

Additional Materials: Appendix for Online publication

Sooner or later?

The impact of child education on household consumption

Content

We organise this Appendix as follows. In the first part, we describe how we proxy family's income shocks (Section A1) and family fixed effects related to the educational family background (Section A2). In Section B1, we specify our regression model in a potential outcomes framework. The control function method is described in Section B2. In Section B2.1, we present a non-parametric analysis based on Huber and Mellace (2015). This evidence supports the validity of our instrument. Moreover, it indicates that education is a costly production good. In Section C1, we provide the first set of robustness checks using overall consumption, rather than non-durable consumption as the dependent variable. We then present the reduced form analysis in Section D1 and placebo estimates in Section D2. In Section E1, we report additional robustness checks. Finally, Section F1 reports additional tables and figures.

A1 Proxy of permanent income shocks

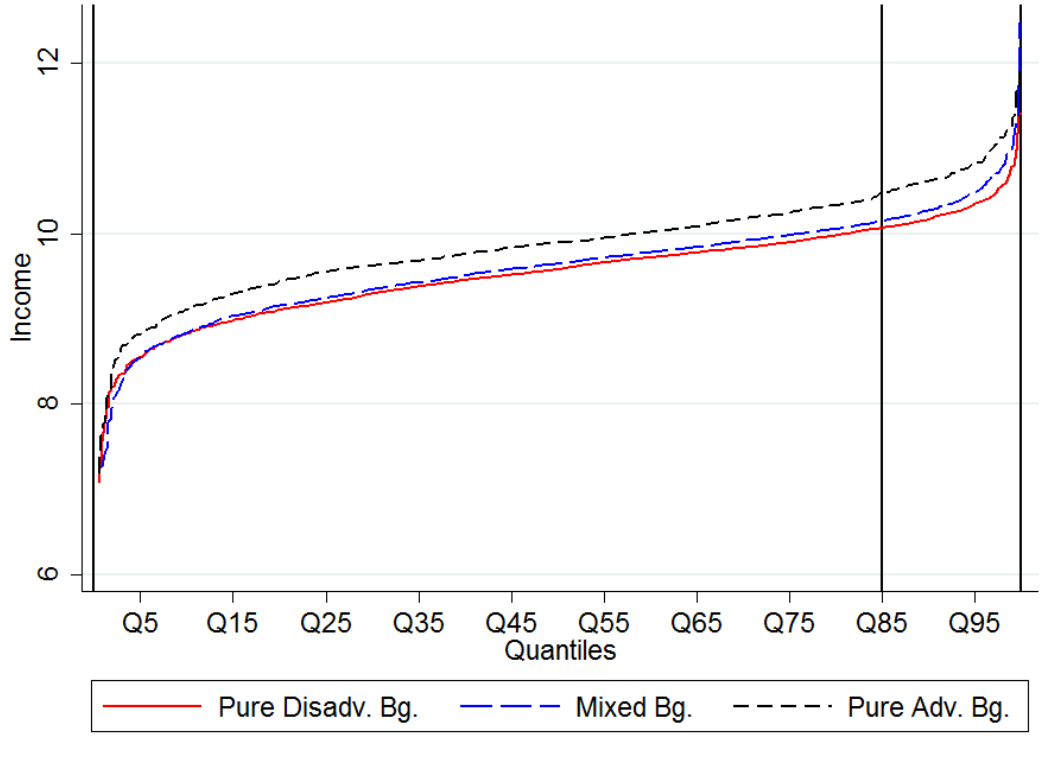
Jappelli and Pistaferri (2006)’s empirical findings show that different population groups are systematically exposed to different idiosyncratic shocks facing consequently different income processes. They find that the estimated variance signal that the less educated face a higher variance of permanent income shocks, a pattern also uncovered by Carroll and Samwick (1997) with US data. Drawing on this evidence, we assume that the lottery of birth randomly assigns family incomes and distributes abilities and parenting accordingly. There are two channels through which the family background impacts the income process of the household. First, *the direct* effect (i.e. identified across family background groups) of providing the environment where the child grows up (inherited abilities and networks). Second, *an indirect* effect (i.e. identified within the family background group), contributing to the development of the innate abilities, preferences, and traits that determine the position in the distribution of income conditional family background. Hence, we attempt at measuring the permanent component of income innovations by assuming that the common underlying distribution from which the joint time series processes of consumption and income are drawn, depends upon some unobserved characteristics of the household related to the family background. In other words, we aim at finding an empirical counterpart of $\int_{i=0}^t \psi_{h,t} dt$ that is independent of the reform (i.e. a proxy of the permanent income shock in the absence of the reform). We are not decomposing income shocks into permanent and transitory components as commonly used in the literature (see for instance Meghir and Pistaferri 2004, Blundell, Pistaferri and Preston 2008, Jappelli and Pistaferri 2011). Our measure of permanent income innovations is much simpler. It corresponds to a family fixed effect that captures the household lifetime budget constraint in the absence of the reform. The inclusion of these shocks allows us to discriminate between considering education as a consumption rather than a production good. If permanent income innovations have no impact on children’s schooling years, education is a production good. The degree of the endogeneity between non-durable consumption and children’s years of schooling draws on the correlation between the error terms in the first stage and the main regression model. In these error terms enter household preferences, traits, and abilities that our covariates cannot control. As long as the permanent component of the income innovations and a proxy of unobservable characteristics related to the family educational background capture part of these preferences, abilities and traits, they may shape this correlation. For this reason, we include them in the error structure. The key maintained hypothesis to retrieve is that both the permanent component of the income innovations and our proxy of unobservable characteristics related to the family educational background are mean independent of the instrument so that the university reform is *as good as randomly assigned*.

We use SHIW data which provide information on the education and socio-economic position of the grandparents.¹ We cut the lowest and the highest 5% of the age of the head of the household distribution, retaining all 69,740 individuals in the entire dataset.

We draw on the assumption that assortative mating shapes children’s abilities, traits and preferences. For each year of the survey from 1995 to 2006, we start by partitioning the observed families into two groups according to the grandfather’s occupational background: one, the low skilled family background group, gathering the grandfathers who were unemployed or employed either in agriculture or as an unskilled manual worker and the other, the skilled family background group, comprising all the other cases. Starting from this broad classification, we define three family background groups. The low skilled background group includes all the families

¹The questionnaire of the survey reports this questions: *What were the educational qualifications, employment status and sector of activity of your parents when they were your present age? (If the parent was retired or deceased at that age, refer to the time preceding retirement or death).*

Figure A1: Income distributions across family background groups



Note: Our elaboration using SHIW, Bank of Italy, wave 2002.

for which the fathers of both spouses were low skilled. Symmetrically, the skilled group refers to all the families where both grandfathers were skilled. Residually, we define a third group comprising all families with a grandfather belonging to the skilled category and the other one to the unskilled group. Since missing data on family background indicators are likely to be related to the household's unobservable characteristics, we keep observations with missing values for the grandfathers' occupational conditions assigning the family to the mixed background group.

For each of these three groups and each year of the survey, we rank households within each group according to their (log) net of taxes income,² and (log) consumption. As long as the rank position within the group-specific income (consumption) distribution depends on the household's decisions, the properties of the distribution itself (such as the percentiles, the median, the mean, and variance) are exogenous to the family's choice. Households sitting in the same percentile have similar unobservable characteristics.³ We, then, compare the income (consumption) of a family at a given rank (percentile) of the group-specific income (consumption) distribution with the income (consumption) that this family would have reached if all families shared the backgrounds of origin. This counterfactual income (consumption) corresponds to the weighted average income (consumption), μ , at a given percentile p of the full sample distribution $F_j(\cdot)$ of either income or consumption, given the weight w_j of group j .

The empirical counterpart of the vertical distance between the family background specific quantile functions $F_j^{-1}(p)$ and the weighted average quantile function can be proxied by the estimated residuals ε_Y of the following regression model, described for expositional purposes in terms of income Y :

²We equalise net of taxes income using the square root of household size.

³These unobservable characteristics relate to the occupational condition of the grandfathers. However, other unobservable characteristics might correlate with them.

$$Y = \sum_{p=1}^{100} \gamma_j \cdot \mathbf{1}[Y \in P(p_j)] + \varepsilon_Y, \quad (\text{A1})$$

Where $\mathbf{1}[\cdot]$ is an indicator function for the condition expressed in its argument to be satisfied, sets of dummies measure this indicator function taking the value of 1 in correspondence of the rank occupied by the household in her group-specific income Y (consumption C) distribution. We also include a dummy variable, that controls for missing information on the background of origin, into equation (A1).

As illustrated by figure A1, the residuals ε_Y correspond to the vertical distance between the estimated reference income (solid line) and the family background group-specific income distributions for a given percentile (i.e. for instance the 85th) in a given year (i.e. 2002). When these residuals are statistically equal to zero for each percentile of the income (consumption) distribution, we argue that the family background group-specific distributions are identical. Hence, family background has no impact on idiosyncratic household shocks.

In fact, for a given year, these residuals ε_Y reflect both idiosyncratic household shocks related to the family background. To separate the influence of the family background from such residuals, we follow the procedure suggested by Björklund, Jäntti and Roemer (2012) adding and subtracting to the residuals ε_Y an innovation term u_Y which corresponds to the residuals ε_Y normalised by the fraction of overall variation explained by the family background group-specific variation.

$$Y = \sum_{p=1}^{100} \gamma_j \cdot \mathbf{1}[Y \in P(p_j)] + \tilde{\varepsilon}_Y^j + u_Y, \quad (\text{A2})$$

where $k = \left(\frac{1}{\sum_j \sigma_j^2} \right)^{-\frac{1}{2}} = \frac{1}{\sigma}$; $u_Y = \frac{\varepsilon_Y}{k\sigma_Y}$ and $\tilde{\varepsilon}_Y^j = \varepsilon_Y - \frac{\varepsilon_Y}{k\sigma_j}$.

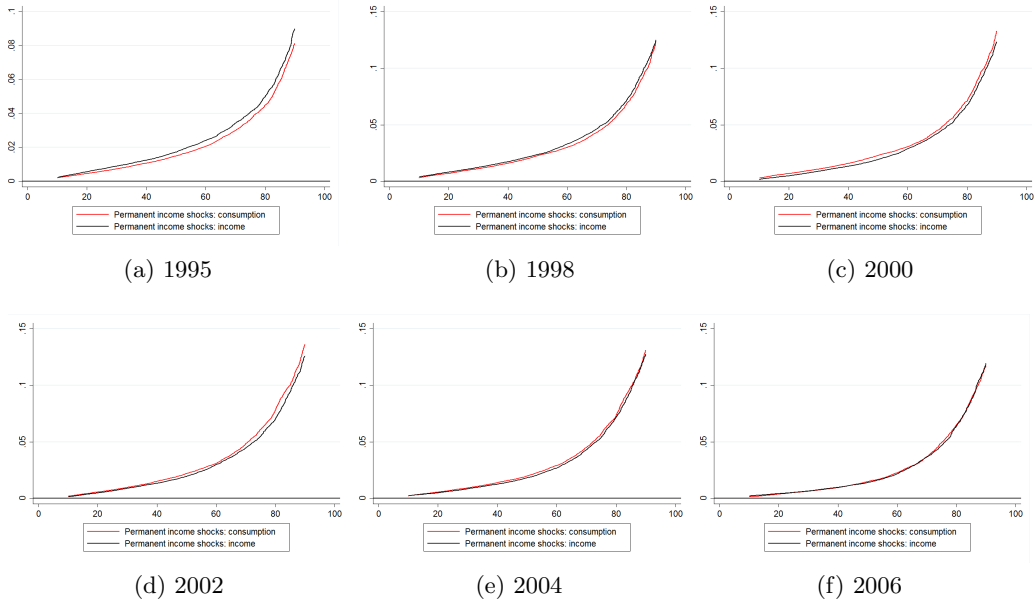
The term $\tilde{\varepsilon}_Y^j$ hence captures both the direct and the indirect contributions of the family background to the income (consumption) innovation in a given year by capturing the influence of family background on the conditional variation of income (consumption) around the expected value for each group. The idiosyncratic innovation u_Y has, instead, a common variance $\frac{1}{k^2} = \sigma^2$ across all family background groups.

This decomposition can be obtained starting from the OLS residuals ε_Y in (A1) and then calculating the family background group-specific variances σ_j^2 . In the case of very few observations for some groups and tiny, estimated variances (leading to substantial standardised residuals u_Y), we follow what suggested by Björklund et al. (2012). We regress the estimated variances on the background characteristics and use the fitted values from that regression as the basis for $\frac{\varepsilon_Y}{k\sigma_j}$.

Yearly from 1995 to 2006, we sum the innovations u_Y of consumption and income processes, for each household up to that time point. Since the sum of innovations depends upon individual's labour history, we divide this sum by the household potential working age which is an average of the potential working age (age minus 15, the legal age to enter into the labour market) of all adults in the family. The resulting sum of innovations is then averaged across time (age) to retrieve the permanent component of both consumption and income processes.

Figure A2 presents suggestive evidence on the difference between permanent income distribution and consumption innovations. Since the two distributions almost coincide, we include into the regression models our measure of the permanent income innovations as the

Figure A2: Differences between the consumption and income innovation distributions



Notes: Our elaboration using SHIW, Bank of Italy, waves 1995-2006.

empirical counterpart of the average $\int_{i=0}^t \psi_{h,t} dt$. We interpret this average as a proxy of the average household permanent income innovation in the absence of the reform. After the reform, this proxy does not change for never and always affected families. We use as a last year of the survey, the year 2006. Hence, almost all children of complying households are still at university, and the observed family income cannot yet benefit from permanent income shocks earned by these children.

A2 Proxy of unobservable characteristics related to the educational background of the family

Other characteristics than the occupation of the grandfathers could contribute to explain the family educational choice. The low enrolment rate at university of individuals coming from low-income families and poorly educated parents explain the strong intergenerational correlation in educational attainment in Italy (Hanushek and Wößmann (2006); Checchi and Flabbi (2013)). This strong intergenerational correlation persists despite the expansion of higher education (Bratti, Checchi and de Blasio 2008). We attempt at controlling for household unobservable characteristics related to the educational background of the family. More educated parents are likely to be more effective in encouraging traits and preferences in their children, impacting their marginal costs and benefits of schooling (for instance, by training them to learn). Moreover, even for a given level of education, these preferences and traits might directly impact household consumption. They can relate to abilities that, independently of education, will affect the offspring's lifetime income and through this may impact consumption. They can also be related to either (both) time preferences or (and) the risk attitude of the household, which affect the family's (non-durable) consumption decision. Finally, we allow this measure of unobservable characteristics related to the family educational background to affect children's years of schooling and consumption directly but to shape also the correlation between the error terms in the first stage and primary regression model under the assumption of such characteristics to being mean independent from the instrument.

We classify households according to the years of schooling of the grandparents. The low (high) educated background group includes all households for which both spouses' parents had, on average, either less (more) than five years of education. The mixed (third) group has one spouse's parents belonging to the low educated category and one spouse's parents to the highly educated one. We assign to this group also families with missing information on the educational level of the grandparents. We keep observations with missing values. We control for the potential correlation between these values and unobservable characteristics of the household using a dummy variable taking the value of one in case of missing information.

We rank households within each group according to the parents' average years of schooling (if the spouse is present, otherwise we consider the years of schooling of the head of the family). We consider deciles to identify the rank position in the parents' years of schooling distribution. We regress the parents' average years of schooling on dummies, capturing the rank position into the group-specific (i.e. low, high, mixed educated grandparents) years of schooling distribution and a dummy variable controlling for the missing values. We interpret the residuals of such regression as a fixed component of the household unobservable characteristics related to the educational background of origin. To clarify the concept, families with positive residuals are those which have unobservable characteristics (such as abilities, traits or preferences) providing an advantage in the parents' years of schooling, compared to the other households with a diverse family background but sitting in the same decile of the years of schooling distribution. There are no differences in families' abilities (traits, preferences), generated by the grandparents' average educational level when the residuals are statistically equal to zero for each decile of the parents' years of schooling distribution. In such circumstances the distributions of the three groups are identical.

B1 Potential outcomes framework.

Consider the potential year of schooling, $y_{2,0}$ before the introduction of the reform. Assume that this potential outcome is a function of the child's age a as follows:

$$E[y_{2,0}|a] = \mu_0$$

where:

$$\mu_0 = \alpha_0 + f(a)$$

where $f(a)$ is a second order polynomial in a . For simplicity sake other covariates X are omitted here.

Consider the potential years of schooling, $y_{2,1}$ after the introduction of the reform.

$$E[y_{2,1}|a] = \mu_1$$

where:

$$\mu_1 = \alpha_0 + \rho + f(a)$$

The assignment into treatment is based on the following rule:

$$Z = \begin{cases} 1 & \text{if } yob \geq yob_m \\ 0 & \text{if } yob < yob_m \end{cases}$$

where yob_m is the year of birth cutoff (i.e. the first cohort of birth to be treated by the reform at a given age).

We take expectations under independence assumption: $y_{2,1} \perp Z$ and $y_{2,0} \perp Z$)

Observed years of schooling are equal to:

$$\begin{aligned} y_{2i} &= y_{2,1}Z + y_{2,0}(1 - Z) \\ E[y_i|Z, a] &= E[y_{2,0}|a] + (E[y_{2,1}|a] - E[y_{2,0}|a])Z \\ E[y_{2i}|a] &= \mu_0 + [\mu_1 - \mu_0]Z \end{aligned}$$

where

$$\begin{aligned} \mu_0 &= \alpha_0 + \beta_0 a + \gamma_0 a^2 \\ \mu_1 &= \alpha_0 + \rho + \beta_1 a + \gamma_1 a^2 \\ \mu_1 - \mu_0 &= \rho + (\beta_1 - \beta_0)a + (\gamma_1 - \gamma_0)a^2 \end{aligned}$$

B1.1 First stage

Hence, the first stage regression model corresponds to:

$$y_{2i} = \alpha_0 + \beta_0 a + \gamma_0 a^2 + \rho Z + (\beta_1 - \beta_0)aZ + (\gamma_1 - \gamma_0)a^2 Z + \epsilon_{it} \quad (\text{B3})$$

The age specific effect of the reform is then equal to:

$$\mu_1 - \mu_0 = \rho + (\beta_1 - \beta_0)a + (\gamma_1 - \gamma_0)a^2$$

Similar analysis can be carried-out on the potential household non-durable consumption before and after the reform. However, the only way to have the same polynomial function for both the child's years of schooling and the household non-durable consumption as we do is to assume that potential household non-durable consumption is not a function of the child's age. We maintain this assumption in our empirical model specification.

B2 Model specification using a control function approach

Consider a general setting which considers heterogeneous effects, which affect both the intercept and the slope of the relationship between a child's years of schooling and household non-durable consumption. Proxy of family permanent income shocks and family educational background characteristics capture these heterogeneous effects.⁴ This amounts to the following model specification:

$$y_{2ia} = \pi_0 + \pi z_{aj} + \lambda_2 s_h + \nu_2 \quad (\text{B4})$$

This model specification corresponds to Equation (9) in the main text where we omit for the sake of simplicity, the age, cohort, income quintile dummies and the term f_h . Results are invariant to their inclusions. For that reason, we simplify Equation (8) in the main text as:

$$y_{1ha} = \bar{\alpha} + \bar{\beta} y_{2ia} + \alpha_i - \bar{\alpha} + (\beta_i - \bar{\beta}) y_{2ia} + \gamma_s(s_h - \bar{s}_h) + \gamma_{sy}(s_h - \bar{s}_h) y_{2ia} + u_{1ha} \quad (\text{B5})$$

where $\nu_1 = \alpha_i - \bar{\alpha} + (\beta_i - \bar{\beta}) y_{2ia} + \gamma_s(s_h - \bar{s}_h) + \gamma_{sy}(s_h - \bar{s}_h) y_{2ia}$

We apply this model specification for each age of the child. However, the age-specific model can be nested into a more general model by interacting the effect of the child's years of schooling on household non-durable consumption with a polynomial function in age. In what follows, we show the model specification that allows estimating $\bar{\beta}$, which corresponds to the average effect of one more year of education, y_{2ia} , on household non-durable consumption, y_{1ha} . To simplify further the exposition we drop the indexes i , a and h .

Assume now:

$$\begin{aligned} E[(\alpha_i - \alpha)|z] &= 0 \\ E[(\beta_i - \bar{\beta})|z] &= 0 \\ E[(\alpha_i - \alpha)|y_2, z] &= \lambda_1 y_2 + \lambda_z z \\ E[(\beta_i - \bar{\beta})|y_2, z] &= \psi_1 y_2 + \psi_z z \\ E[s_h - \bar{s}_h|z] &= 0 \\ E[s_h|z] &= E[s_h] = \bar{s}_h \\ E[s_h z] &= 0 \\ E[s_h - \bar{s}_h|y_2, z] &= \lambda_2 y_2 + \lambda_{F1} z \\ E[\nu_2|z] &= 0 \end{aligned}$$

We start by calculating the following expected values:

⁴In other words, these family background characteristics shape the relationship between the error terms ν_2 and ν_1 as in equation B5.

$$\begin{aligned}
E[E[\alpha_i - \alpha|y_2, z]|z] &= 0 \\
0 &= E[\lambda_1 y_2 + \lambda_z z|z] \\
0 &= \lambda_1 E[y_2|z] + \lambda_z z \\
E[y_2|z] &= \pi_0 + \pi z + \lambda_2 \bar{s}_h \\
E[y_2|z] &= \pi_0 + \pi z + \lambda_2 s_h - \lambda_2(s_h - \bar{s}_h) \\
\lambda_z z &= -\lambda_1[\pi_0 + \pi z + \lambda_2 s_h - \lambda_2(s_h - \bar{s}_h)]
\end{aligned}$$

$$\begin{aligned}
E[E[\beta_i - \bar{\beta}|y_2, z]|z] &= 0 \\
0 &= E[\psi_1 y_2 + \psi_z z|z] \\
0 &= \psi_1 E[y_2|z] + \psi_z z \\
E[y_2|z] &= \pi_0 + \pi z + \lambda_2 \bar{s}_h \\
E[y_2|z] &= \pi_0 + \pi z + \lambda_2 s_h - \lambda_2(s_h - \bar{s}_h) \\
\psi_z z &= -\psi_1[\pi_0 + \pi z + \lambda_2 s_h - \lambda_2(s_h - \bar{s}_h)]
\end{aligned}$$

$$\begin{aligned}
E[E[S_h - \bar{S}_1|y_2, z]|z] &= 0 \\
0 &= E[\lambda_2 y_2 + \lambda_{F1} z|z] \\
0 &= \lambda_2 E[y_2|z] + \lambda_{F1} z \\
E[y_2|z] &= \pi_0 + \pi z + \lambda_2 \bar{s}_1 \\
E[y_2|z] &= \pi_0 + \pi z + \lambda_2 s_h - \lambda_2(s_h - \bar{s}_h) \\
\lambda_{F1} z &= -\lambda_2[\pi_0 + \pi z + \lambda_2 s_h - \lambda_2(s_h - \bar{s}_h)]
\end{aligned}$$

It is now possible to proceed calculating $E[y_1|y_2, z]$:

$$\begin{aligned}
E[y_1|y_2, z] &= \bar{\alpha} + \bar{\beta} y_2 + E[\alpha_i - \bar{\alpha}|y_2, z] + E[\beta_i - \bar{\beta}|y_2, z] y_2 + \\
&+ E[s_h - \bar{s}_h|y_2, z] + E[s_h - \bar{s}_1|y_2, z] y_2
\end{aligned}$$

$$\begin{aligned}
E[y_1|y_2, z] &= \bar{\alpha} + \bar{\beta} y_2 + \lambda_1 y_2 + \lambda_z z + \psi_1 y_2^2 + \psi_z z y_2 + \\
&+ \lambda_2 y_2 + \lambda_{F1} z + \lambda_2 y_2^2 + \lambda_{F1} z y_2
\end{aligned}$$

$$\begin{aligned}
E[y_1|y_2, z] &= \bar{\alpha} + \bar{\beta} y_2 + \lambda_1 y_2 - \lambda_1[\pi_0 + \pi z + \lambda_2 s_h - \lambda_2(s_h - \bar{s}_h)] + \psi_1 y_2^2 - \\
&- y_2 \psi_1[\pi_0 + \pi z + \lambda_2 s_h - \lambda_2(s_h - \bar{s}_h)] + \lambda_2 y_2 - \lambda_2[\pi_0 + \pi z + \lambda_2 s_h - \lambda_2(s_h - \bar{s}_h)] + \\
&+ \lambda_2 y_2^2 - \lambda_2[\pi_0 + \pi z + \lambda_2 s_h - \lambda_2(s_h - \bar{s}_h)] y_2
\end{aligned}$$

since the residuals of the first stage reduced form regression corresponds to $\nu_2 = y_2 - \pi_0 - \pi z - \lambda_2 s_h$ we have:

$$\begin{aligned}
E[y_1|y_2, z] &= \bar{\alpha} + \bar{\beta} y_2 + (\lambda_1 + \lambda_2) \nu_2 + (\lambda_1 + \lambda_2) \lambda_2 (s_h - \bar{s}_h) \\
&+ (\lambda_2 + \psi_1) \nu_2 y_2 + \lambda_2 (\lambda_2 + \psi_1) y_2 (s_h - \bar{s}_h)
\end{aligned}$$

We, therefore, estimate the following model:

$$y_2 = \pi_0 + \pi z + \lambda_2 s_h + \nu_2 \tag{B6}$$

$$y_1 = \bar{\alpha} + \bar{\beta}y_2 + (\lambda_1 + \lambda_2)\nu_2 + (\lambda_1 + \lambda_2)\lambda_2(s_h - \bar{s}_1) + (\lambda_2 + \psi_1)\nu_2y_2 + \lambda_2(\lambda_2 + \psi_1)y_2(s_h - \bar{s}_1) + u_1 \quad (B7)$$

Equations B6 and B7 are the age specific version of equations 9 and 10 reported in the main text. The coefficient ($\bar{\beta}$) of the endogenous variable y_2 , years of schooling, corresponds to the average effect of one more year of schooling on the dependent variable y_1 , the household non-durable consumption. When $(\lambda_2 + \psi_1) = 0$ (i.e. the linear combination of $(\gamma_3 + \gamma_{3age_{it}} * age_{it} + \gamma_{3age_{it}}^2 * age_{it} * age_{it})$ and $(\gamma_4 + \gamma_{4age_{it}} * age_{it} + \gamma_{4age_{it}}^2 * age_{it} * age_{it})$). This implies that the linear combination of $(\gamma_0 + \gamma_{age_{it}} * age_{it} + \gamma_{age_{it}}^2 * age_{it} * age_{it})$ in the main text, is not statistically different from zero.) control function and instrumental variable techniques are equivalent.

B2.1 Non-parametric analysis on inequality moments constraints

Angrist, Imbens and Rubin (1996) classify the population into four groups (the always takers (at), the never takers (nt), the compliers (c) and the defiers (d)) based on the treatment behaviour as a function of a binary instrument. Following Huber and Mellace (2015), we can calculate the proportions of always takers, never takers and compliers in the population and the sub-populations conditioned on the endogenous treatment status. To do this, we have to consider the probability of being a student at least for another year as a binary endogenous treatment. Hence, EE is a dichotomous indicator of whether or not the individual is a student). We cannot identify either the groups' share π_i ($i=at,nt,c,d$) or their mean potential outcome without further assumptions. Since we claim that our instrument is as good as randomly assigned, the unconfounded group assumption holds in our case implying that the proportion of any group conditional on the instrument is equal to its unconditional share in the entire population. Moreover, there is a clear relationship between any of the four conditional observed probabilities and the group proportions described by Table B1. (For an extensive discussion on assumptions and implications see Huber and Mellace (2015).)

Table B1: Observed conditional treatment probabilities and group shares

Conditional Treatment Probabilities	Group proportions
$P_{1,1}=Pr(EE = 1, Z = 1)$	$\pi_{at} + \pi_c$
$P_{0,1}=Pr(EE = 0, Z = 1)$	$\pi_{nt} + \pi_d$
$P_{1,0}=Pr(EE = 1, Z = 0)$	$\pi_{at} + \pi_d$
$P_{0,0}=Pr(EE = 0, Z = 0)$	$\pi_{nt} + \pi_c$
Under Treatment: $EE=1$	Under No treatment $EE=0$
$\frac{\pi_{at}}{P_{1,1}} = \frac{P_{1,0}}{P_{1,1}}$	-
$\frac{\pi_c}{P_{1,1}} = 1 - \frac{P_{1,0}}{P_{1,1}}$	-
-	$\frac{\pi_{nt}}{P_{0,0}} = \frac{P_{0,1}}{P_{0,0}}$
-	$\frac{\pi_c}{P_{0,0}} = 1 - \frac{P_{0,1}}{P_{0,0}}$

Under the assumption of monotonicity (i.e. the absence of defiers), it is possible to calculate the group proportions from the observed conditional probabilities. In fact, as described by the second part of Table B1, the share of the always treated in the treated population corresponds to the observed conditional probability $P_{1,0} = Pr(EE = 1, Z = 0)$ over the conditional probability of treatment $P_{1,1} = Pr(EE = 1, Z = 1)$. Subtracting this fraction from 1, we obtain the share of compliers within the treated population. Similarly, the proportion of the never takers in the untreated population amounts to the ratio between the conditional probability $P_{0,1} = Pr(EE = 0, Z = 1)$ and the conditional probability of no treatment $P_{0,0} = Pr(EE = 0, Z = 0)$. The difference between 1 and this latter ratio measures the fraction of compliers within the

untreated population. Then, to calculate the unconditional share in the population, we weight each of these proportions by the fraction of observations in each of the two treatment status $n_{EE=t}$ ($t=1,0$) over the population size n . For instance, under treatment, the always takers and compliers share are normalised by the ratio $\frac{n_{EE=1}}{n}$. Table B2 reports the group proportions in our data. The fraction of compliers, albeit not too small, is not too high while the share of never takers is relevant. One possible interpretation relies on the fact that even if the reform has mainly reduced the cost of enrolment into tertiary education for those who lag in the accumulation of the effective years of schooling this reduction is not enough to modify their behaviour.

The exclusion restriction for identifying the effect of children’s years of schooling on non-durable consumption requires that the university reform indicator does not directly impact non-durable consumption. This assumption holds if children’s schooling years enter negatively into the household lifetime utility function in an additive separable way and affects non-durable consumption through unexpected changes of the household’s lifetime budget constraint as sketched by our model. To support this assumption and interpretation, we use the bootstrap test on inequality moment constraints suggested by Huber and Mellace (2015). Starting on the proportion of always (never) takers in the treated (untreated) populations calculated above, we can identify sharp lower and upper bounds of the mean potential outcomes of the always (never). Given these sharp bounds, it is possible to define and test four inequality moment constraints. Under the null hypothesis, both the monotonicity and the exclusion restriction must hold. If monotonicity holds a violation of the four testable constraints points to a non-satisfaction of the exclusion restriction hypothesis.

Table B3 shows that the test fails to reject the null hypothesis; all the weaker inequality constraints are satisfied. The standardised differences between the nearest bound and point estimate under both treatment status are negative. Hence, the always and never takers’ point estimates mean potential outcome do not fall outside their bounds. This result is reassuring.

We then apply the difference of means test by Huber and Mellace (2015). There is the mean dominance of compliers under treatment; and the mean dominance of never takers under no treatment. The compliers mean potential outcome under treatment is at least as high as that of the always takers. The mean potential outcome of the never takers under no treatment is at least as high as that of the compliers. As suggested by the authors, given these findings, we have re-tested the four inequality moment constraints substituting the upper (lower) bound of the mean potential outcome of the always (never) takers to tighten to the conditional mean $E[y|EE = 1, Z = 1]$ ($E[y|EE = 0, Z = 0]$). Results from Table B3 are confirmed.⁵ Finally, we replicate both tests conditioning on age. Here the tests are more restrictive with narrower inequality moments constraints. The test always fails to reject the null hypothesis. Table B6 confirms that there is the mean dominance of compliers under treatment and the mean dominance of never takers under no treatment.

In summary, these tests provide support in favour of the validity of the CF assumptions. Moreover, we interpret the mean dominance of compliers under treatment and the mean dominance of never takers under no treatment as evidence that education is a costly production good (Lazear 1977). The university reform has reduced the costs of accumulating one more year of human capital, raising the household’s potential lifetime income with positive consequences on the family (non-durable) consumption.

⁵This table is available from request upon the authors.

Table B2: Group Proportions

	Always Takers	Never Takers	Compliers	Sample size
Affected Cohorts	85.579	-	14.421	4214
Unaffected Cohorts	-	73.860	26.140	6702
Population	33.037	45.347	21.616	10 916
<i>Age: 15</i>				
Affected	95.107	-	4.893	431
Unaffected	-	55.722	44.278	586
Population	40.306	32.108	27.586	1017
<i>Age: 16</i>				
Affected	94.194	-	5.806	553
Unaffected	-	58.602	41.398	679
Population	42.280	32.298	25.422	1232
<i>Age: 17</i>				
Affected	93.749	-	6.251	590
Unaffected	-	71.798	28.202	774
Population	40.551	40.742	18.707	1364
<i>Age: 18</i>				
Affected	91.349	-	8.651	571
Unaffected	-	71.543	28.457	801
Population	38.018	41.768	20.214	1372
<i>Age: 19</i>				
Affected	87.264	-	12.736	654
Unaffected	-	80.568	19.432	837
Population	38.277	45.228	16.495	1491
<i>Age: 20</i>				
Affected	93.354	-	6.646	594
Unaffected	-	93.363	6.637	885
Population	37.493	55.866	6.641	1479
<i>Age: 21</i>				
Affected	87.191	-	12.809	443
Unaffected	-	89.817	10.183	1087
Population	25.245	63.811	10.943	1530
<i>Age: 22</i>				
Affected	87.903	-	12.097	378
Unaffected	-	92.165	7.835	1053
Population	23.220	67.820	8.961	1431

Table B3: Huber and Mellace (2015): instrument validity test

Statistics	st.dist1	st.dist0	n.bs	mP.p	mP.f
All sample	-0.106	-0.247	1000	1	1

Note: $st.dist1(0)$ measures the standardised difference between the nearest bound and point estimate under treatment (no treatment); $mP.p(f)$ indicates bootstrapped p -value under partial (full) recentering; $n.bs$ is the number of bootstrap draws.

Table B4: Huber and Mellace (2015): difference of means test

Mean Outcome								
Under treatment					Under no treatment			
	Y_E=1,Z=1	Y_E=1,Z=0	diff	pval	Y_E=0,Z=0	Y_E=0,Z=1	diff	pval
All sample	9.306	9.237	0.069	0	8.993	9.089	-0.096	0

Note: $Y_{E=k,Z=l}$ is the average non-durable consumption conditioned on education enrolment ($k=0,1$) and being affected by the university reform ($l=0,1$); $diff$ is the corresponding difference of the means under treatment status; $pval$ is the p -value of the difference of means test.

Table B5: Huber and Mellace (2015): Instrument validity tests by age

Statistics	st.dist1	st.dist0	n.bs	mP.p	mP.f
Age: 15	0.088	-0.178	1000	0.185	0.425
Age: 16	0.146	-0.525	1000	0.184	0.207
Age: 17	0.060	-0.361	1000	0.414	0.636
Age: 18	0.001	-0.365	1000	0.619	0.906
Age: 19	-0.108	-0.039	1000	0.727	0.962
Age: 20	0.028	0.021	1000	0.716	0.839
Age: 21	-0.082	-0.000	1000	0.712	0.900
Age: 22	-0.192	0.180	1000	0.348	0.397

Note: $st.dist1(0)$ measures the standardised difference between the nearest bound and point estimate under treatment (no treatment); $mP.p(f)$ indicates bootstrapped p -value under partial (full) recentering; $n.bs$ is the number of bootstrap draws.

Table B6: Huber and Mellace (2015): difference of means test by age

Mean Outcome								
Under treatment					Under no treatment			
	Y_E=1,Z=1	Y_E=1,Z=0	diff	pval	Y_E=0,Z=0	Y_E=0,Z=1	diff	pval
Age: 15	9.260	9.167	0.093	0.002	8.610	8.866	-0.256	0.017
Age: 16	9.258	9.137	0.121	0	8.791	8.772	0.019	0.841
Age: 17	9.311	9.219	0.092	0.001	8.802	8.854	-0.052	0.493
Age: 18	9.285	9.208	0.077	0.005	8.916	8.973	-0.056	0.347
Age: 19	9.318	9.263	0.055	0.059	8.947	9.089	-0.141	0.001
Age: 20	9.350	9.269	0.081	0.017	9.030	9.112	-0.082	0.024
Age: 21	9.405	9.334	0.071	0.065	9.054	9.150	-0.097	0.007
Age: 22	9.385	9.387	-0.002	0.969	9.061	9.218	-0.157	0

Note: $Y_{E=k,Z=l}$ is the average non-durable consumption conditioned on education enrolment ($k=0,1$) and being affected by the university reform ($l=0,1$); $diff$ is the corresponding difference of the means under treatment status; $pval$ is the p -value of the difference of means test.

C1 Appendix C: Robustness I

C1.1 Overall consumption as dependent variable

Table C1: Huber and Mellace (2015): Instrument validity test

Statistics	st.dist1	st.dist0	n.bs	mP.p	mP.f
All sample	-0.128	-0.278	1000	1	1

Note: $st.dist1(0)$ measures the standardised difference between the nearest bound and point estimate under treatment (no treatment); $mP.p(f)$ indicates bootstrapped p -value under partial (full) recentering; $n.bs$ is the number of bootstrap draws.

Table C2: Huber and Mellace (2015): difference of means test

Mean Outcome								
	Under treatment				Under no treatment			
	Y_E=1,Z=1	Y_E=1,Z=0	diff	pval	Y_E=0,Z=0	Y_E=0,Z=1	diff	pval
All sample	9.375	9.313	0.062	0	9.082	9.165	-0.083	0

Note: $Y_{E=k,Z=l}$ is the average non-durable consumption conditioned on education enrolment ($k=0,1$) and being affected by the university reform ($l=0,1$); $diff$ is the corresponding difference of the means under treatment status; $pval$ is the p -value of the difference of means test.

Table C3: Main Regression

	OLS	IV	CF
<i>Age: 15</i>			
Years of schooling	0.031 ^{***}	0.218	0.257 ^{***}
	0.013	0.144	0.106
<i>Age: 16</i>			
Years of schooling	0.024 ^{***}	0.224	0.258 ^{***}
	0.009	0.144	0.106
<i>Age: 17</i>			
Years of schooling	0.019 ^{***}	0.230	0.259 ^{***}
	0.005	0.144	0.106
<i>Age: 18</i>			
Years of schooling	0.015 ^{***}	0.233	0.258 ^{***}
	0.004	0.144	0.106
<i>Age: 19</i>			
Years of schooling	0.013 ^{***}	0.235	0.257 ^{***}
	0.003	0.144	0.106
<i>Age: 20</i>			
Years of schooling	0.012 ^{***}	0.235	0.254 ^{***}
	0.003	0.143	0.106
<i>Age: 21</i>			
Years of schooling	0.014 ^{***}	0.233	0.250 ^{***}
	0.002	0.143	0.106
<i>Age: 22</i>			
Years of schooling	0.016 ^{***}	0.230	0.246 ^{***}
	0.003	0.143	0.106

Note: We include as further regressors individual's, household's characteristics and income quintiles. Bootstrapped standard errors (1000 draws).

Table C4: Consumption equation: covariates

	OLS	IV	CF
GDP per employee	-0.002 (0.00)	0.004 (0.01)	0.005 (0.01)
Unemployment rate	-0.555* (0.31)	-1.101** (0.54)	-1.149** (0.47)
Gender	-0.008 (0.01)	-0.097 (0.06)	-0.106** (0.04)
Siblings, (number)	-0.036*** (0.01)	0.010 (0.03)	0.014 (0.02)
Hh education, (years)	0.013*** (0.00)	-0.017 (0.02)	-0.020 (0.01)
Sp education, (years)	0.007*** (0.00)	-0.011 (0.01)	-0.013 (0.01)
Both parents, (dummy)	-0.017 (0.02)	0.054 (0.06)	0.058 (0.05)
Hh age	0.019 (0.02)	0.007 (0.02)	0.005 (0.02)
Hh age squared	-0.000 (0.00)	-0.000 (0.00)	-0.000 (0.00)

Note: We include as further regressors income quintile, age and year of birth dummies.

D1 Appendix D: Robustness II

D1.1 Reduced form regression

Table D1: Log Non-durable consumption reduced form regression

	Non-durable consumption		
	(1)	(2)	(3)
University Reform	0.07*** (0.01)	0.04*** (0.02)	0.03* (0.02)
F test	82.360	7.533	3.031
<i>Age: 15</i>			
University Reform	0.100^*** 0.015	−0.017 0.028	−0.032 0.028
<i>Age: 16</i>			
University Reform	0.080^*** 0.011	−0.014 0.022	−0.029 0.022
<i>Age: 17</i>			
University Reform	0.067^*** 0.009	−0.006 0.019	−0.019 0.019
<i>Age: 18</i>			
University Reform	0.060^*** 0.010	0.009 0.018	−0.002 0.018
<i>Age: 19</i>			
University Reform	0.058^*** 0.010	0.031^* 0.018	0.020 0.018
<i>Age: 20</i>			
University Reform	0.063^*** 0.009	0.058^*** 0.018	0.050^*** 0.018
<i>Age: 21</i>			
University Reform	0.073^*** 0.010	0.091^*** 0.019	0.086^*** 0.020
<i>Age: 22</i>			
University Reform	0.089^*** 0.014	0.131^*** 0.023	0.128^*** 0.025
Family Background	YES	YES	YES
Age and Cohort dummies	NO	YES	YES
Local labour market controls	NO	NO	YES

Note: We include as further regressors individual's, household's characteristics and income quintiles. Bootstrapped standard errors (1000 draws).

D2 Placebo estimates

Table D2: First Stage Regression: placebo

	Years of schooling		
	(1)	(2)	(3)
University Reform	-0.02 (0.06)	0.03 (0.11)	0.04 (0.12)
F test	0.119	0.061	0.111
<i>Age: 15</i>			
University Reform	-1.260 ^{***} 0.069	0.164 0.142	0.136 0.151
<i>Age: 16</i>			
University Reform	-0.922 ^{***} 0.057	0.129 0.119	0.108 0.124
<i>Age: 17</i>			
University Reform	-0.585 ^{***} 0.050	0.093 0.104	0.079 0.111
<i>Age: 18</i>			
University Reform	-0.248 ^{***} 0.050	0.058 0.099	0.051 0.115
<i>Age: 19</i>			
University Reform	0.090 0.057	0.023 0.108	0.022 0.135
<i>Age: 20</i>			
University Reform	0.427 ^{***} 0.068	-0.013 0.126	-0.006 0.166
<i>Age: 21</i>			
University Reform	0.764 ^{***} 0.082	-0.048 0.151	-0.034 0.202
<i>Age: 22</i>			
University Reform	1.102 ^{***} 0.097	-0.083 0.180	-0.063 0.241
Family Background	YES	YES	YES
Age and Cohort dummies	NO	YES	YES
Local labour market controls	NO	NO	YES

Note: We include as further regressors individual's, household's characteristics and income quintiles. Bootstrapped standard errors (1000 draws).

Table D3: Non-durable consumption: main regression allowing for heterogeneity of the average marginal effect across ages

	OLS	IV	CF
<i>Age: 15</i>			
Years of schooling	0.013 ^{***}	−0.534	−0.193
	0.006	1.347	0.334
<i>Age: 16</i>			
Years of schooling	0.013 ^{***}	−0.533	−0.196
	0.005	1.347	0.334
<i>Age: 17</i>			
Years of schooling	0.014 ^{***}	−0.531	−0.198
	0.004	1.347	0.334
<i>Age: 18</i>			
Years of schooling	0.014 ^{***}	−0.530	−0.201
	0.003	1.347	0.334
<i>Age: 19</i>			
Years of schooling	0.015 ^{***}	−0.529	−0.204
	0.002	1.347	0.334
<i>Age: 20</i>			
Years of schooling	0.015 ^{***}	−0.527	−0.207
	0.002	1.347	0.335
<i>Age: 21</i>			
Years of schooling	0.016 ^{***}	−0.526	−0.209
	0.002	1.347	0.335
<i>Age: 22</i>			
Years of schooling	0.016 ^{***}	−0.525	−0.212
	0.002	1.347	0.335

Note: Marginal effects of one more year of schooling on non-durable consumption. These marginal effects are estimated using a flexible parametric model specification across ages (second order polynomial) and using a second order polynomial across ages and income quintiles for the unobservable characteristics related to the family educational background and the permanent component of income innovations. We include as further regressors individual's and household's characteristics, local market conditions proxied by regional variables, income quintile, age and year of birth dummies. Bootstrapped standard errors (1000 draws).

Table D4: Overall consumption: main regression allowing for heterogeneity of the average marginal effect across ages

	OLS	IV	CF
<i>Age: 15</i>			
Years of schooling	0.015 ^{***}	−0.215	−0.230
	0.006	1.411	0.293
<i>Age: 16</i>			
Years of schooling	0.014 ^{***}	−0.215	−0.234
	0.005	1.410	0.293
<i>Age: 17</i>			
Years of schooling	0.014 ^{***}	−0.216	−0.238
	0.004	1.410	0.293
<i>Age: 18</i>			
Years of schooling	0.014 ^{***}	−0.216	−0.242
	0.003	1.410	0.293
<i>Age: 19</i>			
Years of schooling	0.014 ^{***}	−0.216	−0.246
	0.003	1.410	0.293
<i>Age: 20</i>			
Years of schooling	0.014 ^{***}	−0.217	−0.250
	0.002	1.410	0.293
<i>Age: 21</i>			
Years of schooling	0.013 ^{***}	−0.217	−0.254
	0.002	1.410	0.293
<i>Age: 22</i>			
Years of schooling	0.013 ^{***}	−0.218	−0.259
	0.002	1.410	0.293

Note: Marginal effects of one more year of schooling on non-durable consumption. These marginal effects are estimated using a flexible parametric model specification across ages (second order polynomial) and using a second order polynomial across ages and income quintiles for the unobservable characteristics related to the family educational background and the permanent component of income innovations. We include as further regressors individual's and household's characteristics, local market conditions proxied by regional variables, income quintile, age and year of birth dummies. Bootstrapped standard errors (1000 draws).

E1 Appendix E: Robustness III

E1.1 Age window:19-22

Table E1: First Stage Regression: Age window 19-22

	Years of schooling		
	(1)	(2)	(3)
University Reform	0.05 (0.08)	-0.11 (0.29)	0.06 (0.32)
F test	0.400	0.144	0.033
<i>Age: 19</i>			
University Reform	-0.403 ^{***} 0.097	-0.109 0.285	0.027 0.319
<i>Age: 20</i>			
University Reform	-0.094 0.083	-0.109 0.308	0.028 0.332
<i>Age: 21</i>			
University Reform	0.263 ^{***} 0.094	-0.029 0.326	0.108 0.343
<i>Age: 22</i>			
University Reform	0.671 ^{***} 0.153	0.134 0.353	0.269 0.363
Family Background	YES	YES	YES
Age and Cohort dummies	NO	YES	YES
Local labour market controls	NO	NO	YES

Note: We include as further regressors individual's, household's characteristics and income quintiles. Bootstrapped standard errors (1000 draws).

Table E2: Non-durable consumption: main regression

	OLS	IV	CF
<i>Age: 19</i>			
Years of schooling	0.013 ^{***} 0.004	0.209 0.309	0.216 0.165
<i>Age: 20</i>			
Years of schooling	0.015 ^{***} 0.003	0.216 0.309	0.221 0.165
<i>Age: 21</i>			
Years of schooling	0.017 ^{***} 0.002	0.216 0.309	0.220 0.165
<i>Age: 22</i>			
Years of schooling	0.018 ^{***} 0.003	0.210 0.309	0.212 0.165

Note: Marginal effects of one more year of schooling on non-durable consumption. These marginal effects are estimated using a flexible parametric model specification across ages (second order polynomial) and using a second order polynomial across ages and income quintiles for the unobservable characteristics related to the family educational background and the permanent component of income innovations. We include as further regressors individual's and household's characteristics, local market conditions proxied by regional variables, income quintile, age and year of birth dummies. Bootstrapped standard errors (1000 draws).

E1.2 Age window:17-22

Table E3: First Stage Regression: Age window 17-22

	Years of schooling		
	(1)	(2)	(3)
University Reform	-0.05 (0.06)	0.21** (0.10)	0.23** (0.11)
F test	0.647	4.106	4.789
<i>Age: 17</i>			
University Reform	-0.919^*** 0.063	0.150 0.126	0.177 0.135
<i>Age: 18</i>			
University Reform	-0.520^*** 0.052	0.101 0.119	0.132 0.118
<i>Age: 19</i>			
University Reform	-0.140^** 0.064	0.107 0.126	0.138 0.127
<i>Age: 20</i>			
University Reform	0.220^*** 0.071	0.167 0.124	0.198 0.132
<i>Age: 21</i>			
University Reform	0.559^*** 0.091	0.281^** 0.123	0.310^** 0.139
<i>Age: 22</i>			
University Reform	0.879^*** 0.148	0.450^*** 0.161	0.476^*** 0.178
Family Background	YES	YES	YES
Age and Cohort dummies	NO	YES	YES
Local labour market controls	NO	NO	YES

Note: We include as further regressors individual's, household's characteristics and income quintiles. Bootstrapped standard errors (1000 draws).

Table E4: Non-durable consumption: main regression

	OLS	IV	CF
<i>Age: 17</i>			
Years of schooling	0.018 ^{***} 0.007	0.187 ^{**} 0.086	0.213 ^{***} 0.079
<i>Age: 18</i>			
Years of schooling	0.015 ^{***} 0.004	0.191 ^{**} 0.087	0.214 ^{***} 0.079
<i>Age: 19</i>			
Years of schooling	0.013 ^{***} 0.003	0.194 ^{**} 0.087	0.214 ^{***} 0.079
<i>Age: 20</i>			
Years of schooling	0.013 ^{***} 0.002	0.195 ^{**} 0.087	0.213 ^{***} 0.079
<i>Age: 21</i>			
Years of schooling	0.015 ^{***} 0.002	0.196 ^{**} 0.087	0.211 ^{***} 0.079
<i>Age: 22</i>			
Years of schooling	0.019 ^{***} 0.003	0.195 ^{**} 0.086	0.209 ^{***} 0.079

Note: Marginal effects of one more year of schooling on non-durable consumption. These marginal effects are estimated using a flexible parametric model specification across ages (second order polynomial) and using a second order polynomial across ages and income quintiles for the unobservable characteristics related to the family educational background and the permanent component of income innovations. We include as further regressors individual's and household's characteristics, local market conditions proxied by regional variables, income quintile, age and year of birth dummies. Bootstrapped standard errors (1000 draws).

E1.3 Age window:15-24

Table E5: First Stage Regression: Age window 15-24

	Years of schooling		
	(1)	(2)	(3)
University Reform	-0.30*** (0.05)	0.17** (0.08)	0.21*** (0.08)
F test	32.720	4.444	7.519
<i>Age: 15</i>			
University Reform	-2.034*** 0.073	-0.066 0.111	0.027 0.112
<i>Age: 16</i>			
University Reform	-1.430*** 0.054	0.018 0.095	0.097 0.090
<i>Age: 17</i>			
University Reform	-0.897*** 0.053	0.093 0.094	0.158** 0.088
<i>Age: 18</i>			
University Reform	-0.434*** 0.058	0.157 0.098	0.212*** 0.094
<i>Age: 19</i>			
University Reform	-0.041 0.061	0.212** 0.099	0.257** 0.101
<i>Age: 20</i>			
University Reform	0.283*** 0.062	0.258*** 0.097	0.294*** 0.106
<i>Age: 21</i>			
University Reform	0.536*** 0.069	0.293*** 0.095	0.323*** 0.112
<i>Age: 22</i>			
University Reform	0.719*** 0.089	0.319*** 0.103	0.343*** 0.127
<i>Age: 23</i>			
University Reform	0.832*** 0.127	0.335** 0.130	0.355** 0.158
<i>Age: 24</i>			
University Reform	0.876*** 0.181	0.341* 0.179	0.359* 0.207
Family Background	YES	YES	YES
Age and Cohort dummies	NO	YES	YES
Local labour market controls	NO	NO	YES

Note: We include as further regressors individual's, household's characteristics and income quintiles. Bootstrapped standard errors (1000 draws).

Table E6: Non-durable consumption: main regression

	OLS	IV	CF
<i>Age: 15</i>			
Years of schooling	0.019 [*]	0.155	0.197 ^{**}
	0.010	0.152	0.080
<i>Age: 16</i>			
Years of schooling	0.019 ^{***}	0.163	0.198 ^{**}
	0.007	0.152	0.080
<i>Age: 17</i>			
Years of schooling	0.019 ^{***}	0.170	0.198 ^{**}
	0.005	0.152	0.080
<i>Age: 18</i>			
Years of schooling	0.018 ^{***}	0.174	0.198 ^{**}
	0.003	0.152	0.080
<i>Age: 19</i>			
Years of schooling	0.018 ^{***}	0.178	0.198 ^{**}
	0.002	0.152	0.080
<i>Age: 20</i>			
Years of schooling	0.017 ^{***}	0.179	0.198 ^{**}
	0.002	0.152	0.080
<i>Age: 21</i>			
Years of schooling	0.016 ^{***}	0.179	0.197 ^{**}
	0.002	0.152	0.080
<i>Age: 22</i>			
Years of schooling	0.014 ^{***}	0.177	0.196 ^{**}
	0.001	0.152	0.080
<i>Age: 23</i>			
Years of schooling	0.012 ^{***}	0.173	0.195 ^{**}
	0.001	0.152	0.080
<i>Age: 24</i>			
Years of schooling	0.011 ^{***}	0.168	0.194 ^{**}
	0.002	0.152	0.080

Note: Marginal effects of one more year of schooling on non-durable consumption. These marginal effects are estimated using a flexible parametric model specification across ages (second order polynomial) and using a second order polynomial across ages and income quintiles for the unobservable characteristics related to the family educational background and the permanent component of income innovations. We include as further regressors individual's and household's characteristics, local market conditions proxied by regional variables, income quintile, age and year of birth dummies. Bootstrapped standard errors (1000 draws).

E1.4 Treating also those who are aged twenty or more

Table E7: First Stage Regression: Treating those who are aged twenty or more

	Years of schooling		
	(1)	(2)	(3)
University Reform	0.01 (0.05)	0.13* (0.07)	0.15** (0.07)
F test	0.030	3.575	4.404
<i>Age: 15</i>			
University Reform	-1.652*** 0.068	0.030 0.097	0.077 0.107
<i>Age: 16</i>			
University Reform	-1.116*** 0.044	0.009 0.080	0.051 0.083
<i>Age: 17</i>			
University Reform	-0.621*** 0.045	0.008 0.079	0.046 0.079
<i>Age: 18</i>			
University Reform	-0.165*** 0.052	0.028 0.081	0.062 0.082
<i>Age: 19</i>			
University Reform	0.250*** 0.056	0.070 0.080	0.099 0.084
<i>Age: 20</i>			
University Reform	0.626*** 0.060	0.132* 0.079	0.157* 0.088
<i>Age: 21</i>			
University Reform	0.962*** 0.076	0.216*** 0.094	0.236*** 0.107
<i>Age: 22</i>			
University Reform	1.257*** 0.111	0.321*** 0.136	0.335*** 0.148
Family Background	YES	YES	YES
Age and Cohort dummies	NO	YES	YES
Local labour market controls	NO	NO	YES

Note: We include as further regressors individual's, household's characteristics and income quintiles. Bootstrapped standard errors (1000 draws).

Table E8: Non-durable consumption: main regression

	OLS	IV	CF
<i>Age: 15</i>			
Years of schooling	0.039 ^{***}	0.202	0.254 ^{***}
	0.012	0.150	0.121
<i>Age: 16</i>			
Years of schooling	0.029 ^{***}	0.209	0.255 ^{***}
	0.008	0.149	0.121
<i>Age: 17</i>			
Years of schooling	0.021 ^{***}	0.215	0.256 ^{***}
	0.005	0.149	0.121
<i>Age: 18</i>			
Years of schooling	0.016 ^{***}	0.219	0.255 ^{***}
	0.003	0.149	0.120
<i>Age: 19</i>			
Years of schooling	0.014 ^{***}	0.222	0.254 ^{***}
	0.003	0.149	0.120
<i>Age: 20</i>			
Years of schooling	0.013 ^{***}	0.223	0.252 ^{***}
	0.002	0.149	0.120
<i>Age: 21</i>			
Years of schooling	0.015 ^{***}	0.224	0.250 ^{***}
	0.002	0.149	0.120
<i>Age: 22</i>			
Years of schooling	0.020 ^{***}	0.223	0.247 ^{***}
	0.003	0.148	0.120

Note: Marginal effects of one more year of schooling on non-durable consumption. These marginal effects are estimated using a flexible parametric model specification across ages (second order polynomial) and using a second order polynomial across ages and income quintiles for the unobservable characteristics related to the family educational background and the permanent component of income innovations. We include as further regressors individual's and household's characteristics, local market conditions proxied by regional variables, income quintile, age and year of birth dummies. Bootstrapped standard errors (1000 draws).

E1.5 Parsimonious specification

Table E9: First Stage Regression: Parsimonious specification			
	Years of schooling		
	(1)	(2)	(3)
University Reform	-0.14** (0.05)	0.21** (0.08)	0.21*** (0.08)
F test	6.512	6.502	6.935
<i>Age: 15</i>			
University Reform	-2.469^*** 0.050	0.044 0.088	0.074 0.097
<i>Age: 16</i>			
University Reform	-1.629^*** 0.039	0.041 0.079	0.070 0.077
<i>Age: 17</i>			
University Reform	-0.874^*** 0.043	0.059 0.083	0.087 0.079
<i>Age: 18</i>			
University Reform	-0.204^*** 0.047	0.098 0.087	0.124 0.087
<i>Age: 19</i>			
University Reform	0.382^*** 0.051	0.160^* 0.090	0.182^* 0.096
<i>Age: 20</i>			
University Reform	0.882^*** 0.060	0.243^*** 0.097	0.261^*** 0.109
<i>Age: 21</i>			
University Reform	1.298^*** 0.082	0.349^*** 0.120	0.361^*** 0.134
<i>Age: 22</i>			
University Reform	1.628^*** 0.119	0.476^*** 0.165	0.482^*** 0.177
Family Background	YES	YES	YES
Age and Cohort dummies	NO	YES	YES
Local labour market controls	NO	NO	YES

Note: We include as further regressors individual's, household's characteristics and income quintiles. Bootstrapped standard errors (1000 draws).

Table E10: Non-durable consumption: main regression

	OLS	IV
<i>Age: 15</i>		
Years of schooling	0.045 ^{***} 0.013	0.249 ^{***} 0.094
<i>Age: 16</i>		
Years of schooling	0.033 ^{***} 0.009	0.253 ^{***} 0.093
<i>Age: 17</i>		
Years of schooling	0.024 ^{***} 0.006	0.257 ^{***} 0.093
<i>Age: 18</i>		
Years of schooling	0.018 ^{***} 0.004	0.259 ^{***} 0.093
<i>Age: 19</i>		
Years of schooling	0.014 ^{***} 0.003	0.262 ^{***} 0.093
<i>Age: 20</i>		
Years of schooling	0.013 ^{***} 0.002	0.264 ^{***} 0.093
<i>Age: 21</i>		
Years of schooling	0.015 ^{***} 0.002	0.265 ^{***} 0.093
<i>Age: 22</i>		
Years of schooling	0.019 ^{***} 0.002	0.265 ^{***} 0.093

Note: Marginal effects of one more year of schooling on non-durable consumption. These marginal effects are estimated using a flexible parametric model specification across ages (second order polynomial) and using a second order polynomial across ages and income quintiles for the unobservable characteristics related to the family educational background and the permanent component of income innovations. We include as further regressors individual's and household's characteristics, local market conditions proxied by regional variables, income quintile, age and year of birth dummies. Bootstrapped standard errors (1000 draws).

Table E11: Non-durable consumption: main regression, age-homogeneous effect

	Years of schooling endogenous variable					
	(OLS)	(OLS)	(OLS)	(IV)	(IV)	(IV)
Years of schooling	0.012 ^{***} 0.001	0.018 ^{***} 0.002	0.017 ^{***} 0.002	-0.557 [*] 0.312	0.239 0.170	0.145 0.131
Family Background	YES	YES	YES	YES	YES	YES
Age and Cohort dummies	NO	YES	YES	NO	YES	YES
Local labour market controls	NO	NO	YES	NO	NO	YES

Note: Marginal effects of one more year of schooling on non-durable consumption. These marginal effects are estimated using a flexible parametric model specification across ages (second order polynomial) and using a second order polynomial across ages and income quintiles for the unobservable characteristics related to the family educational background and the permanent component of income innovations. We include as further regressors individual's and household's characteristics, local market conditions proxied by regional variables, income quintile, age and year of birth dummies. Bootstrapped standard errors (1000 draws).

E1.6 Fixed effects

Table E12: First Stage Regression: Fixed effects			
University Reform	-0.29*** (0.10)	0.18** (0.08)	0.21** (0.08)
F test	9.363	5.394	6.447
<i>Age: 15</i>			
University Reform	-1.713^*** 0.126	0.052 0.112	0.055 0.118
<i>Age: 16</i>			
University Reform	-1.225^*** 0.100	0.012 0.084	0.027 0.085
<i>Age: 17</i>			
University Reform	-0.764^***	0.009	0.036
<i>Age: 18</i>			
University Reform	-0.328^*** 0.093	0.044 0.083	0.081 0.086
<i>Age: 19</i>			
University Reform	0.082 0.096	0.117 0.090	0.163^* 0.098
<i>Age: 20</i>			
University Reform	0.465^*** 0.103	0.227^** 0.100	0.281^** 0.113
<i>Age: 21</i>			
University Reform	0.823^*** 0.121	0.374^*** 0.120	0.436^*** 0.136
<i>Age: 22</i>			
University Reform	1.155^*** 0.157	0.559^*** 0.158	0.628^*** 0.174
Family Background	YES	YES	YES
Age and Cohort dummies	NO	YES	YES
Local labour market controls	NO	NO	YES

Note: We include as further regressors individual's, household's characteristics and income quintiles. Bootstrapped standard errors (1000 draws).

Table E13: Non-durable consumption: main regression

	OLS	IV
<i>Age: 15</i>		
Years of schooling	0.039 ^{***} 0.012	0.264 [*] 0.137
<i>Age: 16</i>		
Years of schooling	0.029 ^{***} 0.008	0.270 ^{**} 0.137
<i>Age: 17</i>		
Years of schooling	0.021 ^{***} 0.005	0.275 ^{**} 0.137
<i>Age: 18</i>		
Years of schooling	0.016 ^{***} 0.003	0.279 ^{**} 0.137
<i>Age: 19</i>		
Years of schooling	0.014 ^{***} 0.003	0.282 ^{**} 0.137
<i>Age: 20</i>		
Years of schooling	0.013 ^{***} 0.002	0.284 ^{**} 0.137
<i>Age: 21</i>		
Years of schooling	0.015 ^{***} 0.002	0.285 ^{**} 0.137
<i>Age: 22</i>		
Years of schooling	0.020 ^{***} 0.003	0.285 ^{**} 0.137

Note: Marginal effects of one more year of schooling on non-durable consumption. These marginal effects are estimated using a flexible parametric model specification across ages (second order polynomial) and using a second order polynomial across ages and income quintiles for the unobservable characteristics related to the family educational background and the permanent component of income innovations. We include as further regressors individual's and household's characteristics, local market conditions proxied by regional variables, income quintile, age and year of birth dummies. Bootstrapped standard errors (1000 draws).

Table E14: Non-durable consumption: main regression, fixed effects age-homogeneous effect

	Years of schooling endogenous variable					
	(FE)	(FE)	(FE)	(IV-FE)	(IV-FE)	(IV-FE)
Years of schooling	0.000	0.002	0.002	-0.160	0.123	0.078
	0.001	0.002	0.002	0.866	6.708	3.379
Family Background	YES	YES	YES	YES	YES	YES
Age and Cohort dummies	NO	YES	YES	NO	YES	YES
Local labour market controls	NO	NO	YES	NO	NO	YES

Note: Marginal effects of one more year of schooling on non-durable consumption. These marginal effects are estimated using a flexible parametric model specification across ages (second order polynomial) and using a second order polynomial across ages and income quintiles for the unobservable characteristics related to the family educational background and the permanent component of income innovations. We include as further regressors individual's and household's characteristics, local market conditions proxied by regional variables, income quintile, age and year of birth dummies. Bootstrapped standard errors (1000 draws).

F1 Appendix F: Additional Tables and Figures

Table F1: Exogeneity of the treatment

	Treatment
Gender	0.01 (0.00)
Siblings, (number)	-0.00 (0.00)
Hh education, (years)	-0.00** (0.00)
Sp education, (years)	-0.00 (0.00)
Both parents, (dummy)	0.01 (0.01)
Hh age	-0.00 (0.01)
Hh age	0.00 (0.00)
Family educational background, (years)	0.00 (0.00)
Permanent component income innovations	0.00 (0.03)
F test	1.579
Age and Cohort dummies	YES

Table F2: First stage regression: covariates

	FS
Hh education, (years)	0.138*** (0.01)
Sp education, (years)	0.087*** (0.01)
Both parents, (dummy)	-0.333** (0.13)
Hh age	0.059 (0.07)
Hh age squared	-0.000 (0.00)
Gender	0.411*** (0.04)
Siblings, (number)	-0.210*** (0.03)
GDP per employee	-0.026 (0.02)
Unemployment rate	3.201** (1.55)

Note: We include as further regressors income quintile, age and year of birth dummies, permanent income innovations of household income and unobservable characteristics related to the educational family background.

Table F3: Non-durable consumption equation: covariates

	OLS	IV	CF
GDP per employee	-0.006* (0.00)	0.002 (0.01)	0.003 (0.01)
Unemployment rate	-0.705*** (0.27)	-1.369*** (0.50)	-1.370*** (0.49)
Gender	0.002 (0.01)	-0.106** (0.05)	-0.112** (0.04)
Siblings, (number)	-0.040*** (0.01)	0.016 (0.03)	0.019 (0.02)
Hh education, (years)	0.013*** (0.00)	-0.023 (0.02)	-0.025* (0.01)
Sp education, (years)	0.009*** (0.00)	-0.014 (0.01)	-0.015 (0.01)
Both parents, (dummy)	-0.039* (0.02)	0.046 (0.05)	0.049 (0.05)
Hh age	0.028** (0.01)	0.014 (0.02)	0.012 (0.02)
Hh age squared	-0.000* (0.00)	-0.000 (0.00)	-0.000 (0.00)

Note: We include as further regressors income quintile, age and year of birth dummies.

Table F4: Main Regressions: linear model specification

	Years of schooling endogenous variable								
	(OLS)	(OLS)	(OLS)	(IV)	(IV)	(IV)	(CF)	(CF)	(CF)
Years of schooling	0.013***	0.017***	0.016***	-0.525	0.248	0.144	-0.049***	0.326**	0.230
	0.002	0.002	0.002	0.413	1.589	0.613	0.008	0.172	0.167
Family Background	YES	YES	YES	YES	YES	YES	YES	YES	YES
Age and Cohort dummies	NO	YES	YES	NO	YES	YES	NO	YES	YES
Local labour market controls	NO	NO	YES	NO	NO	YES	NO	NO	YES

Note: We include as further regressors individual's, household's characteristics and income quintiles. Bootstrapped standard errors (1000 draws).

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