocks on contemporary savings levels, reported in Norwegian kroner. It shows that a positive shock to fathers' transitory income raises net assets and household assets, but it has no effect on debt levels. Therefore, a positive shock to household transitory income is reflected in higher savings. Permanent income shocks do not translate into asset changes.

The fact that impacts on assets are larger for transitory than for permanent shocks may be a consequence of households using their assets to insure their consumption more in reaction to transitory shocks than in reaction to permanent shocks. This reaction exists even in the presence of a very generous welfare system, which further helps households to insure their consumption against income shocks. It is perhaps surprising that the impact of permanent shocks on assets is

so small, but there are several other margins on which households are able to adjust, such as labor supply of different household members, or the consumption of durables, among others.

6 Conclusion

This paper studies how well parents are able to insure the human capital of their children against (the timing of) permanent and transitory shocks to income occurring during their childhood. We began by estimating the income process in Norway, for the population of parents giving birth to children in the 1970s. Similarly to studies of other countries, the Norwegian household income process is best described by the sum of a deterministic, permanent and transitory component where the permanent component follows a martingale and the transitory a moving average process of order 1 or 2. Given this model for income, the next stage was to estimate annual deviations of log household income from a life cycle profile, and decompose these into yearly permanent and transitory income shocks.

The effect of the shocks was then estimated upon a range of child outcomes, to understand in which stages of child development the income shocks drive the stock of adolescent human capital. We find that, in Norway, the timing of permanent and transitory shocks to household income has small impacts on different dimensions of children's human capital. The intergenerational transmission of economic status is primarily driven by an initial and more permanent source of inequality ([Huggett et al. 2011](#)), rather than by the sequence of permanent or transitory shocks affecting a household (see also [Carneiro et al. 2021](#)).

We observe, nevertheless, some small impacts of the timing of income on different outcomes. For example, for high school graduation, permanent shocks have a stronger impact if they occur in late childhood. College enrolment is more affected by permanent shocks occurring at the beginning and end of childhood than shocks in middle childhood, and by transitory shocks occurring during the early years of the child's life. We would expect permanent shocks to have larger impacts if they occurred during early childhood, because they affect income for all subsequent childhood year, whereas for permanent shocks occurring later in childhood the exposure of children is much more limited. The finding that, for some outcomes like high school graduation, late permanent shocks have slightly more importance, suggests that they may be operating through channels other

than just income, such as parental and child stress. It is possible that high school graduation is particularly sensitive to the stress induced by permanent shocks to income occurring close to the high school graduation years (as in, for example, [Carneiro et al. 2023](#)).

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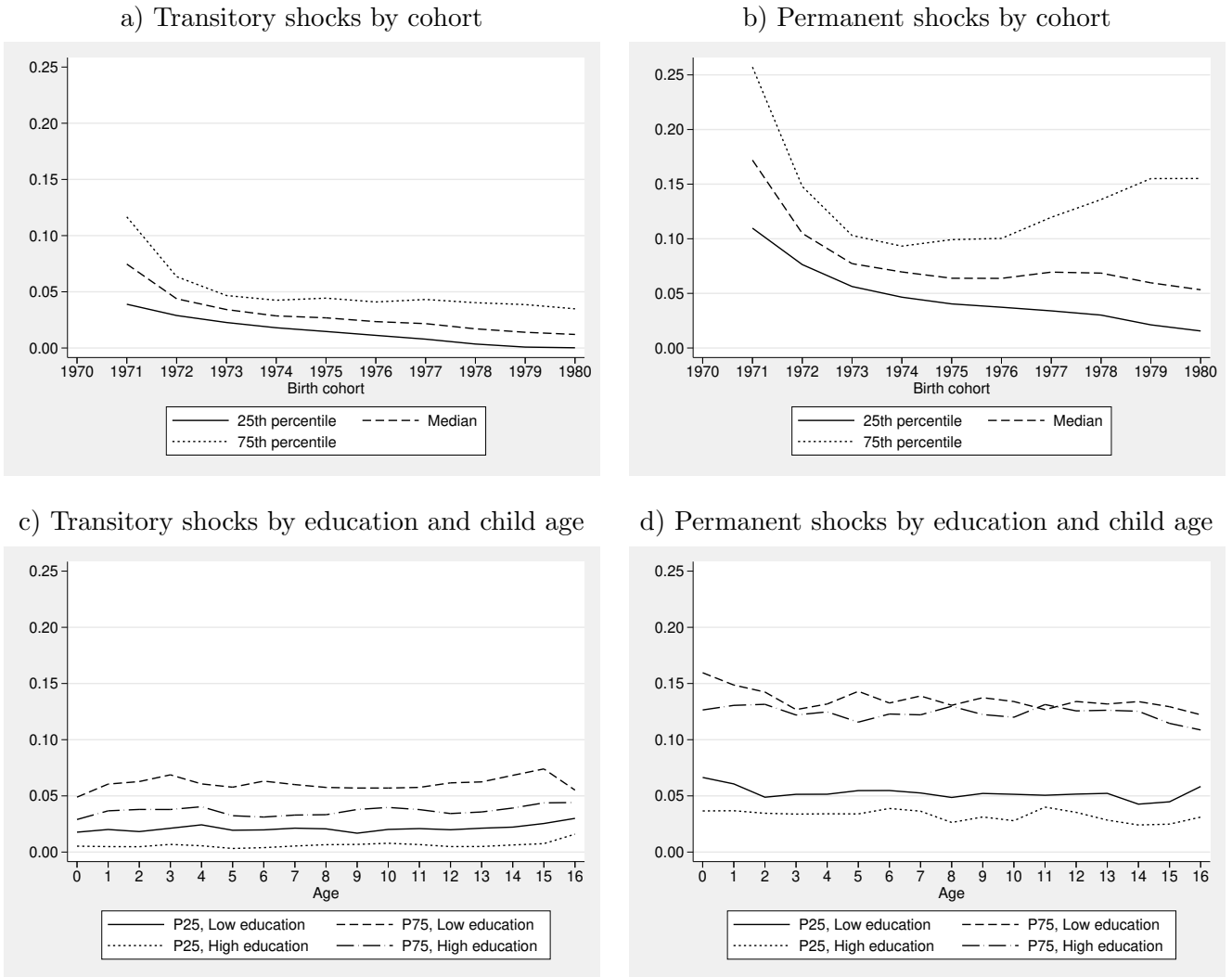
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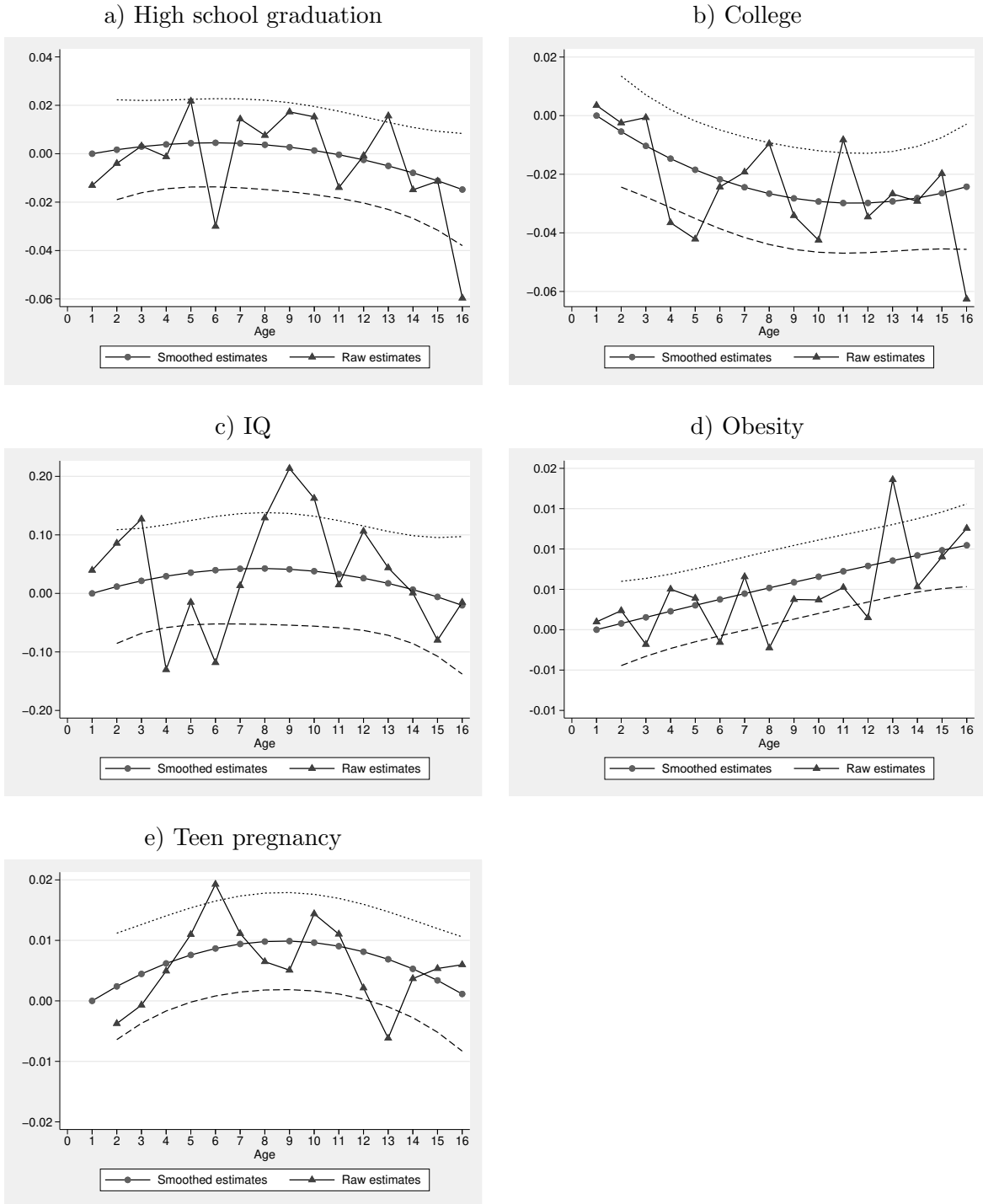
Figures and Tables

Figure 1: Distribution of variance of transitory and permanent income shocks across cells



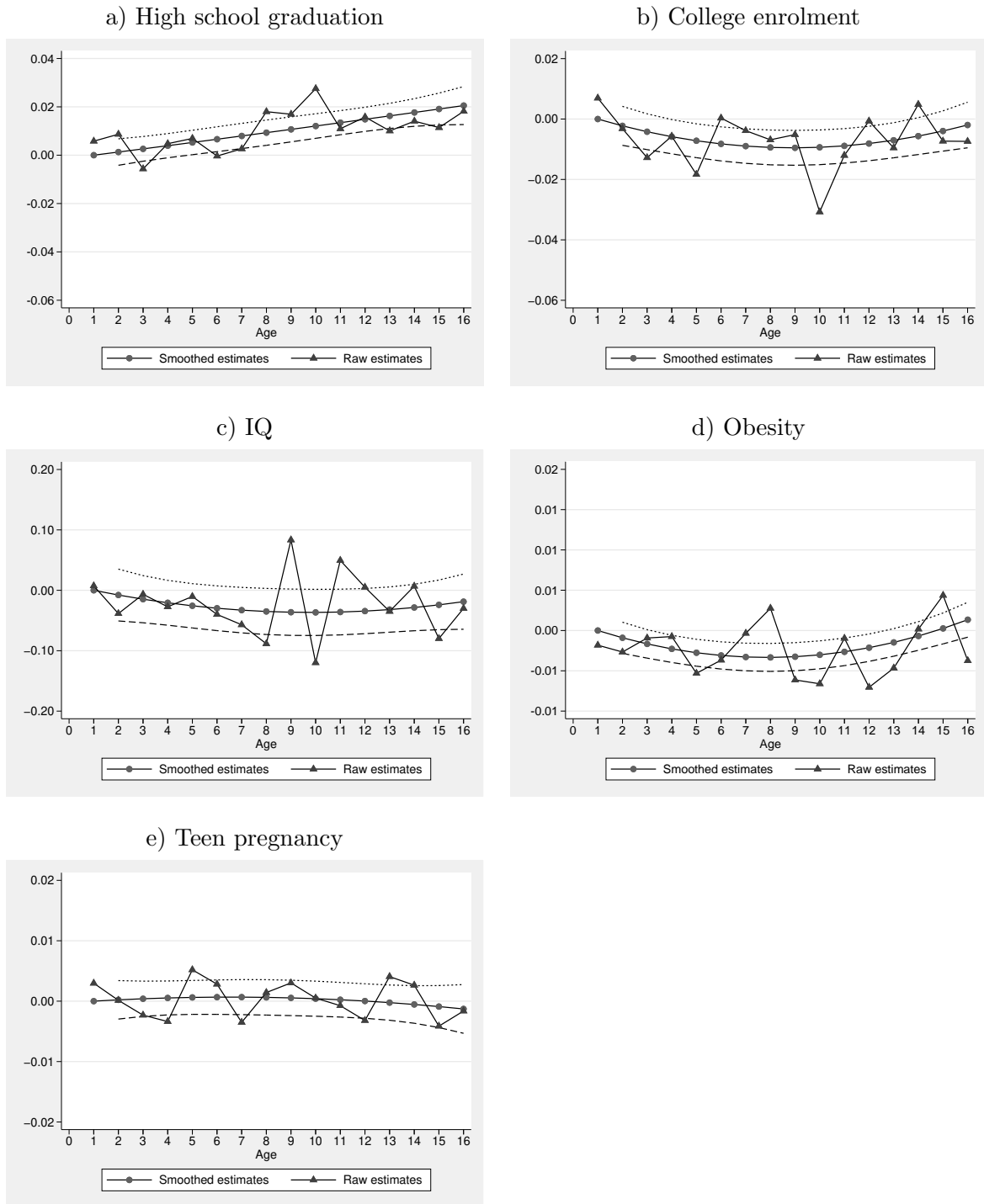
Notes: Figures plot the distribution (first quartile, median, third quartile) of the variance of transitory and permanent income shocks across the cells of child's birth cohort (panels a and b), household education and child age (panels c and d). Sample from Norwegian administrative data is population of households having a child between 1970-1980. To estimate the variance of income shocks, first stage residuals were predicted from a regression of log annual household earnings on a quadratic in mother and father age at birth, mother and father years of schooling, dummy variable for municipality, run for each year of data, as described in [Section 4.1](#). The first difference residuals decomposed into variance of transitory and permanent income shocks following [Equation 5](#).

Figure 2: Effect of household transitory income shocks: Effects relative to age 1.



Notes: The figures plot the effect of transitory income shocks across child age relative to age 1, on child human capital outcomes. Sample from Norwegian administrative data is population of households having a child between 1970-1980. To estimate the variance of income shocks, first stage residuals were predicted from a regression of log annual household earnings on a quadratic in mother and father age at birth, mother and father years of schooling, dummy variable for municipality, run for each year of data, as described in [Section 4.1](#). The first difference residuals decomposed into variance of transitory and permanent income shocks following [Equation 5](#). The effect of transitory income shocks on child human capital estimated according to [Equation 7](#) and a smooth function across child age (and standard errors) estimated by minimum distance, fitting a quadratic in age.

Figure 3: Effect of household permanent income shocks: Effects relative to age 1.



Notes: The figures plot the effect of permanent income shocks across child age relative to age 1, on child human capital outcomes. Sample from Norwegian administrative data is population of households having a child between 1970-1980. To estimate the variance of income shocks, first stage residuals were predicted from a regression of log annual household earnings on a quadratic in mother and father age at birth, mother and father years of schooling, dummy variable for municipality, run for each year of data, as described in [Section 4.1](#). The first difference residuals decomposed into variance of transitory and permanent income shocks following [Equation 5](#). The effect of permanent income shocks on child human capital estimated according to [Equation 7](#) and a smooth function across child age (and standard errors) estimated by minimum distance, fitting a quadratic in age.

Table 1: Sample statistics

Variable	N	Mean	Std. Dev.
Child Human Capital Outcomes			
High School Graduation	586,069	0.780	0.414
College	586,069	0.394	0.489
IQ (males)	278,825	5.226	1.795
Obese (males)	293,825	0.029	0.169
Teen Pregnancy (females)	292,244	0.043	0.203
Parent Characteristics			
Mother Age at Birth	586,069	26.237	5.096
Father Age at Birth	586,069	29.042	5.886
Mother Years of Schooling	586,069	11.032	2.759
Father Years of Schooling	586,069	11.345	3.071
High education household	586,069	0.349	0.477
Child Year of Birth	586,069	1974.75	3.163

Notes: Sample from Norwegian administrative data is population of households having a child between 1970-1980. IQ and obesity measured for males from the military service test at around age 18. A high education household is one in which either the mother or father has completed higher education.

Table 2: Distribution of variances of household permanent and transitory income shocks

	P10	P25	Median	P75	P90
ϵ_1	0.0002	0.0091	0.0282	0.0505	0.0833
ϵ_2	0.0002	0.0080	0.0270	0.0516	0.0919
ϵ_3	0.0004	0.0113	0.0282	0.0553	0.0911
ϵ_4	0.0002	0.0114	0.0312	0.0542	0.0798
ϵ_5	0.0001	0.0096	0.0261	0.0502	0.0840
ϵ_6	0.0003	0.0089	0.0245	0.0525	0.0916
ϵ_7	0.0005	0.0090	0.0272	0.0512	0.0766
ϵ_8	0.0005	0.0116	0.0268	0.0471	0.0739
ϵ_9	0.0006	0.0106	0.0266	0.0492	0.0822
ϵ_{10}	0.0013	0.0122	0.0278	0.0503	0.0819
ϵ_{11}	0.0016	0.0110	0.0284	0.0503	0.0799
ϵ_{12}	0.0002	0.0105	0.0265	0.0524	0.0824
ϵ_{13}	0.0005	0.0095	0.0278	0.0510	0.0820
ϵ_{14}	0.0005	0.0126	0.0305	0.0558	0.0940
ϵ_{15}	0.0008	0.0140	0.0343	0.0625	0.0952
ϵ_{16}	0.0121	0.0214	0.0350	0.0510	0.0761
ζ_1	0.0174	0.0497	0.0847	0.1431	0.2314
ζ_2	0.0126	0.0403	0.0827	0.1383	0.2498
ζ_3	0.0169	0.0432	0.0744	0.1250	0.2240
ζ_4	0.0214	0.0411	0.0779	0.1295	0.2130
ζ_5	0.0156	0.0433	0.0792	0.1319	0.2340
ζ_6	0.0224	0.0444	0.0792	0.1278	0.2174
ζ_7	0.0157	0.0437	0.0804	0.1303	0.2109
ζ_8	0.0109	0.0390	0.0753	0.1302	0.2002
ζ_9	0.0129	0.0408	0.0766	0.1321	0.2138
ζ_{10}	0.0106	0.0394	0.0744	0.1265	0.1993
ζ_{11}	0.0132	0.0444	0.0800	0.1295	0.2095
ζ_{12}	0.0145	0.0413	0.0808	0.1305	0.2178
ζ_{13}	0.0126	0.0373	0.0776	0.1317	0.2176
ζ_{14}	0.0067	0.0335	0.0748	0.1305	0.2255
ζ_{15}	0.0054	0.0323	0.0681	0.1224	0.2104
ζ_{16}	0.0238	0.0425	0.0744	0.1170	0.2060

Notes: Sample from Norwegian administrative data is population of households having a child between 1970-1980. Income measure is gross household income. First stage residuals predicted from a regression of log annual earnings (household) on a quadratic in mother and father age at birth, mother and father years of schooling, dummy variable for municipality, run for each year of data and decomposed into variance of transitory and permanent income shocks following [Equation 5](#).

Table 3: The asset response to transitory and permanent income shocks

	(1)	(2)	(3)
	Net assets	Assets	Debt
Variance of shocks			
Transitory	0.078*	0.077*	-0.004
	(0.043)	(0.043)	(0.004)
Permanent	-0.008	-0.008	0.000
	(0.013)	(0.013)	(0.001)
Observations	772	772	772
R-squared	0.005	0.005	0.002

Notes: Sample from Norwegian administrative data is population of households having a child between 1970-1980. The log of net assets (column 1) measure log of total household assets including bank deposits, stocks and shares (column 2) minus the log of all debts including mortgage, bank and credit cards (column 3). First stage residuals predicted from a regression of log annual earnings (household or fathers') on a quadratic in mother and father age at birth, mother and father years of schooling, dummy variable for municipality, run for each year of data and decomposed into variance of transitory and permanent income shocks following [Equation 5](#). The change in assets in response to income shocks estimated from [Equation 16](#).

Online Appendix

A Empirical Strategy

Here we explain the steps taken in the paper to estimate the effect of permanent and transitory shocks to household income, on child human capital.

1. First, we estimate the income process in Norway. [Appendix B](#) suggests that transitory income follows an MA(1) process. Given this, in our model permanent income follows a random walk and transitory income an MA(1) process.
2. Taking the raw data, income residuals are estimated from [Equation 1](#). For each year t , we regress household income on the set of controls Z which include a quadratic in mother and father age at birth, mother and father years of schooling and a dummy variable for municipality at birth. The first difference residuals used to decompose income shocks following [Equation 5](#)
3. The human capital outcomes are residualised, controlling for an identical set of controls as the residualised income measures. The covariance between income and (residualised) human capital, calculated within cells, is regressed in a system of equations from [Equation 7](#), to estimate the coefficients on the transitory and permanent household income shocks across the child ages 1-16.
4. Standard errors are calculated by bootstrapping with 500 replications from step 2 onwards.
5. Smoothed estimates of the coefficients from [Equation 7](#) by using GMM to fit a quadratic in child age to the coefficients. The standard errors are calculated using the estimated coefficients and 500 bootstrap estimates (for each parameter).

B Defining a Household Income Process for Norway

In our paper, the effects of transitory and permanent income shocks across child age are identified for a particular income process. We follow the literature in estimating the income process using very detailed administrative income data for the population of Norway, from 1970 to 2000. [Meghir](#)

and Pistaferri (2004) and Blundell et al. (2008) suggest that, in the US, a permanent transitory model of income is appropriate, whereby permanent income is a martingale and transitory income is serially uncorrelated or a first order Moving Average process (MA(1)). In the UK, Dickens (2000) estimate a random walk in age for permanent income and a serially correlated transitory component. Bonhomme and Robin (2009) model income in France as a (deterministic component plus) a fixed effect, and first order Markov process for transitory income. In Norway, Blundell et al. (2015) find the magnitude of permanent and transitory shocks to vary across the life cycle and across skill groups.

Two methods are used to understand the time series properties of the income process. A panel of household income is constructed across time, from 1970-2000, for those who had a child between 1970-1980. Income levels are deflated to 2000 prices. This panel includes nearly 400,000 households.²² First, the variance of income is plotted across the life cycle for the sample of mothers and fathers. If a random walk describes permanent income, the variance of income will be an increasing function of age, assuming independence of the shocks, as each shock lasts for a lifetime. Figure A.1 plots the variance of income for the mothers (panel a) and fathers (panel b) across their working life. For the mothers and fathers, there is a clear increasing relationship in the variance of earnings across age. Of course, there are other reasons why variance of income may increase across time, however this evidence is consistent with a random walk permanent component to income.

The second methodology employed, following MaCurdy (1982), seeks to understand the ARMA transitory income process. Similarly to the aforementioned papers, we assume a permanent component to income and estimate the income process for fathers' transitory income.

Consider the following model

$$\ln w_{it} = Z'_{it}\varphi + P_{it} + v_{it}$$

where P and v are the permanent and transitory components respectively of log income ($\ln w$) for household i in period t . Z denotes a set of covariates²³ and φ a vector of coefficients. The permanent component follows a martingale, hence $P_{it} = P_{it-1} + \zeta_{it}$ where ζ denotes the mean-zero

²²There are slightly more households than in Table 1 as we do not condition on non-missing child human capital outcomes.

²³these include a quadratic in mother and father age at birth, mother and father years of schooling, dummy variable for municipality, run for each year of data.

permanent income shock, independently and identically distributed (iid) across i and t . This section estimates the ARMA(p, q) process for the transitory component of income. The orders p and q of the AR and MA components are to be established empirically. In a general model, transitory income is given by $v_{it} = -\sum_{j=1}^p a_j v_{it-j} + \sum_{j=0}^q m_j \varepsilon_{it-j}$ where $m_0 = 1$. a_t and m_t are the lag coefficients and equal zero if there is no persistence in transitory income. ε denotes the transitory income shock to the level of transitory income (v).

To analyse the persistence of the transitory income component separately to the permanent component, we follow [MaCurdy \(1982\)](#), [Meghir and Pistaferri \(2004\)](#) and [Blundell et al. \(2008\)](#) and estimate the residuals from first differences in income $\Delta \ln w_{it} = \Delta Z'_{it} \varphi + \zeta_{it} + \Delta v_{it}$, where for each $x = \{w, Z, v\}$, $\Delta x_t = x_t - x_{t-1}$. The order of the AR process of the first differenced disturbances is the same as in the levels, however first differencing changes the order of the estimated MA process to $(q + 1)$.

We estimate the residuals from a system of equations of first difference log wages in period t for household i where coefficients are restricted to be constant across equations. The sample is defined as all households who have children during the sample period (1970-1980) and we observe income during the period 1970-1998. In total we consider 379,772 households. The controls (Z) are a quadratic in maternal and paternal age, maternal and paternal years of schooling, municipality of residence and year dummy variables.

Results in column 1 of [Table A.1](#) show that income growth is increasing in the age of the women at a decreasing rate whilst the opposite is true for fathers. Income growth is increasing in education and marital status. Column 2 shows that the income level process is represented by a hump-shaped profile across mother and fathers' age and is increasing in education and marital status. The residuals from the regression in column 2 feed into the next stage of the analysis which estimates then autocovariance process of household income and then decomposes the residuals into permanent and transitory components.

The second stage estimates autocovariances of residuals (γ) at different lags (k) from the equation $E(v_t v'_{t-k}) = \gamma_{kt} + \omega_t$, where ω is the error in the autocovariance process and $k = \{1, \dots, 8\}$. For each lag k , the autocovariances are estimated in a system of equations across t where the coefficient on the autocovariance is constrained to be constant in each regression. Two potential difficulties with estimating the autocovariances are firstly that the residuals are estimated in a first

stage and secondly that there may be serial correlation across time. However, [MaCurdy \(1981\)](#) notes that using a seemingly unrelated regression procedure to estimate autocovariances will result in parameters and test statistics that are asymptotically valid.

The results are reported in [Table A.2](#). The estimated autocovariances are initially negative at one lag but fall close to zero after the first lag, although it remains statistically significant. Again, between lags 2 and 3 there is another sharp drop in the autocovariances and after lag 3, they are no longer statistically significant. This is suggestive of a low order MA process, of the order of 2 or 3 in differences, or of order 1 or 2 in levels.

In conclusion, in the remaining of this paper we postulate that permanent income follows a random walk and transitory income follows an MA process, where we will estimate the model initially for a first order MA process and test the robustness of results to a second order MA process. This is the similar income process found in the studies mentioned above, suggesting a similar income process in Norway as in the UK and the US.

B.1 Appendix A1. Estimation by DWMD

Estimation is by minimum distance. For each observation, we observe the scalar h_i and define the dummy variable d_i^h to equal 1 if human capital is non-missing for this observation, and 0 otherwise. Define observations over parental income y_i and the relevant non-missing dummy variable d_i^y as follows

$$y_i = \begin{pmatrix} y_{1,i} \\ y_{t,i} \\ \cdot \\ \cdot \\ y_{16,i} \end{pmatrix} \quad d_i^y = \begin{pmatrix} d_{1,i} \\ d_{t,i} \\ \cdot \\ \cdot \\ d_{16,i} \end{pmatrix} \quad (\text{A6})$$

we define the vector x_i and d_i by

$$x_i = \begin{pmatrix} h_i \\ y_i \end{pmatrix} \quad d_i = \begin{pmatrix} d_i^h \\ d_i^y \end{pmatrix} \quad (\text{A7})$$

The empirical moments are given by

$$\mathbf{m} = vech \left\{ \left(\sum_{i=1}^N x_i x_i' \right) \oslash \left(\sum_{i=1}^N d_i d_i' \right) \right\} \quad (\text{A8})$$

The vector of theoretical moments is given by $f(\Lambda)$ where $\Lambda = \{\sigma_{P_0}^2, \sigma_{\varepsilon_0}^2, \sigma_{\varepsilon_1}^2, \dots, \sigma_{\varepsilon_{16}}^2, \sigma_{\zeta_1}^2, \sigma_{\zeta_2}^2, \dots, \sigma_{\zeta_{16}}^2, \theta_1, \theta_2\}$ and \oslash denotes element wise division.

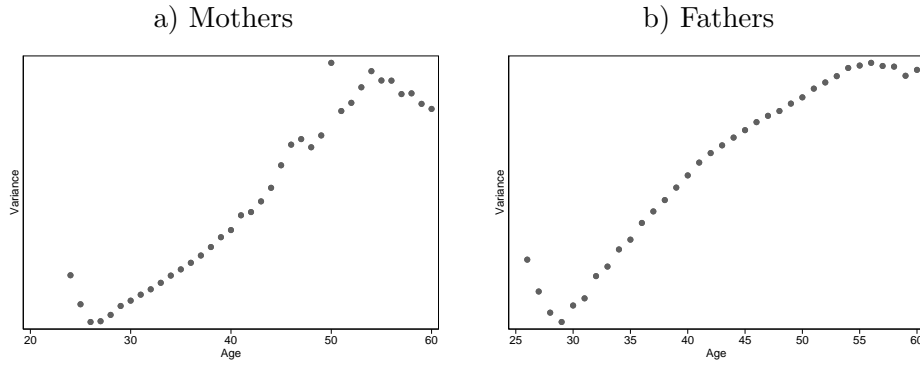
$$f(\Lambda) = \begin{pmatrix} v * (y_1) \\ cov * (y_1, y_2) \\ cov * (y_1, y_3) \\ \cdot \\ \cdot \\ cov * (y_1, y_{16}) \\ cov * (y_1, h) \\ v * (y_2) \\ \cdot \\ \cdot \\ cov * (y_2, h) \\ \cdot \\ \cdot \\ cov * (y_{16}, h) \end{pmatrix} \quad (\text{A9})$$

Parameter values are chosen to minimise the difference between the theoretical moments, given in the identification section above, and the empirical moments contained in \mathbf{m} .

$$\min_{\Lambda} (\mathbf{m} - f(\Lambda))' \mathbf{A} (\mathbf{m} - f(\Lambda)) \quad (\text{A10})$$

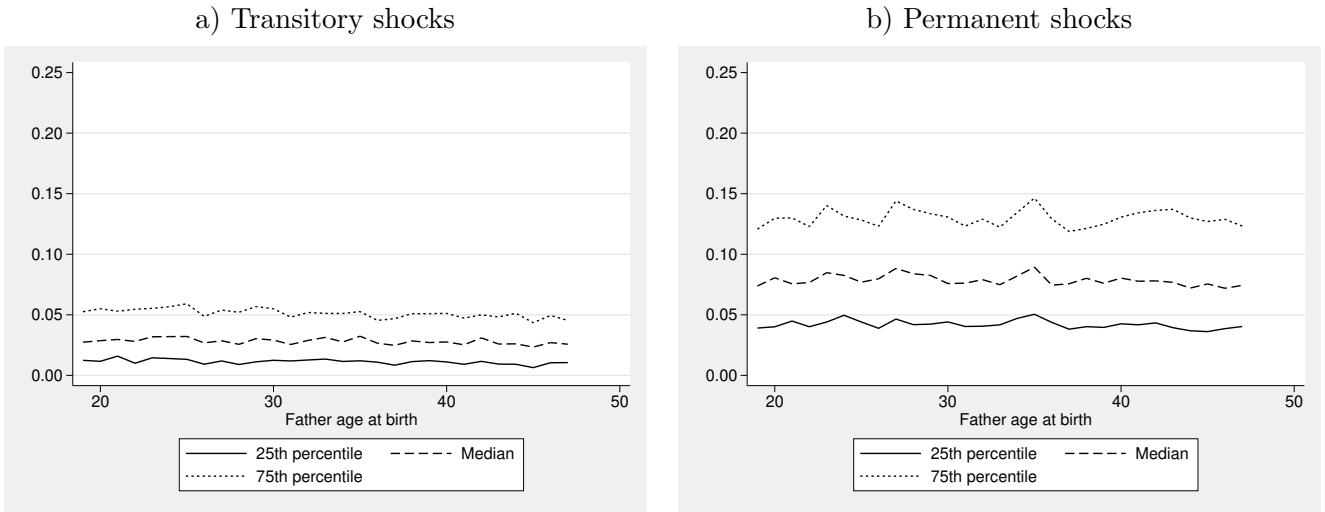
We use diagonally-weighted minimum distance (DWMD) and weighting matrix (\mathbf{A}) is the diagonal from (V^{-1}) , where V is a consistent estimate of the variance-covariance matrix of \mathbf{m} .

Figure A.1: Variance of income across the lifecycle



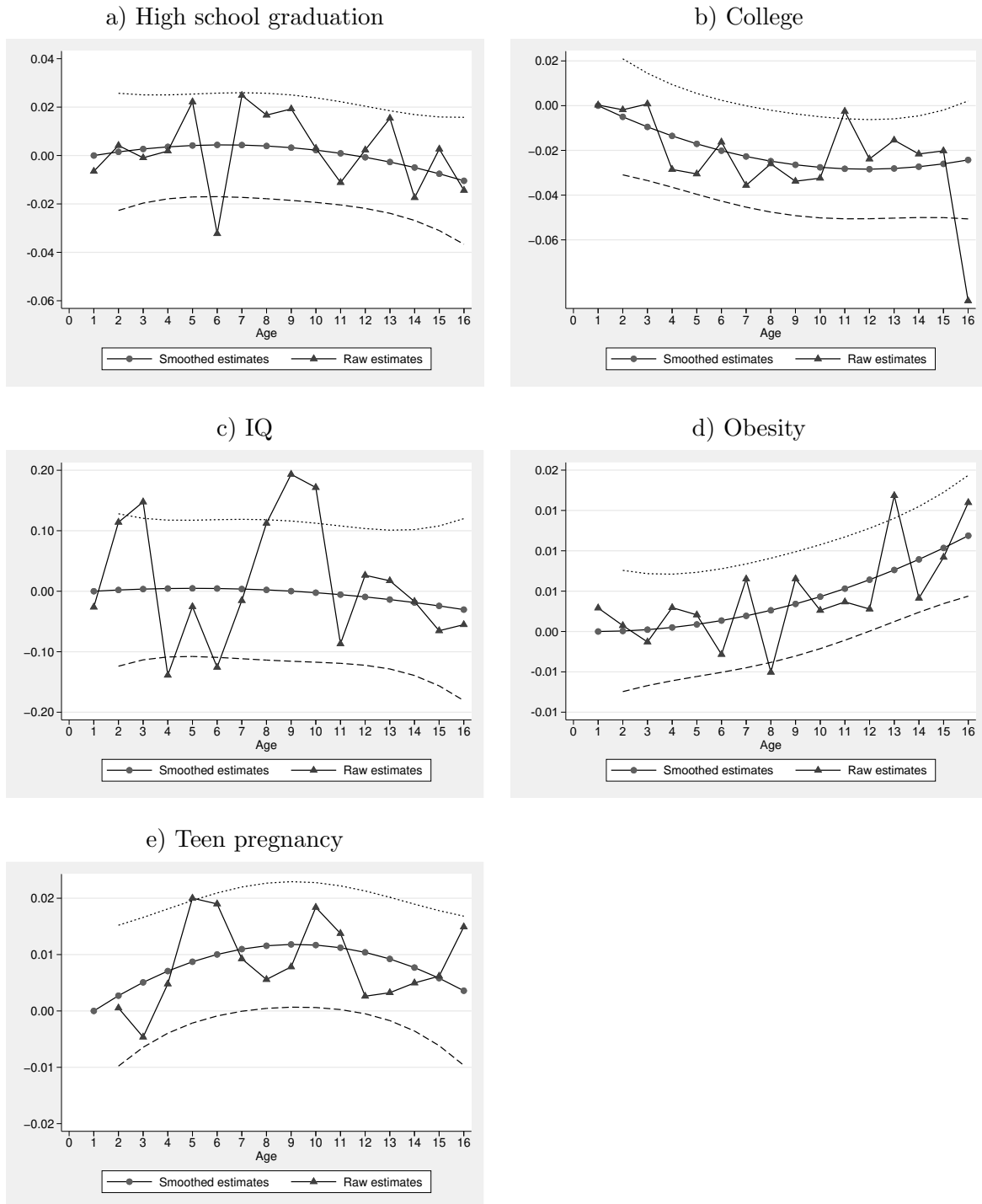
Notes: The (unconditional) life cycle variance for mothers and fathers. Sample from Norwegian administrative data is population of households having a child between 1970-1980. Real income measured between years 1970-2000. Variance of income is calculated at each age of mothers (panel a) and fathers (panel b).

Figure A.2: Distribution of variance of transitory and permanent income shocks across fathers' age at birth



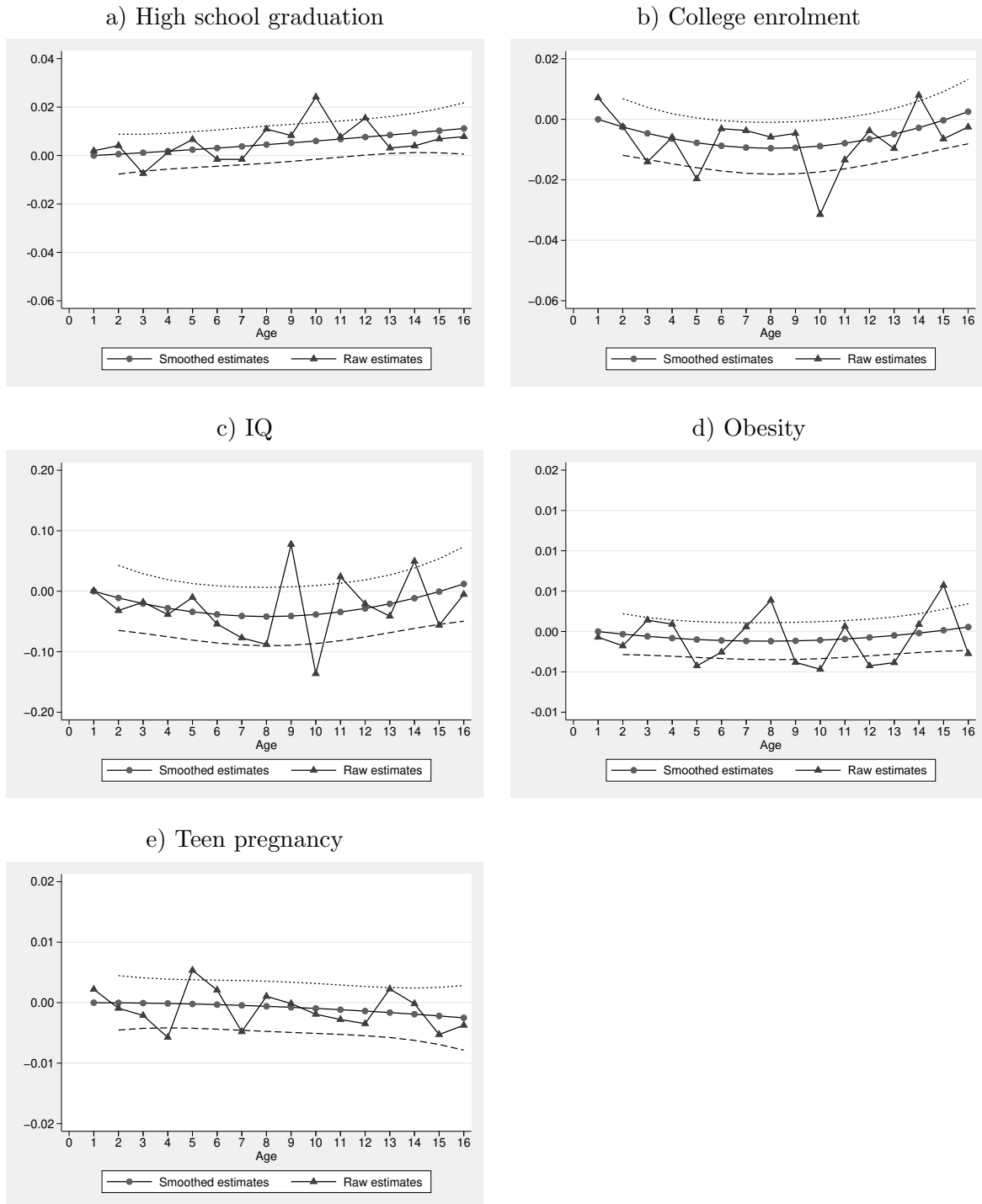
Notes: Figures plot the distribution (first quartile, median, third quartile) of the variance of transitory and permanent income shocks across the cells of fathers' age at birth. Sample from Norwegian administrative data is population of households having a child between 1970-1980. To estimate the variance of income shocks, first stage residuals were predicted from a regression of log annual household earnings on a quadratic in mother and father age at birth, mother and father years of schooling, dummy variable for municipality, run for each year of data, as described in [Section 4.1](#). The first difference residuals decomposed into variance of transitory and permanent income shocks following [Equation 5](#).

Figure A.3: Effect of household transitory income shocks: Effects relative to age 1. Controls for fixed effects of father age, education and cohort.



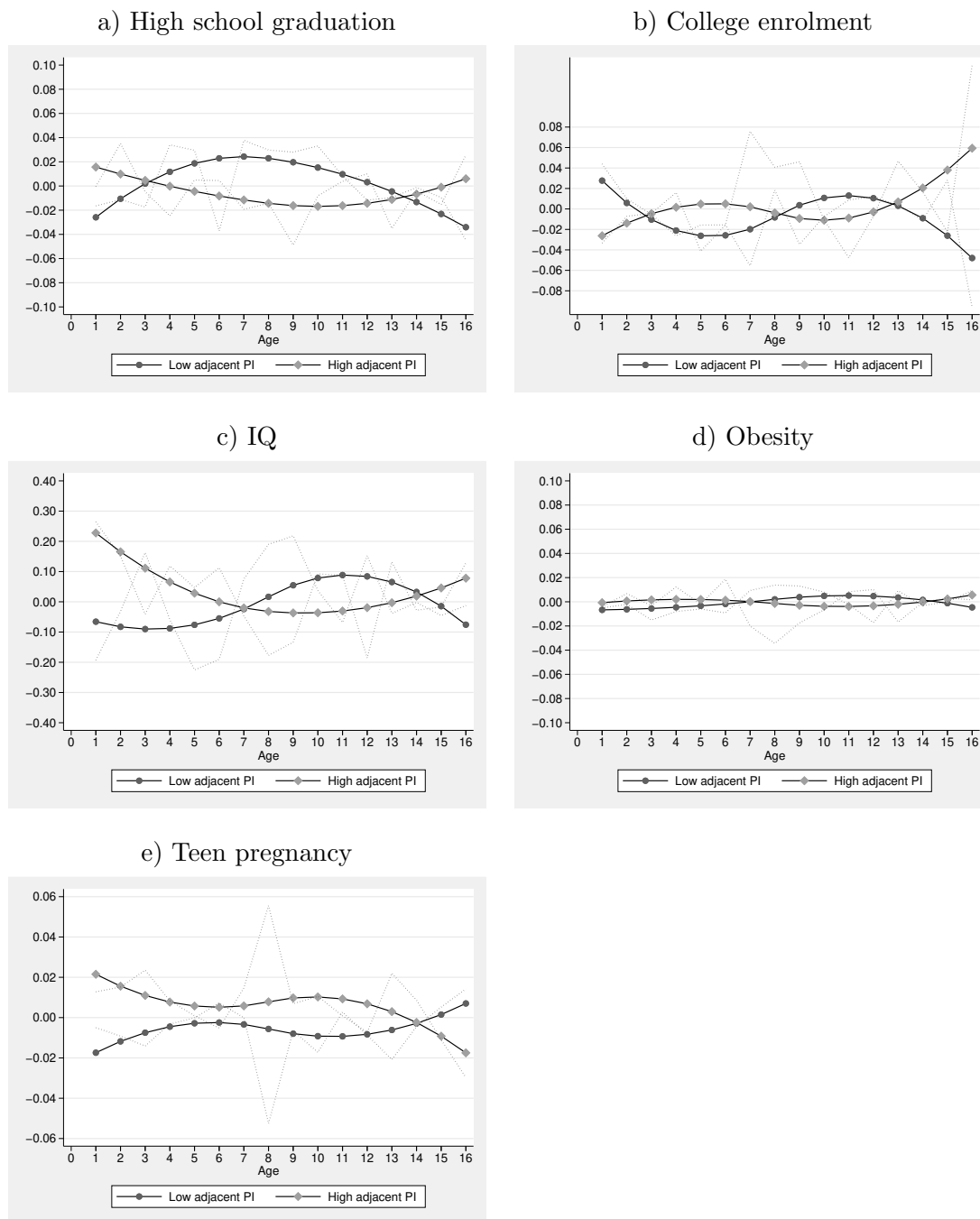
Notes: The figures plot the effect of transitory income shocks across child age relative to age 1, on child human capital outcomes. The sample and estimation strategy is described in [Figure 2](#), except the effect of transitory income shocks on child human capital estimated according to a version of [Equation 7](#) which is augmented by including fixed effects for the cells of fathers' age, education and cohort. A smooth function across child age (and standard errors) estimated by minimum distance, fitting a quadratic in age_i

Figure A.4: Effect of household permanent income shocks: Effects relative to age 1. Controls for fixed effects of father age, education and cohort.



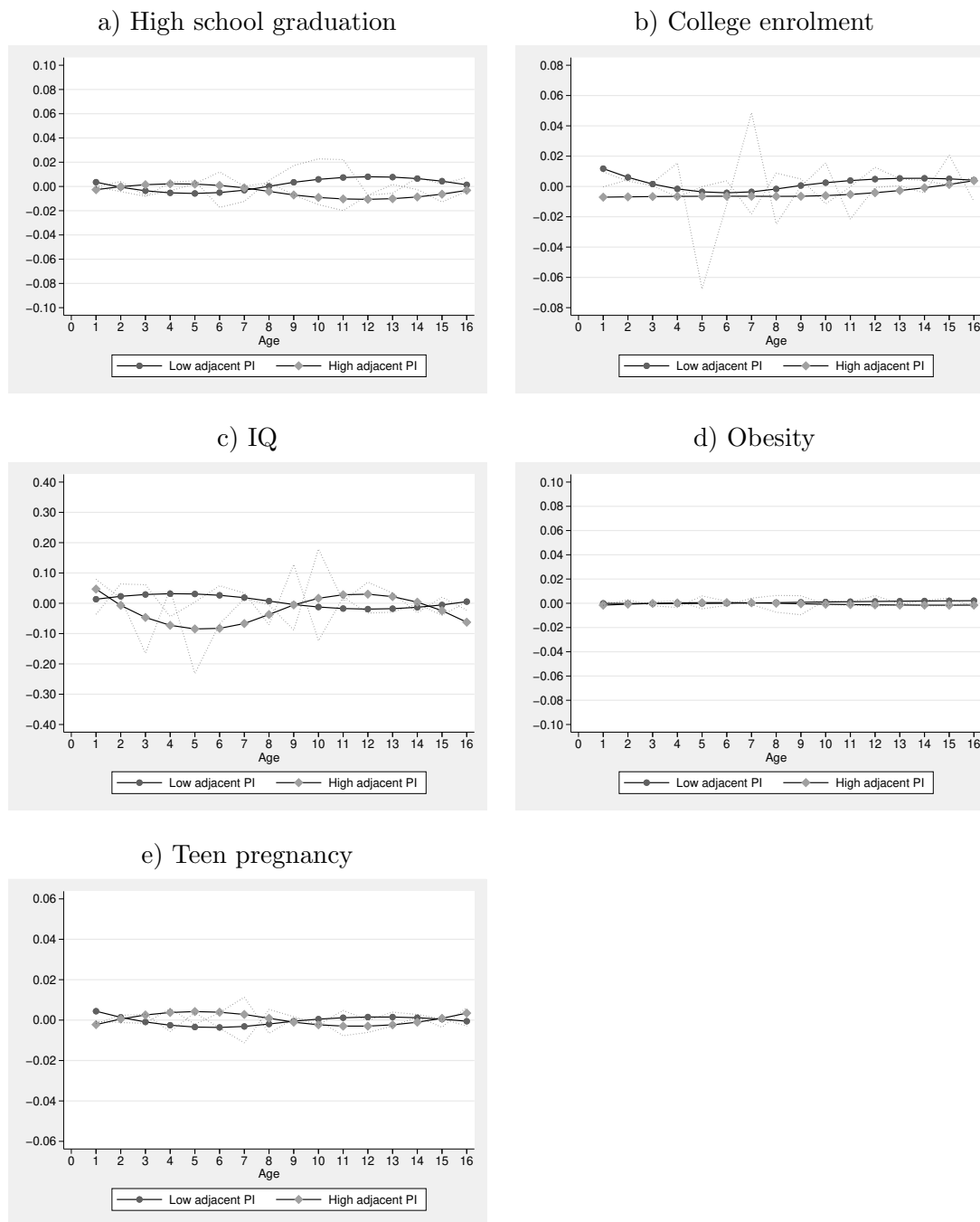
Notes: The figures plot the effect of permanent income shocks across child age relative to age 1, on child human capital outcomes. The sample and estimation strategy is described in [Figure 3](#), except the effect of permanent income shocks on child human capital estimated according to a version of [Equation 7](#) which is augmented by including fixed effects for the cells of fathers' age, education and cohort. A smooth function across child age (and standard errors) estimated by minimum distance, fitting a quadratic in age.

Figure A.5: Dynamic complementarity: Level effects of household transitory income shocks.



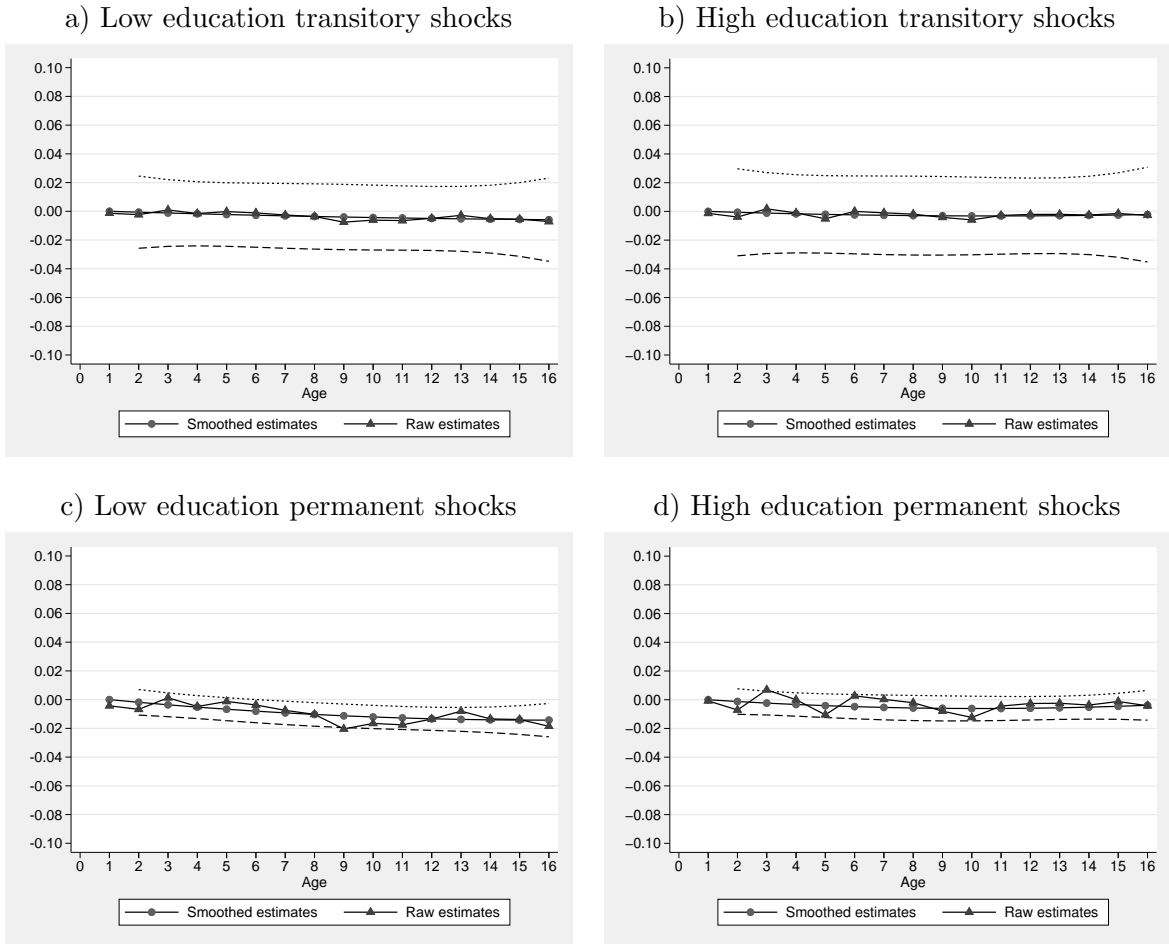
Notes: Sample from Norwegian administrative data is population of households having a child between 1970-1980. Income measure is gross household income. First stage residuals predicted from a regression of log annual earnings (household or fathers') on a quadratic in mother and father age at birth, mother and father years of schooling, dummy variable for municipality, run for each year of data and decomposed into variance of transitory and permanent income shocks following Equation 5. Low (high) PI refers to the sum of income between ages 1-8 (or 9-16) being below (above) average. The effect of shocks on child human capital augmented with interaction between low early PI and income shocks age 9-16 and low late PI and income shocks age 1-8. A smooth function across child age (and standard errors) estimated by minimum distance, fitting a quadratic spline (knot at age 8) in age.

Figure A.6: Dynamic complementarity: Level effects of household permanent income shocks.



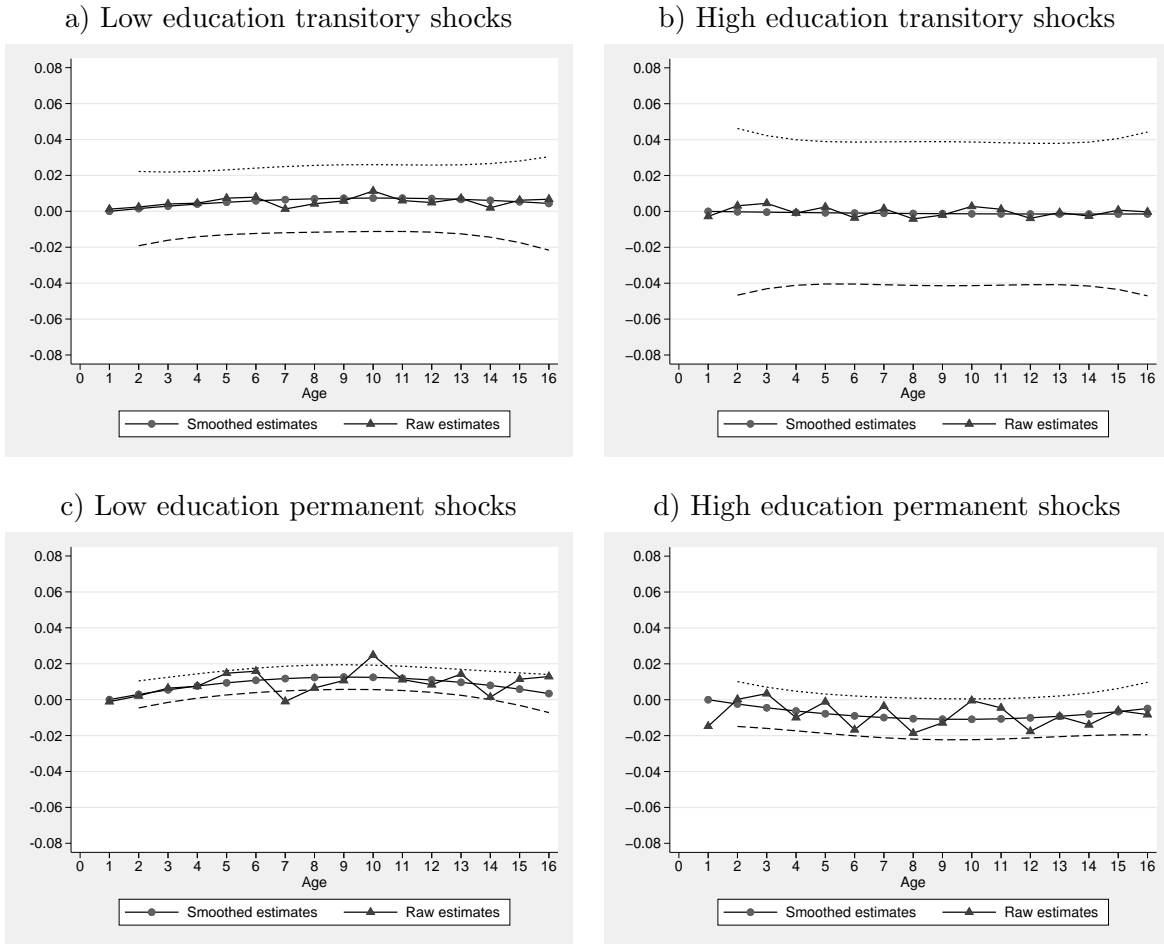
Notes: Sample from Norwegian administrative data is population of households having a child between 1970-1980. Income measure is gross household income. First stage residuals predicted from a regression of log annual earnings (household or fathers') on a quadratic in mother and father age at birth, mother and father years of schooling, dummy variable for municipality, run for each year of data and decomposed into variance of transitory and permanent income shocks following Equation 5. Low (high) PI refers to the sum of income between ages 1-8 (or 9-16) being below (above) average. The effect of shocks on child human capital augmented with interaction between low early PI and income shocks age 9-16 and low late PI and income shocks age 1-8. A smooth function across child age (and standard errors) estimated by minimum distance, fitting a quadratic spline (knot at age 8) in age.

Figure A.7: Heterogeneity. Household income shocks on high school graduation: Effects relative to age 1.



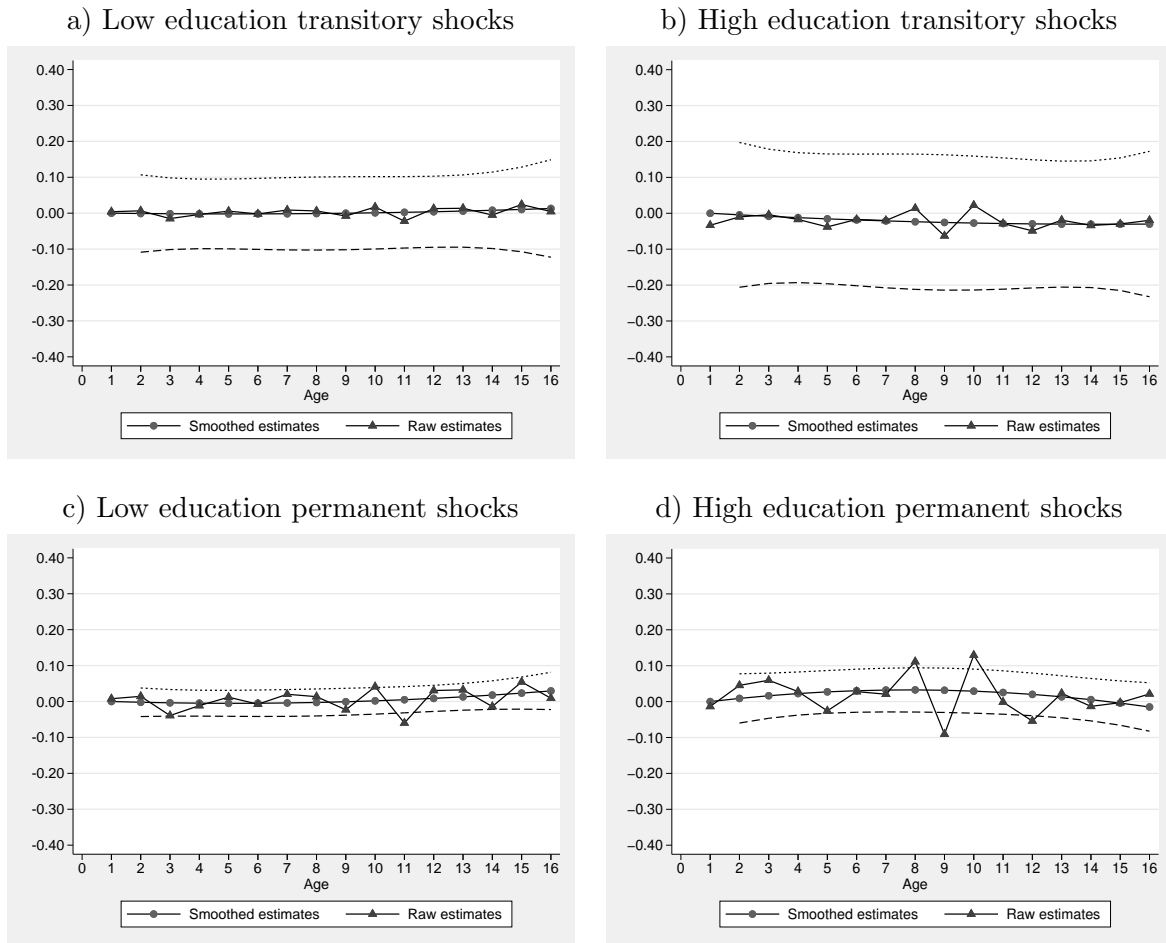
Notes: Sample and estimation strategy as [Figure 2](#). Low (high) education household in panels a and c (b and d) defined as those with no college degree (at least one parent with college degree).

Figure A.8: Heterogeneity. Household income shocks on college enrolment: Effects relative to age 1.



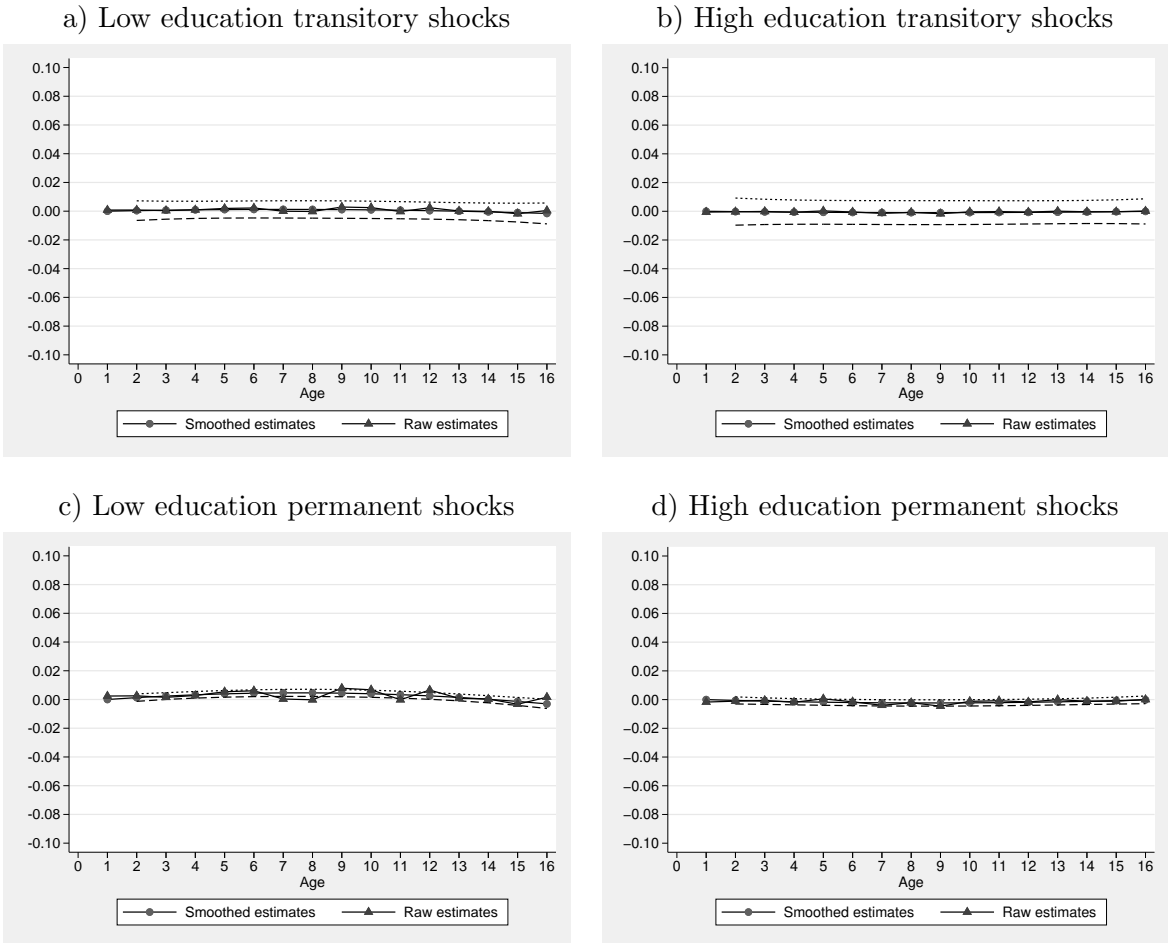
Notes: Sample and estimation strategy as [Figure 2](#). Low (high) education household in panels a and c (b and d) defined as those with no college degree (at least one parent with college degree).

Figure A.9: Heterogeneity. Household income shocks on IQ: Effects relative to age 1.



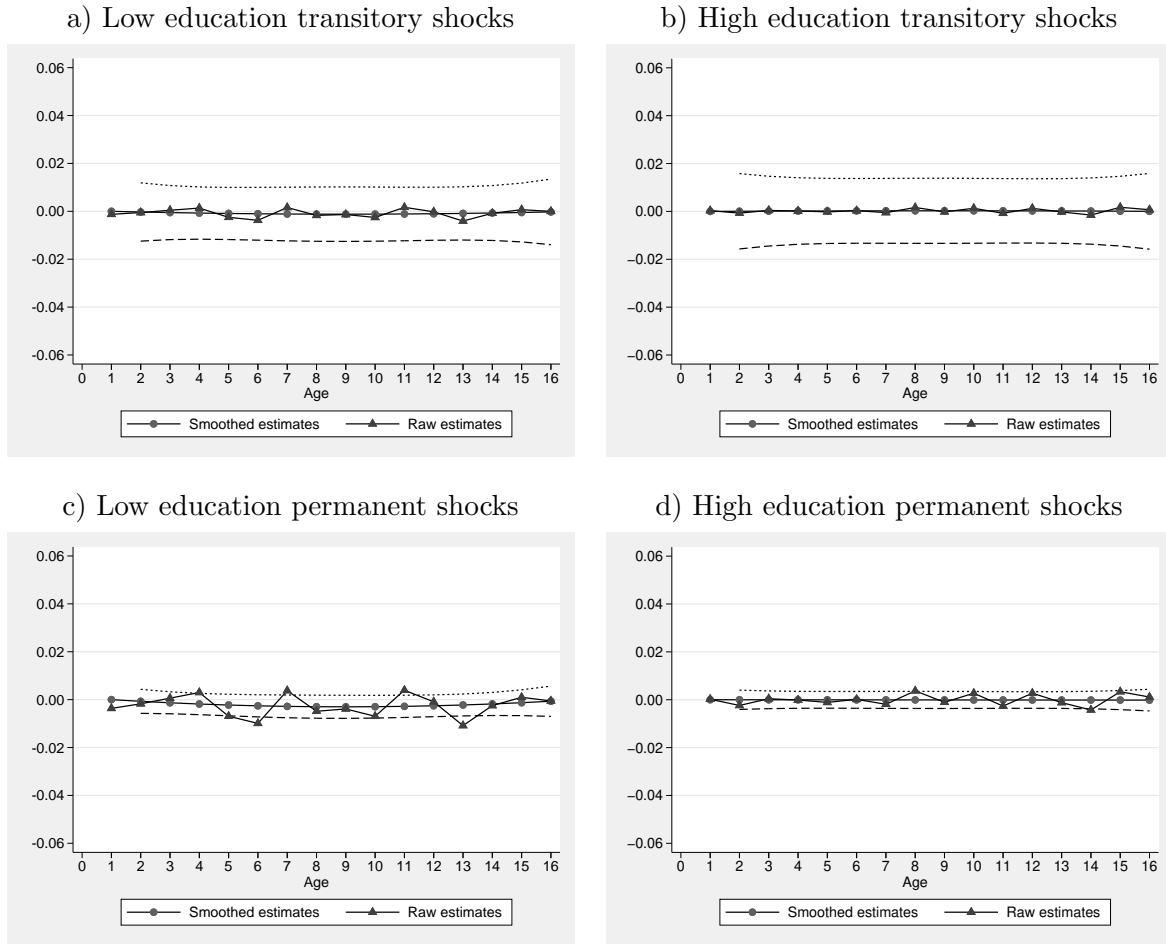
Notes: Sample and estimation strategy as [Figure 2](#). Low (high) education household in panels a and c (b and d) defined as those with no college degree (at least one parent with college degree).

Figure A.10: Heterogeneity. Household income shocks on Obesity: Effects relative to age 1.



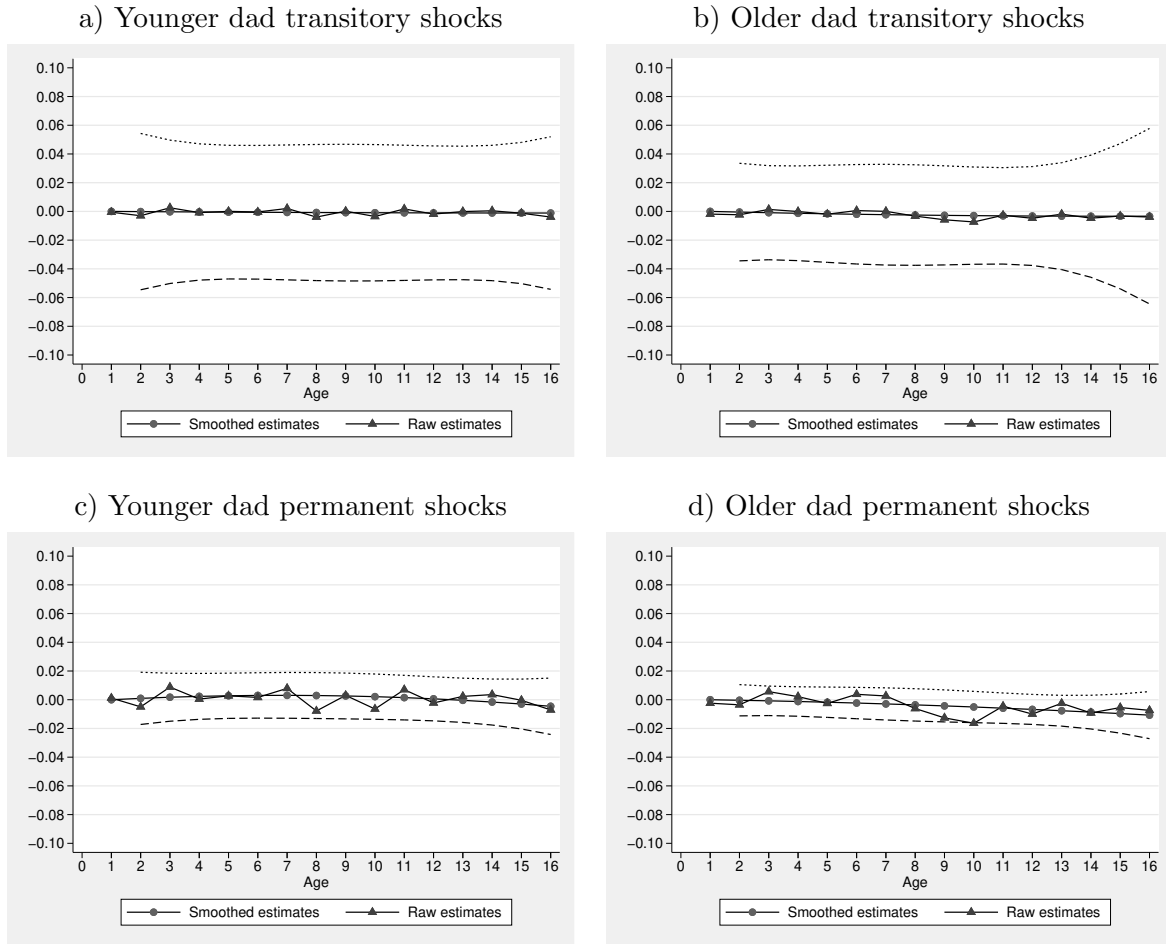
Notes: Sample and estimation strategy as [Figure 2](#). Low (high) education household in panels a and c (b and d) defined as those with no college degree (at least one parent with college degree).

Figure A.11: Heterogeneity. Household income shocks on teen pregnancy: Effects relative to age 1.



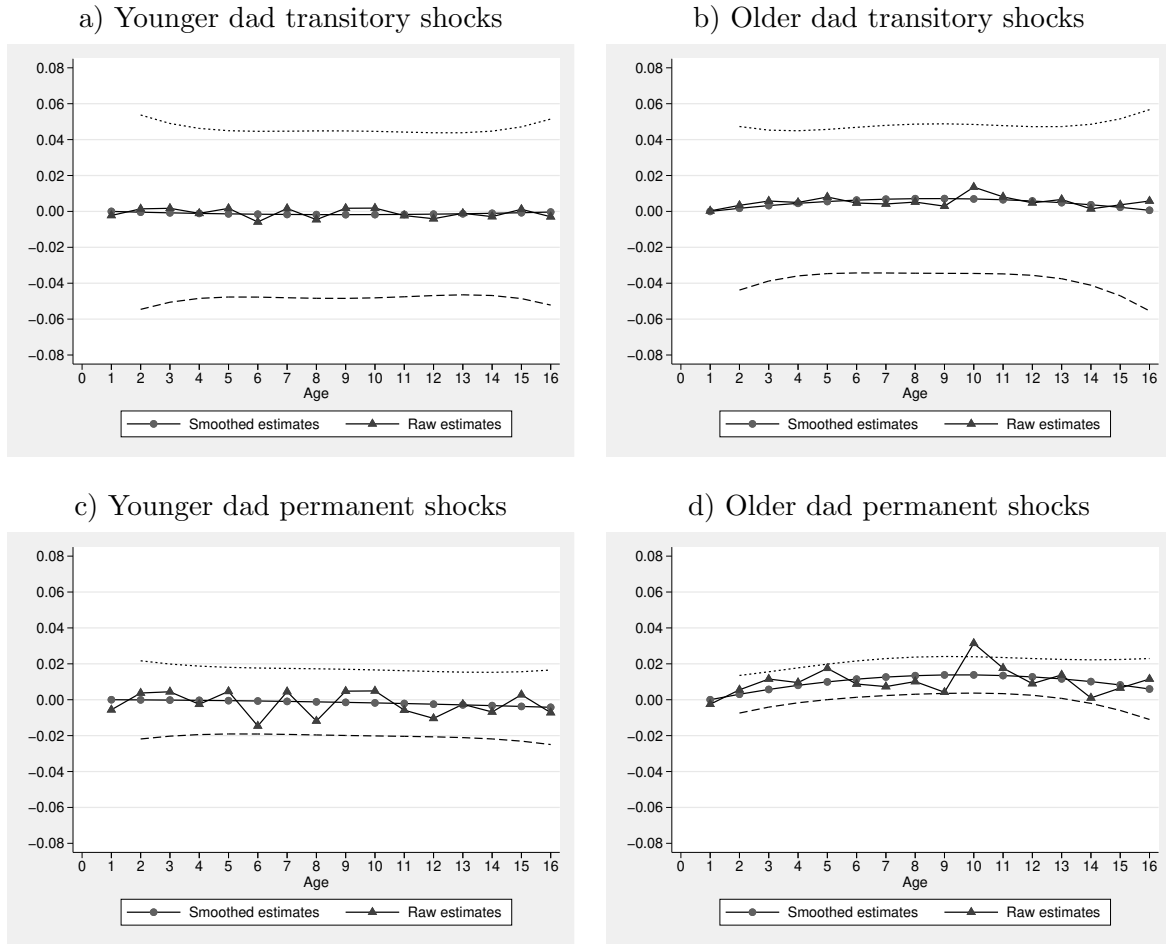
Notes: Sample and estimation strategy as [Figure 2](#). Low (high) education household in panels a and c (b and d) defined as those with no college degree (at least one parent with college degree).

Figure A.12: Heterogeneity. Household income shocks on high school graduation: Effects relative to age 1.



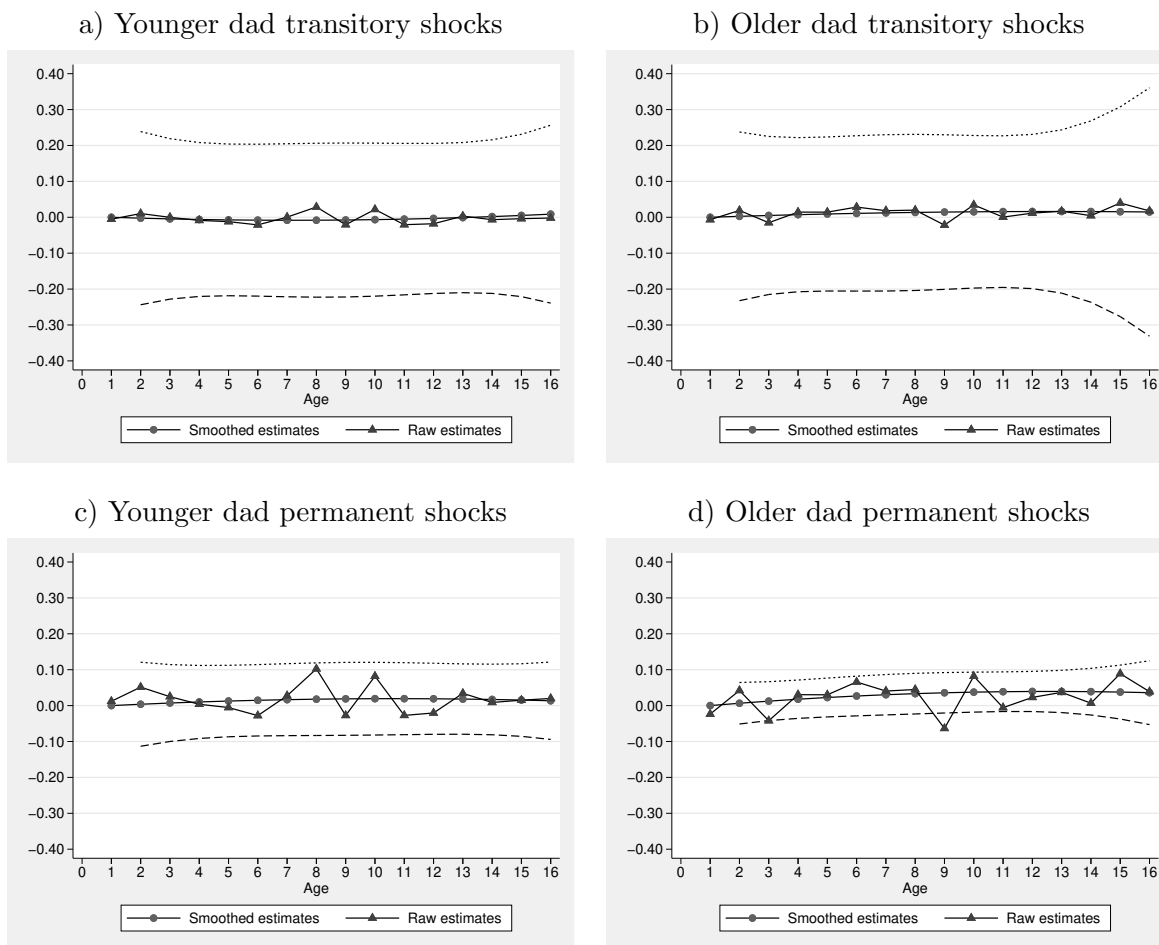
Notes: Sample and estimation strategy as [Figure 2](#). Younger (older) dads in panels a and c (b and d) aged below (above) median age 27.

Figure A.13: Heterogeneity. Household income shocks on college enrolment: Effects relative to age 1.



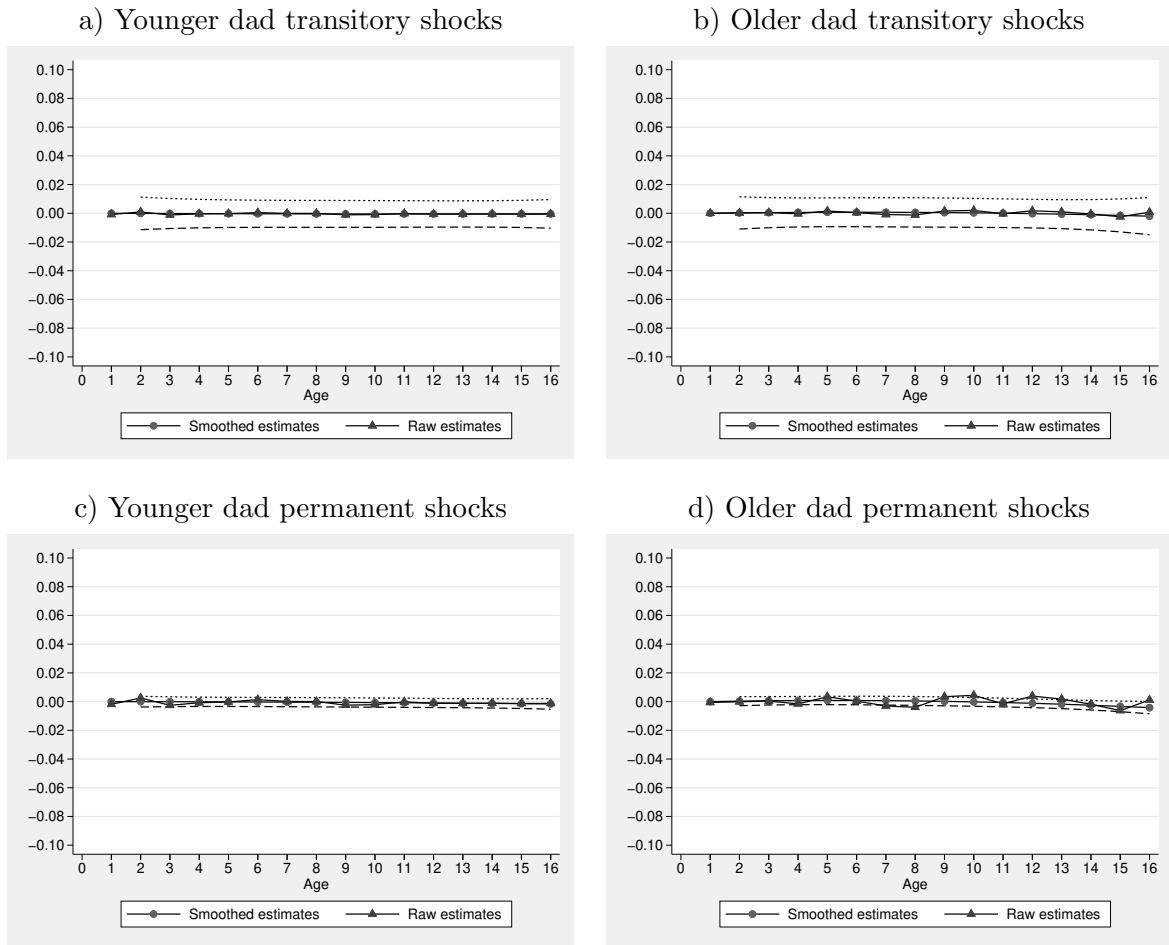
Notes: Sample and estimation strategy as [Figure 2](#). Younger (older) dads in panels a and c (b and d) aged below (above) median age 27.

Figure A.14: Heterogeneity. Household income shocks on IQ: Effects relative to age 1.



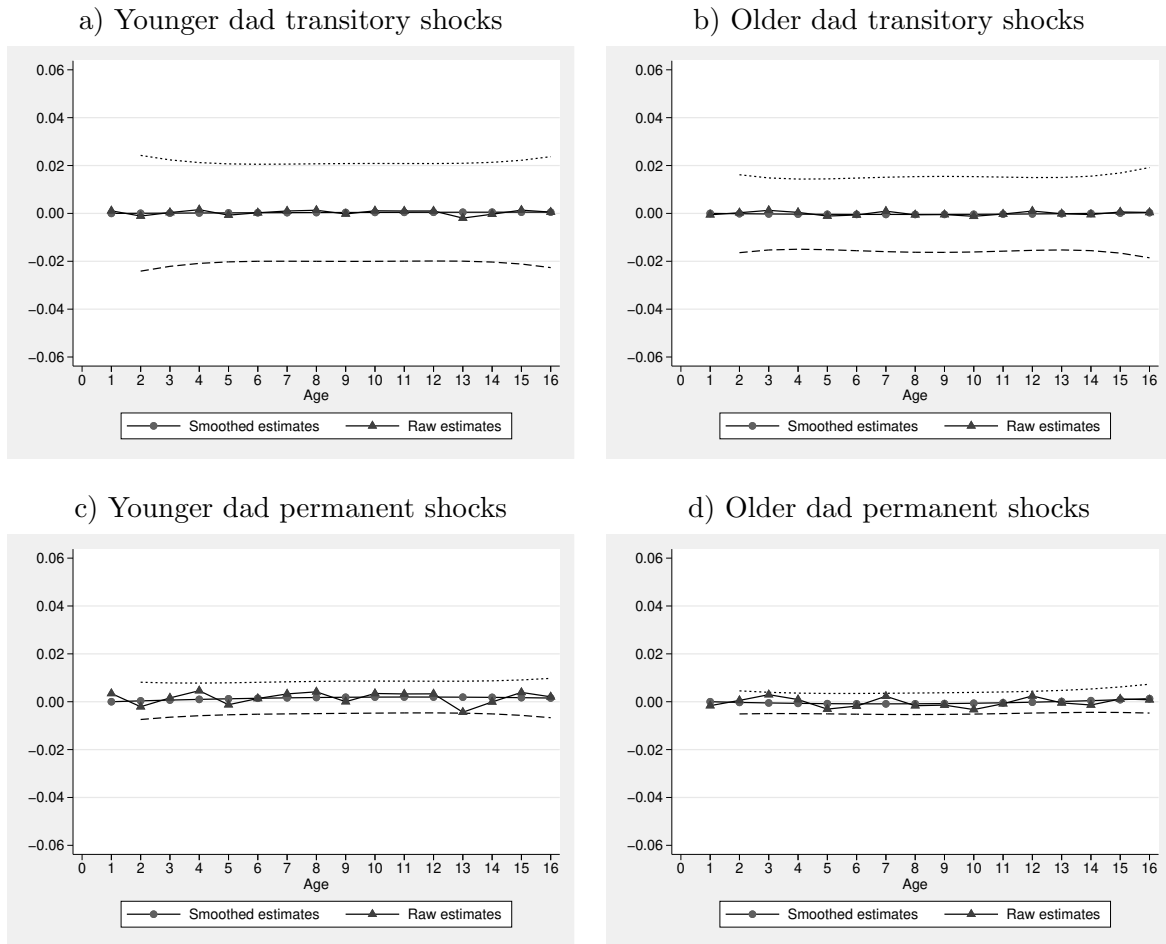
Notes: Sample and estimation strategy as [Figure 2](#). Younger (older) dads in panels a and c (b and d) aged below (above) median age 27.

Figure A.15: Heterogeneity. Household income shocks on obesity: Effects relative to age 1.



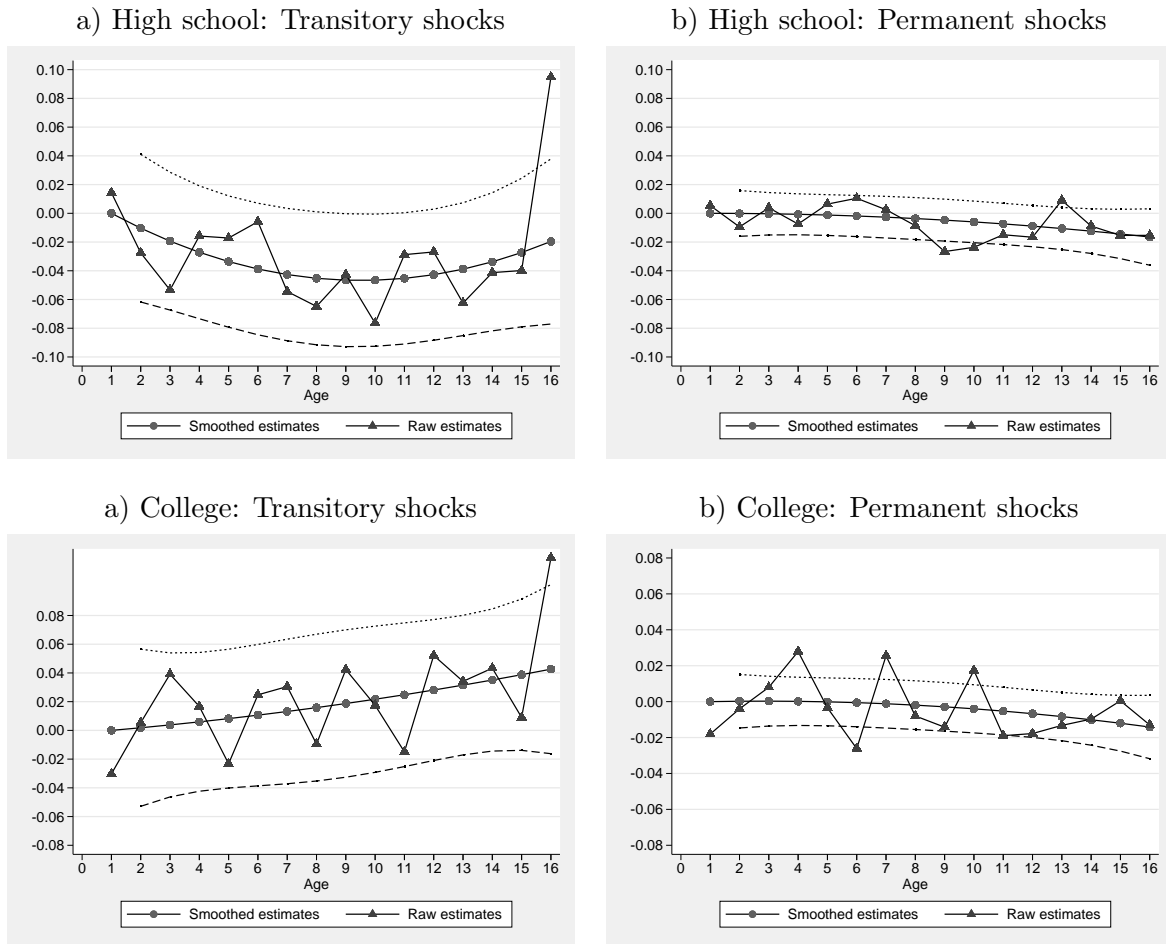
Notes: Sample and estimation strategy as [Figure 2](#). Younger (older) dads in panels a and c (b and d) aged below (above) median age 27.

Figure A.16: Heterogeneity. Household income shocks on teenpregnancy: Effects relative to age 1.



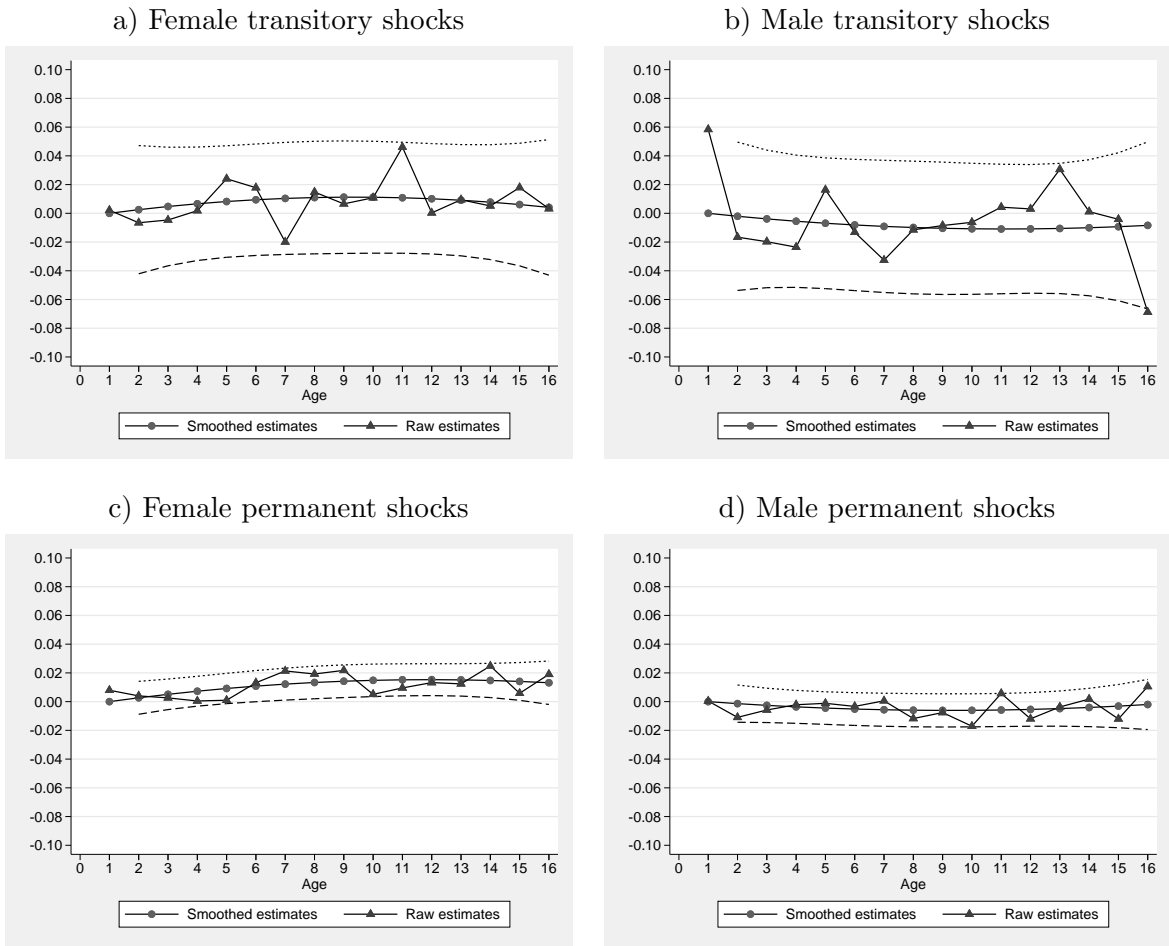
Notes: Sample and estimation strategy as [Figure 2](#). Younger (older) dads in panels a and c (b and d) aged below (above) median age 27.

Figure A.17: Low permanent income households. Household income shocks on education outcomes: Effects relative to age 1.



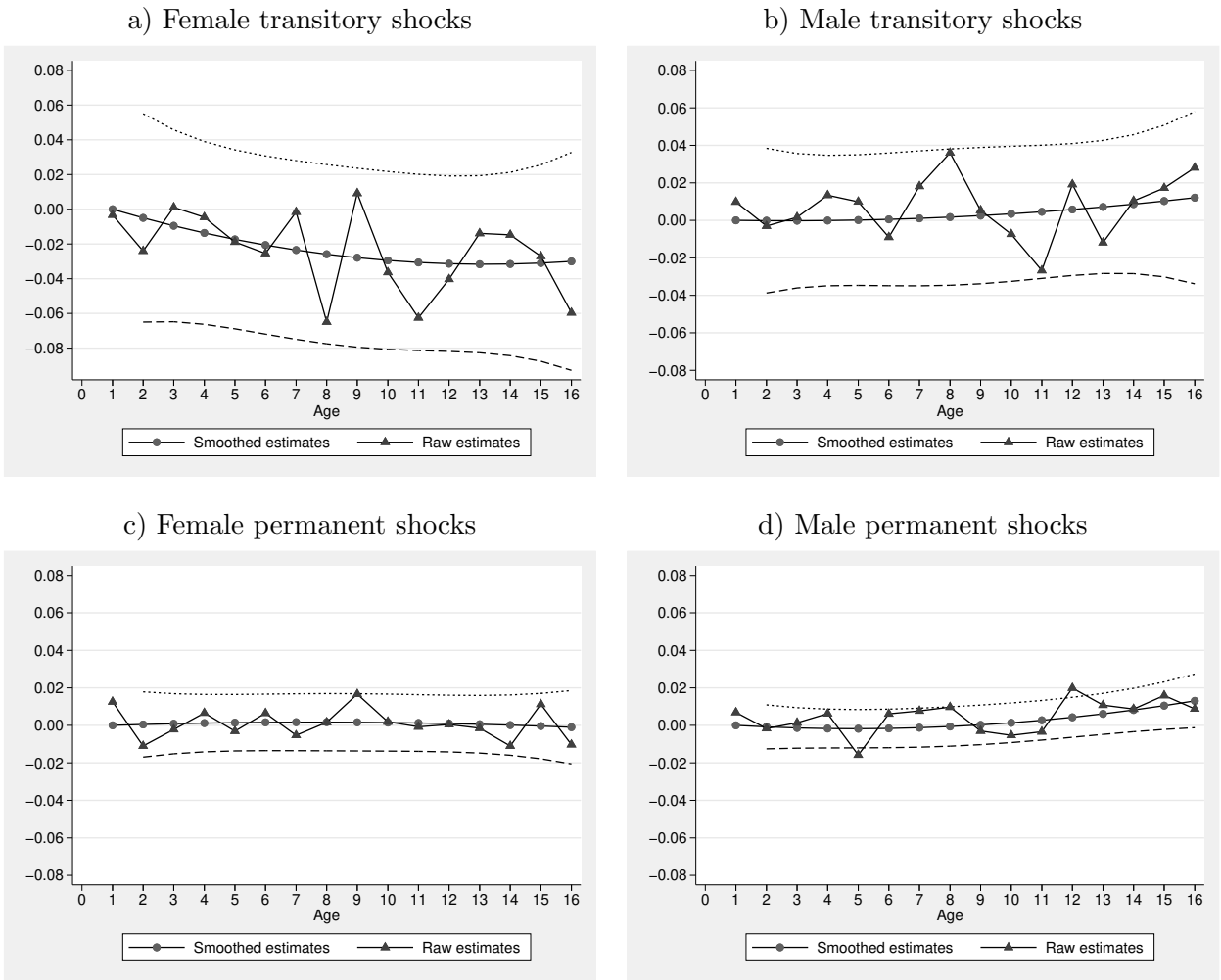
Notes: Sample and estimation strategy as [Figure 2](#). Low permanent income households defined as those whose income age 1-8 and 9-16 is below the mean.

Figure A.18: Heterogeneity. Household income shocks on high school graduation: Effects relative to age 1.



Notes: Sample and estimation strategy as [Figure 2](#). Sample of females (panels a and c) and males (panels b and d).

Figure A.19: Heterogeneity. Household income shocks on college: Effects relative to age 1.



Notes: Sample and estimation strategy as [Figure 2](#). Sample of females (panels a and c) and males (panels b and d).

Table A.1: First stage regression of life cycle profile of household income

	(1) 1970	(2) 1980	(3) 1990	(4) 2000
Mother age	0.140*** (0.002)	0.042*** (0.001)	0.083*** (0.002)	0.240*** (0.004)
Mother age squared	-0.002*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)
Father age	0.184*** (0.002)	0.066*** (0.001)	0.091*** (0.002)	0.240*** (0.004)
Father age squared	-0.003*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.003*** (0.000)
Mothers years schooling	-0.005*** (0.001)	0.024*** (0.000)	0.037*** (0.000)	0.049*** (0.001)
Father years schooling	-0.013*** (0.000)	0.027*** (0.000)	0.045*** (0.000)	0.052*** (0.000)
Observations	283,345	381,196	375,237	342,265
R-squared	0.246	0.166	0.190	0.292

Notes: The table reports coefficients from a regression relating to [Equation 1](#) of log income upon traits for a subset of years, where the coefficients for region of residence have been omitted. Norwegian Administrative data on population of births 1970-1980.

Table A.2: Autocovariances of residuals from log income differences

Lag	k=0	k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8
Autocovariance	0.061**	-0.015**	-0.004**	-0.003**	-0.001	-0.001	0.000	-0.001	0.001
Standard error	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Notes: Autocovariance of residuals estimated from a regression relating to [Equation 1](#) of log income differences on a set of controls including a quadratic in mother and father age at birth, mother and father's years of schooling, and indicator variables for municipality of residence, at different lags (k) across each column. For each lag, autocovariances estimated using a system of equations described in [Appendix B](#). Norwegian Administrative data on population of households giving birth 1970-1980.

Table A.3: The effect of transitory household income shocks at each age, relative to age 1: 1/2

	(1)		(2)	
	High school		College	
Age	Coefficient	SE	Coefficient	SE
1	0.000		0.000	
2	0.002	(0.011)	-0.005	(0.011)
3	0.003	(0.010)	-0.010	(0.010)
4	0.004	(0.009)	-0.015	(0.009)
5	0.004	(0.009)	-0.018	(0.009)
6	0.005	(0.009)	-0.022	(0.008)
7	0.004	(0.009)	-0.024	(0.009)
8	0.004	(0.009)	-0.027	(0.009)
9	0.003	(0.009)	-0.028	(0.009)
10	0.001	(0.009)	-0.029	(0.009)
11	0.000	(0.009)	-0.030	(0.009)
12	-0.003	(0.009)	-0.030	(0.009)
13	-0.005	(0.009)	-0.029	(0.009)
14	-0.008	(0.010)	-0.028	(0.009)
15	-0.011	(0.010)	-0.026	(0.010)
16	-0.015	(0.011)	-0.024	(0.011)

Notes: Income measure is gross household income. Quadratic specification to estimate smoothed function. First stage residuals predicted from a regression run separately by year of log annual earnings on a quadratic in mother and father age at birth, mother and father years of schooling, dummy variable for municipality run for each year of data. The first difference residuals decomposed into transitory and permanent components and the effect of transitory and permanent shocks on child outcomes is estimated from the model in Equation 7. Estimates of the difference in coefficients for each age a against age 1 on $\sigma_{\zeta_a cfe}^2 - \sigma_{\zeta_1 cfe}^2$ and $\sigma_{\varepsilon_a cfe}^2 - \sigma_{\varepsilon_1 cfe}^2$.

Table A.4: The effect of transitory household income shocks at each age, relative to age 1: 2/2

	(1)		(2)		(3)	
	IQ		Obesity		Teen pregnancy	
Age	Coefficient	SE	Coefficient	SE	Coefficient	SE
1	0.000		0.000		0.000	
2	0.012	(0.050)	0.001	(0.003)	0.002	(0.004)
3	0.021	(0.046)	0.002	(0.003)	0.004	(0.004)
4	0.029	(0.045)	0.002	(0.002)	0.006	(0.004)
5	0.035	(0.046)	0.003	(0.002)	0.008	(0.004)
6	0.040	(0.047)	0.004	(0.002)	0.009	(0.004)
7	0.042	(0.048)	0.004	(0.002)	0.009	(0.004)
8	0.043	(0.049)	0.005	(0.002)	0.010	(0.004)
9	0.041	(0.049)	0.006	(0.002)	0.010	(0.004)
10	0.038	(0.048)	0.007	(0.002)	0.010	(0.004)
11	0.033	(0.047)	0.007	(0.002)	0.009	(0.004)
12	0.026	(0.046)	0.008	(0.002)	0.008	(0.004)
13	0.017	(0.045)	0.009	(0.002)	0.007	(0.004)
14	0.007	(0.047)	0.009	(0.002)	0.005	(0.004)
15	-0.006	(0.052)	0.010	(0.002)	0.003	(0.004)
16	-0.020	(0.060)	0.010	(0.003)	0.001	(0.005)

Notes: Income measure is gross household income. Quadratic specification to estimate smoothed function. First stage residuals predicted from a regression run separately by year of log annual earnings on a quadratic in mother and father age at birth, mother and father years of schooling, dummy variable for municipality run for each year of data. The first difference residuals decomposed into transitory and permanent components and the effect of transitory and permanent shocks on child outcomes is estimated from the model in Equation 7. Estimates of the difference in coefficients for each age a against age 1 on $\sigma_{\zeta_{acfe}}^2 - \sigma_{\zeta_{1cfe}}^2$ and $\sigma_{\varepsilon_{acfe}}^2 - \sigma_{\varepsilon_{1cfe}}^2$.

Table A.5: The effect of permanent household income shocks at each age, relative to age 1 1/2

	(1)		(2)	
	High school		College	
Age	Coefficient	SE	Coefficient	SE
1	0.000		0.000	
2	0.001	(0.003)	-0.002	(0.003)
3	0.003	(0.003)	-0.004	(0.003)
4	0.004	(0.003)	-0.006	(0.003)
5	0.005	(0.003)	-0.007	(0.003)
6	0.007	(0.003)	-0.008	(0.003)
7	0.008	(0.003)	-0.009	(0.003)
8	0.009	(0.003)	-0.009	(0.003)
9	0.011	(0.003)	-0.010	(0.003)
10	0.012	(0.003)	-0.009	(0.003)
11	0.013	(0.003)	-0.009	(0.003)
12	0.015	(0.003)	-0.008	(0.003)
13	0.016	(0.003)	-0.007	(0.003)
14	0.018	(0.003)	-0.006	(0.003)
15	0.019	(0.003)	-0.004	(0.003)
16	0.021	(0.004)	-0.002	(0.004)

Notes: Quadratic specification to estimate smoothed function. First stage residuals predicted from a regression run separately by year of log annual earnings on a quadratic in mother and father age at birth, mother and father years of schooling, dummy variable for municipality run for each year of data. The first difference residuals decomposed into transitory and permanent components and the effect of transitory and permanent shocks on child outcomes is estimated from the model in [Equation 7](#). Estimates of the difference in coefficients for each age a against age 1 on $\sigma_{\zeta_a cfe}^2 - \sigma_{\zeta_1 cfe}^2$ and $\sigma_{\varepsilon_a cfe}^2 - \sigma_{\varepsilon_1 cfe}^2$.

Table A.6: The effect of permanent household income shocks at each age, relative to age 1: 2/2

	(1)		(2)		(3)	
	IQ		Obesity		Teen pregnancy	
Age	Coefficient	SE	Coefficient	SE	Coefficient	SE
1	0.000		0.000		0.000	
2	-0.008	(0.022)	-0.001	(0.001)	0.000	(0.002)
3	-0.015	(0.020)	-0.002	(0.001)	0.000	(0.001)
4	-0.021	(0.019)	-0.002	(0.001)	0.001	(0.001)
5	-0.026	(0.019)	-0.003	(0.001)	0.001	(0.001)
6	-0.030	(0.018)	-0.003	(0.001)	0.001	(0.001)
7	-0.033	(0.019)	-0.003	(0.001)	0.001	(0.001)
8	-0.035	(0.019)	-0.003	(0.001)	0.001	(0.001)
9	-0.036	(0.019)	-0.003	(0.001)	0.001	(0.001)
10	-0.037	(0.019)	-0.003	(0.001)	0.000	(0.001)
11	-0.036	(0.019)	-0.003	(0.001)	0.000	(0.001)
12	-0.034	(0.019)	-0.002	(0.001)	0.000	(0.001)
13	-0.032	(0.019)	-0.001	(0.001)	0.000	(0.001)
14	-0.028	(0.020)	-0.001	(0.001)	-0.001	(0.002)
15	-0.024	(0.021)	0.000	(0.001)	-0.001	(0.002)
16	-0.019	(0.023)	0.001	(0.001)	-0.001	(0.002)

Notes: Quadratic specification to estimate smoothed function. First stage residuals predicted from a regression run separately by year of log annual earnings on a quadratic in mother and father age at birth, mother and father years of schooling, dummy variable for municipality run for each year of data. The first difference residuals decomposed into transitory and permanent components and the effect of transitory and permanent shocks on child outcomes is estimated from the model in [Equation 7](#). Estimates of the difference in coefficients for each age a against age 1 on $\sigma_{\zeta_{ace}}^2 - \sigma_{\zeta_{1cfe}}^2$ and $\sigma_{\varepsilon_{ace}}^2 - \sigma_{\varepsilon_{1cfe}}^2$.

Table A.7: Sample statistics for asset analysis

	N	Mean	Std. Dev.
Child human capital outcomes			
College	194,011	0.370	0.483
High School Graduation	194,011	0.789	0.408
IQ (males)	94,124	5.205	1.741
Teen pregnancy (females)	92,376	0.035	0.184
Obesity (males)	97,898	0.034	0.182
Parent characteristics			
Mother age at birth	194,011	26.585	4.969
Father age at birth	194,011	29.345	5.546
Mother years of schooling	194,011	11.504	2.802
Father years of schooling	194,011	11.701	3.059
Child year of birth	194,011	1978.504	1.115
Assets			
Net assets (NOK)	194,011	8,417.77	17,185.98
Assets (NOK)	194,011	8,570.07	17,590.37
Debt (NOK)	194,011	155.29	2,987.83

Notes: Sub-sample from Norwegian administrative data created for analysis of asset reaction to transitory and permanent income shocks, is population of households having a child between 1977-1980. IQ and obesity measured for males from the military service test at around age 18. Net assets are assets minus debt, in 2000 prices.

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