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Abstract

We estimate structural quantile treatment effects to analyze the relationship between household income and sorting into private or public education, using Italian data. Public education provision is redistributive when rich families, who contribute to its financing, find it optimal to sort out of the public system to buy the educational services in the private market. This may occur when the education quality is lower in the public compared to the private sector, meaning that households with higher income capacity face lower opportunity costs from sorting out of the public system. We exploit heterogeneity in expected tax deductions to exogenously manipulate the distribution of net of taxes income, equalized by family needs, and explore the consequences of this manipulation on various quantiles of the distribution of the amount of the educational transfers in-kind accruing to the households, valuing public education. We find that an increase in income reduces the amount of educational transfers in-kind (i) more for higher quantiles of the educational transfers in-kind, indicating that households with higher preferences for quality sort out of the public education system; (ii) more for lower quantiles of the households' income capacity, indicating that richer households receive lower transfers for a given preference quality.

Keywords: Transfer in kind, public education provision, income distribution, structural quantile treatment effects.

JEL Classification: H40, D30, I20.

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1 Introduction

In many countries public education provision and free accessibility to compulsory education are fundamental constitutional rights. As largely recognized, public education provision accounts, together with health care, for a substantial share of the public budget in countries with developed welfare states. Several reasons justify this spending: among them, a redistributive motive (Aaberge, Langorgen and Lindgren 2013). This paper aims at testing one of the mechanisms behind the redistributiveness of public education provision by analyzing the sorting process into public and private education among Italian households.

Public education provision is redistributive as far as more affluent families with children in education find it optimal to sort out of the public system, while contributing to its financing, and buy the educational services in the private market. Different reasons may justify why families choose private schools, such as the support of common values as religion (Sander 2001) and status symbol (Fershtman, Murphy and Weiss 1996). There is a long tradition within the human capital investment models (see for instance Stiglitz 1974) in claiming that the schooling quality is higher in the private compared to the public sector. Since quality is a normal good, rich households are willing to buy an higher amount of quality, and consequently may opt out for private education even if having to pay for it.[1]

This paper contributes with an innovative empirical analysis that allows to test the mechanism suggested by Besley and Coate (1991), according to which it is the interplay between family income and preferences for quality that delimits the extent of the households sorting into public and private education. This mechanism motivates a government, aiming at redistributing resources from rich to poor households, to use universal public education provision as transfers in-kind in presence of asymmetric information on the households' income capacity. The literature that analyses the role of public education provision (educational transfers in-kind) calls this sorting process into private and public education *self-targeting* (Currie and Gahvari 2008).

According to the Besley and Coate mechanism, the policymaker with redistributive intents imposes costs to the families opting for almost free public education, that take the form of restrictions on the quality of the public educational service. These costs deter the rich households from mimicking the poor ones, thus acting as a separation device. The lower is the quality, the larger is the incentive for the households with higher income capacity to sort out of the public education system while continuing to finance it, which makes the educational transfers in-kind progressive in nature (Besley and Coate 1991, Blackorby and Donaldson 1988, Gahvari and Mattos 2007). The quality of public education should be, however, high enough to insure that low income families are better off when

[1]Quality can be conceived either as a subjective measure of schools' quality, such as the score given by households to the schools in the area of residence, or a more objective measure, linked to observable indicators such as the student-teacher ratio (Checchi and Jappelli 2003).

consuming it. This reasoning applies in full only to mandatory education, where families can decide whether to enroll their children in the public or in the private sector, but they have no option left for choosing to consume no educational services. Whether the mechanism also works in post-mandatory education (i.e. for families with children aged more than 14 years old) is debatable for at least two reasons. First, the household's self-selection into both private and public education can be driven by expected returns to children's education, that are positively correlated with household income, or by costs of attending education, that are negatively correlated with income. Second, the quality of private schooling for upper secondary education is not necessarily higher than the quality in public schools. This occurs, for instance, in Italy where the demand for upper secondary private education seems to be driven by a remedial scope for less talented children coming from rich households (Bertola, Checchi and Oppedisano 2007, Bertola and Checchi 2013).

At the heart of the sorting process into private education described by Besley and Coate (1991), there is the correlation between the unobservable family specific income capacity and preference for quality of the educational good. We propose an estimation strategy based on structural quantile treatment effects (Ma and Koenker (2006)) to investigate the relationship between household income and preferences for quality and verify the premises of the self-targeting mechanism. We exploit heterogeneity in expected tax deductions to exogenously manipulate the prevailing distribution of net of taxes income, equalized by families needs, and explore the consequences of this manipulation on various quantiles of the distribution of the amount of educational transfers in-kind.

On the one hand, for a given degree of quality proxied by the quantiles of the distribution of the educational transfers in-kind, we expect that an increase in household income is associated with decreasing transfers in-kind that go to the households with higher income capacity. On the other hand, for a given degree of the household's income capacity, proxied by the quantiles of the income distribution, the quality of public schools captured by our transfers in-kind measure contributes to households sorting into private and public education. In this case, the magnitude of the negative relation between household income and the transfers in-kind received is expected to grow along the distribution of in-kind transfers, since households revealing higher preferences for the quality of educational services will be ready to devote a larger share of a marginal income gain into private education.

One of the major difficulties in this type of analysis is related to data availability. [2] Our empirical strategy consists in converting the quality of the public education provision into a monetary counterpart that the family would have to spend to buy the same quality on the market. This quantity is the monetary equivalent of a transfer in-kind that the family receives when opting for almost free public education and represents a lower

[2] Aaberge, Bhuller, Langørgen and Mogstad (2010), for instance, use detailed accounting data of municipalities as a basis for estimating the need adjusted scale for local public services in Norway.

bound of the opportunity costs to choose expensive private education. We make use of a study carried out exclusively in 2003 by the Italian National Institute for the Evaluation of Education System (INVALSI) and the Consortium for the Development of the Methodologies and Innovations of the Public Administrations (MIPA), INVALSI-MIPA (2005), to microsimulate the educational transfers in-kind accruing to the households. Following the standard practice, the transfer in-kind accruing to the household equals the average cost of producing the services that the household's children in education benefit from. The main component of this average cost is the teacher-student ratio, hence, our measure of the educational transfers in-kind partly reflects the objective quality of the public service. We use SHIW database (wave 2004) by the Bank of Italy to collect the other data of interest, such as household income, children school attendance and information on the background of origin of the family. Since SHIW does not provide information on the type of school (public *versus* private) attended by children, we weight the per-child educational transfer in-kind by group-specific probabilities to be enrolled in a public school/university.

Our empirical assessment shows that an increase in income reduces the amount of educational transfers in-kind (i) more for higher quantiles of the educational transfers in-kind (ii) more for lower quantiles of the household income capacity. These results are strengthened when we confine our analysis to compulsory education only, where the premises of the self-targeting mechanism should apply in full.

The rest of the paper is organized as follows. Section 2 sets the scene illustrating how income affects the households' sorting into private-public education according to the model by Besley and Coate (1991) and how to assess empirically the mechanism of interest. Section 3 describes the empirical strategy: method, data, the microsimulation exercise on the educational transfers in-kind, descriptive statistics and our instrument. Results and the discussion are reported in section 4. Finally, section 5 concludes.

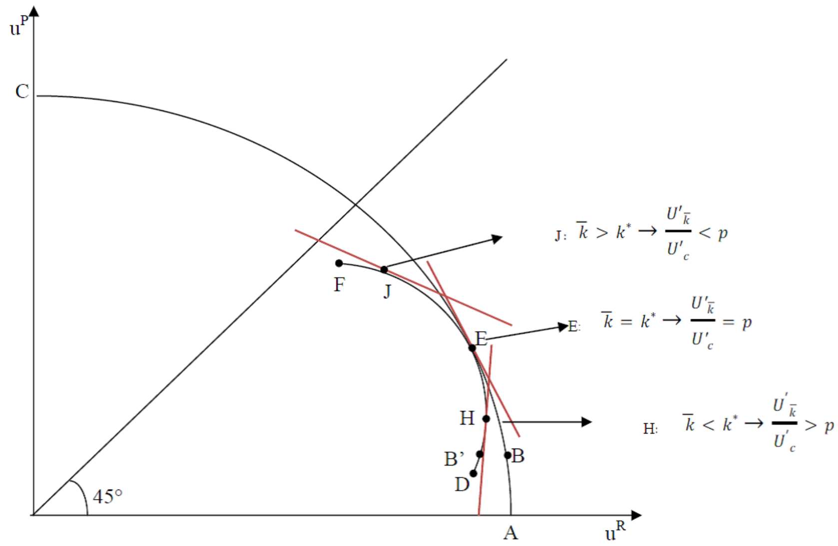
2 Public education provision and in-kind transfers

The mechanism outlined in Besley and Coate (1991) explains how households self-target into public and private education provision on the basis of two components: preferences for school quality and *income capacity*, that is the income potentially earnable by the family and unobservable to the government. The simple model outlined below allows to identify the empirical relations that we aim at testing on the data.

2.1 Quality sorting and educational transfers in-kind

Following Besley and Coate (1991) and Gahvari and Mattos (2007), consider an economy with two types of households, the poor households (with low income $y^P > 0$) and the rich

Figure 1: The economy's Pareto frontier (AC) and utility feasibility frontier ($DB'EF$) with public education provision when $k_{max} > k^*$.



households (with high income $y^R > y^P$). These households are endowed with a utility $u(c, k)$, which depends on the quantity of numéraire good c and on the quality k of the indivisible educational good which these households buy for their children. Every unit of quality is produced with a linear technology and its price on the market is fixed to p. Assume that educational quality is a normal good and that the educational goods are supplied at higher quality in the private market compared to the public sector. Universal public education provision is redistributive when rich households prefer to opt out from the public (almost free) education system and buy higher quality educational services on the market, while bearing its cost in full and, at the same time, financing public education.

Figure 1, from Gahvari and Mattos (2007), shows the Pareto frontier AC of this economy, where education is produced at different quality varieties by the private sector. On the frontier, the locus B represents the solution without public education provision where the rich families are better off compared to the poor ones, since they can afford higher consumption goods and schooling quality.

Consider now a redistributive scheme involving public education, available inexpensively to all households and produced at fixed quality $\bar{k}$ by the public sector, which is financed by levying a lump-sum tax T from all families. The feasibility frontier associated to this scheme is represented by the curve $DB'EF$ in Figure 1.

If the income capacity of households is known, the redistributive scheme implements the first best allocation. Public education is produced at a quality level $\bar{k}$ equal to the level of quality k^* that would have been chosen by the poor household if she had to buy the educational good on the market, but her income was complemented by a positive in-cash transfer. This transfer lets the poor be indifferent between receiving one extra dollar in cash and one extra dollar worth of the publicly provided educational good. This condition identifies the locus E on the graph.

When income capacity is not observable, Besley and Coate (1991) points out that the choice of $\bar{k}$ should act as a separation device of poor and rich households into public and private education, respectively. The *Besley-Coate mechanism* implements, therefore, a separating equilibrium where the incentive compatibility constraints of both types of households are satisfied:

$$u^R(y^R - T, \bar{k}) \leq V^R(p, y^R - T) \tag{1a}$$
$$u^P(y^P - T, \bar{k}) \geq V^P(p, y^P - T) \tag{1b}$$

where $u(y^i - T, \bar{k})$ for $i = R, P$ denotes households' utility if public education of quality $\bar{k}$ is consumed, while $V(p, y^i - T)$ is the indirect utility function of a family buying private education.

As long as the government chooses a quality level of public education provision $\bar{k}$ lower than the level demanded by the rich families ($\bar{k} < k(p, y^R - T) = k_{max}$, corresponding to point F in the Figure) but higher than the minimum value k_{min} that satisfies equation (1b) (corresponding to point D), rich and poor families self-target with respect to participation to the program, making the overall scheme redistributive. However, governments likely implement an inefficient allocation solution, thus shifting the costs of self-targeting towards poorest families.[3] Moreover, the incentive compatibility constraint of the rich in equation (1a) sets the limit on the redistributiveness of the program and for this reason, such schemes may not necessarily form part of a properly designed redistributive policy. Overall, there is a trade-off between the cost to the government to minimize the asymmetric information on the households' income capacity and the deadweight loss inherent in an inefficient quality of the public provision of education. Measuring the extent of such trade-off is a demanding exercise that has an economic meaning only for cases where the premises of the Besley-Coate mechanism are verified on the data. This case is discussed below.

[3] Although there is self-selection in taking up the program on the side of the poor households, the *efficient* quality of the public provision of education that the poor families would choose for themselves if they received its value in cash, remains unobservable. Only point E is on the first best frontier corresponding to this efficient quality level k^*. For all points between D and E, the quality level chosen by the government is less than efficient, $\bar{k} \leq k^*$, while for all points between E and F the quality level is more than efficient $\bar{k} \geq k^*$. To account for these inefficiencies, Gahvari and Mattos (2007) show that a combination of cash (in terms of either a cash rebate or a lump sum tax) and in-kind transfers may allow to achieve first-best redistribution with self-targeting mechanisms.

2.2 Empirical assessment of the sorting mechanism

We investigate the impact of household income on the in-kind transfers distribution to verify if the sorting behavior of the households into private and public education is compatible with the mechanism suggested by Besley and Coate (1991). To assess this, we exploit heterogeneity of the marginal benefits of income across two relevant distributional dimensions: the household's income capacity and her preferences for school quality.

For a given degree of quality of public education, proxied by the quantiles of the distribution of the educational transfers in-kind, household's income capacity determines the sorting into private education.

The Besley and Coate (1991) mechanism implies that when the households' income capacity is unobservable, restrictions on the quality of the public educational service may deter rich households from mimicking the poor ones. Together with household income capacity, quality is, therefore, the other relevant dimension. For a given degree of the household's income capacity measured at a finite quantile of the distribution of household income, the quality of public schools - as measured by our transfers in-kind - may explain the type of school chosen. As long as households renounce to the quality freely provided by public schools, they are revealing a preference for the quality of private schools. The intensity of in-kind transfers reveals information on the households' preferences for quality. This is true in distributional terms, since the in-kind transfers distribution represents the full spectrum of the *opportunity costs* that the households would have to support when self-targeting into private education. By using the quantiles of the in-kind transfers distribution as the dependent variable, we can estimate the marginal benefit of income at fixed levels of households' preferences for quality, revealed by the magnitude of the opportunity costs associated to these quantiles.

Our estimation strategy employs regression analysis of the effect of income on educational transfers in-kind in a quantile setting. Other works have tested the role of income on sorting probabilities. For instance, Checchi and Jappelli (2007), using SHIW 1993 data, provide estimates of the conditional mean probability of enrollment in private schools controlling for income quartiles and indicators of objective and subjective measures of school quality. Our empirical exercise is different in at least two ways. First, we assess the preferences for quality rather than proxying quality with subjective or objective evaluations. Second, we single out the marginal effects of income across the two dimensions of interest.

Public education provision meets the Besley-Coate mechanism if households that benefit less from public education are those who, for a given quality level, have an higher income capacity, and who have higher preferences for quality, for a given income capacity. We adopt a structural perspective for modeling the correlation between these two sources of heterogeneity, whose interplay affects households' sorting behavior.

3 Empirical strategy

3.1 Structural quantile treatment effect estimation

We apply the control variate approach by Ma and Koenker (2006) to exogenously manipulate the income distribution and to estimate the structural quantile treatment effects of exogenous variations of income on the distribution of the transfers in-kind received by the families. This method allows to measure the extent to which an exogenous change in household income affects the amount of transfers in kind accruing to the household, along the distribution of household income capacity and preferences for the quality of the educational services distributions. To do so, we compare the estimated effects of income at different degrees of the two forms of heterogeneity.

Consider the quantile functions of the response variables transfers in-kind, denoted Q_K, and household income, denoted Q_Y. In what follows, we use capital letters to indicate distributions, while bold letters refer to either vectors or matrices. We assume that the two quantile functions are related by the following structural relations:

$$\begin{aligned} Q_K(\tau_K|Y, \mathbf{x}, \nu_Y(\tau_Y)) &= g_K(Y, \mathbf{x}, \nu_Y(\tau_Y); \alpha(\tau_K, \tau_Y)) \\ Q_Y(\tau_Y|z, \mathbf{x}) &= g_Y(z, \mathbf{x}; \beta(\tau_Y)) \end{aligned}$$

where $\mathbf{x}$ are covariates and $\nu_Y(\tau_Y)$ is the control variate. In the equations, τ_Y and τ_K identify the quantiles of the distributions of income Y and educational transfers in-kind K while α and β are the structural parameters. In particular, α depicts the marginal effect of a one euro change in income at fixed quantiles of both income capacity and quality preferences. The variable z is an *instrument* for income. It allows to disentangle the exogenous variations in income from the unobserved components that jointly determine incomes and transfers in-kind accruing to the household. The analysis is at the household level and within this paragraph the subscript h is dropped for expositional purposes.

Conditioning on the estimated control variate, whose coefficient can be interpreted as the degree of endogeneity (i.e. the degree of self-selection) of the income variable, the parameters of the structural equation solve the following minimization problem:

$$\hat{\alpha}(\tau_K, \tau_Y) = \operatorname*{argmin}_{\alpha} \sum_{h=1}^{n} \sigma_K \cdot \rho_{\tau_K}(K - g_K(Y, \mathbf{x}, \hat{\nu}_Y(\tau_Y); \alpha))$$

where σ_K are strictly positive weights and the function ρ_{τ_K} is the check function as in Koenker and Bassett (1978).

Following Ma and Koenker (2006), we focus on parametric estimation based on a linear structural model for conditional quantiles of the form:

$$K = \alpha_0 + \alpha_1 Y + \mathbf{X}_h \cdot \alpha_2 + \mathbf{X}_{hh} \cdot \alpha_3 + \mathbf{X}_r \cdot \alpha_4 + \alpha_5 FB1 + \alpha_6 FB2 + u \tag{2a}$$

$$Y = \beta_0 + \beta_1 Z + \mathbf{X}_h \cdot \beta_2 + \mathbf{X}_{hh} \cdot \beta_3 + \mathbf{X}_r \cdot \beta_4 + \beta_5 FB1 + \beta_6 FB2 + U \tag{2b}$$

where $\mathbf{X}_h$ are household characteristics including the number of earning recipients, dummies for the area of residence of the household and a polynomial of degree one in the cohort of birth of the first child; $\mathbf{X}_{hh}$ are characteristics of the head of the household including gender (i.e. if female), age, age squared, years of schooling; $\mathbf{X}_r$ are local market conditions measured by the regional GDP per head and unemployment rate.

The last two covariates, $FB1$ and $FB2$, denote the distribution of family background differential in incomes made conditional on the degree of abilities of the households and on two background measures (socioeconomic background of the grand-fathers and the educational background of all grandparents). As shown in appendix B, these variables are estimated as transformations of the quantiles of the distributions of incomes made conditional on the background of origin of the observed households. As suggested in Acemoglu and Pischke (2001), the rank occupied by an household in her family background group-specific income distribution is close to be a sufficient statistic for her unobservable abilities, so that we can interpret $FB1$ and $FB2$ as proxies for families' unobservable characteristics inherited from the background of origin.

We assume a flexible specification of the error term u in equation (2a) where income is allowed to influence both the location and scale of the educational transfers in-kind distribution. We also consider the possibility that the location and scale effect might be heterogeneous across families with different background of origin, while holding their abilities (identified by their position in the respective income distribution) as fixed. These considerations lead to formulating the error term in equation (2a) as a linear transformation of income: $u = (\lambda\nu_Y + \nu_K\text{+FB1+FB2})(Y\psi + 1)$ and $U = \nu_Y$, where ν_K and ν_Y are independent of one another and *i.i.d.* over households. The structure of the errors shows that the unobservable family specific income capacity and preference for quality of the educational good are indeed correlated, as required by the self targeting mechanism.

Estimation of the model evolves in a two-step procedure. The first step consists in running a set of quantile regressions of equation (2b) at given quantiles of Y. The set of estimates $\widehat{\beta}$ identifies the distribution of $\nu_Y(\tau_Y)$ for every reference quantile τ_Y. The residuals $\widehat{\nu}_Y(\tau_Y)$ estimate the unexplained part of the gap between the income of a given household and the income quantile, conditional on the covariates. The second step consists in running a set of quantile regressions of equation (2a) at finite quantiles of K controlling for the control variate $\widehat{\nu}_Y(\tau_Y)$ estimated at each quantile τ_Y. The estimated effects $\widehat{\alpha}$ vary therefore in both τ_K and τ_Y dimensions.

We investigate these relationships only for a selected number of quantiles corresponding to 20%, 30%, 50%, 70% and 80% of both the household income capacity and the educational transfers in-kind distributions. The analysis starts at the 2nd decile because, in the main sample, households sitting at the first decile of the educational transfers in kind distribution do not benefit at all of the public spending on education, and for them the outcome variable is zero.[4] For sake of symmetry, we do not consider the last decile, either.

3.2 SHIW Data and sample selection criteria

We make use of the SHIW (Survey on Households Income and Wealth) 2004 wave. SHIW is a nationally representative household survey conducted in Italy every two years by the Bank of Italy and gathers information on net incomes, savings and main characteristics of Italian households.[5] Individual data are collapsed into family income, providing a sample of 8,004 families with positive incomes.

Our sample selection strategy consists in focusing on families who potentially benefit from public spending on education, namely families with children aged 3 to 23 years old.[6] As a result, the sample is reduced to 2,495 households with children born between 1981 and 2001. Out of these families, 271 are dropped because of missing information on either the grandparental background, that we use as covariate to account for household unobserved heterogeneity, or on the education level of the head of the family.[7]

To attenuate the composition effect related to the age of the parents, we further restrict the estimating sample to households whose head is aged 33 to 60 at the time of the survey (i.e. individuals born between 1944 and 1971) after dropping the lower and the upper 5% of the distribution of the age of the head of the family. This last cut shrinks the using sample to 2,030 households.

To account for scale economies within the household, we equalize household income using the EU equivalence scale, which employs different scale factors for children and adults.[8]

[4] Quantiles either equal to or higher than the 20th satisfy the requirement that the continuous densities of the conditional distribution function of the educational transfers in-kind are bounded away from zero for every conditioning variable in the support.

[5] Microsimulated gross income data and personal income taxes are kindly provided by C. Fiorio. These data account for potential tax evasion. For this reason, they constitute a more precise measure of the income earned by the family.

[6] In Italy a university degree is obtained conditional on passing a certain number of exams. This number varies across courses degree. To avoid selection into achievement, we exclude from our working sample families with children aged more than 23. This age can be conceived, in the majority of cases, the minimum age required to complete a university course degree.

[7] Sixteen of these drops only were due to missing information on the level of education of the head of the family.

[8] The EU scale assigns a weight equal to 1 to the head of the household; equal to 0.5 to the other household components, including the spouse and children older than 14 years old, and equal to 0.3 to children under 14 years old, (see Aaberge et al. 2013).

3.3 Public educational services as transfers in-kind: definition and imputation rules

The evaluation of educational transfers in-kind is an empirical demanding exercise as in-kind transfers data availability is very restricted.

We make use of a unique study by INVALSI-MIPA (2005) based on year 2003 data to compute the educational transfers in-kind monetary equivalent. The value of the educational transfers in-kind received by each student is equal to the average cost of producing it, denoted $AC(r, e)$. This cost is allowed to vary across Italian regions r and educational levels e.[9] This monetary value summarizes the information provided by a variety of indicators representing the quality of the schooling inputs. The most relevant of these indicators is the teacher-pupils ratio, a well known measure of educational quality.

We merge these average costs with the data in SHIW. We treat as recipients of the transfers all children in the selected household aged between three and five, and those aged six to 23 who classify themselves as *students* in the survey. Unfortunately, we do not observe the type of school (either private or public) attended by the students. Consequently, we assign to each student the cost of production of the education service he is consuming, and we let this cost vary according to his region of residence and his educational level. This cost is then weighted by the probability the student has to benefit of public education, denoted by $\omega(g)$, where g refers to a given household group, thus incorporating the information on the school selection process from the side of the households. The monetary value of the *expected* educational transfer in-kind associated to each child c in family h of type g, who lives in region r and who is in educational level e is therefore denoted:

$$k_c \;:=\; \omega(g) \cdot AC(r, e) \tag{3}$$

To compute $\omega(g)$ we use Multiscopo Survey 2005 data from ISTAT. The survey collects information on the presence of a child enrolled either in a private or in a public school.[10] After gathering households in homogeneous groups defined on the basis of a variety of household characteristics, such as the macro geographical area of residence, age class of each child, level of education of the parents and occupational conditions of the head of the family.[11] For each group g, we use observed frequencies to determine the probabilities

[9]Since Italy has 20 regions and 5 educational levels (from kindergarten to tertiary education), we end up with a 20×5 matrix of average costs of education. For all details about the calculations of these average costs see appendix A.

[10]Unfortunately, Multiscopo Survey data do not gather information on households' income.

[11]Geographical areas are North West, North East, Centre and South and Islands. Age classes correspond to the five educational levels: kindergarten (i.e. from 3 to 5), primary education (i.e. from 6 to 10), lower secondary education (i.e. from 11 to 13), upper secondary education (i.e. from 14 to 18), and tertiary education (from 19 to 23). Parents' education is categorized in three levels: low educational level (both parents with at most lower secondary school degree), high educational level (both parents with upper secondary school or university degree) and mixed residual category (one parent with a low educational

to enroll a children in public education. We then use these group specific probabilities ω_g to calculate the expected value of the educational transfer in-kind for each children. Two children in education who live in the same region, attend the same educational level and come from families in the same class, receive equal expected value of educational transfers in-kind.[12]

The transfer in-kind accruing to the household h corresponds to the sum of the transfers received by each of her children in education, and it is denoted:

$$k_h = \sum_{c \in h} k_c. \tag{4}$$

The in-kind transfer accruing to the household depends upon the fertility and timing of fertility of the families. To achieve comparability among families with different educational needs, we scale k_h by the needs-adjusted equivalence scale (see Aaberge et al. 2013, Aaberge et al. 2010),[13] which allows to calculate the amount of educational transfers in-kind per equivalent child enrolled at schools.[14] All children in post-compulsory schooling age that do not attend any school are assumed to receive a value of educational transfers in-kind equal to zero.

3.4 Descriptive statistics

The equivalent (net) income in the working sample from SHIW ranges from 94.8 to more than 360,000 euro, with an average of 13,164 euro per household. About 80% of families receive an income between 4,500 and 23,000 euro. The overall educational in-kind transfer accruing to the households is 3,774 euro on average. The equivalized transfer in-kind ranges from 371.5 euro if all children are enrolled in tertiary education, up to 2,239 euro if all children are enrolled in mandatory education. It may be also noted that the variability of these transfers for compulsory education is considerably higher than those of the other educational levels.

level while the other with a high educational level). We consider the lower secondary school degree as the cut-off point since the parents are almost all affected by the 1962 reform which abolished the second track of the schooling system and made compulsory to all children the attendance of the lower secondary school at least up to the age of 14. Finally we identify two different occupational conditions of the households' head: the one (the low-background group) includes unemployed, unskilled manual workers and employees in the agriculture sector, the other (the high-background group) comprises all other cases.

[12] For instance, within a region, the expected educational transfers in-kind may take 30 different positive values, 5 educational level times 6 different probabilities of attending public schools and a zero value for those in post-compulsory schooling age who choose stop studying.

[13] The Simplified Needs-Adjusted equivalence scale (SNA) calculated by Aaberge et al. (2013) for year 2006, the closest to year 2004, amounts to assign to all household components other than children a weight of 0.5, and to each child different weights according to her age: from 3 to 5 years old, 0.3; from 6 to 13, 0.66; from 14 to 23, 0.93.

[14] Additional robustness checks using household size as equivalent scale confirm our results. Results are available from the authors upon request.

Table 1: Descriptive Statistics.

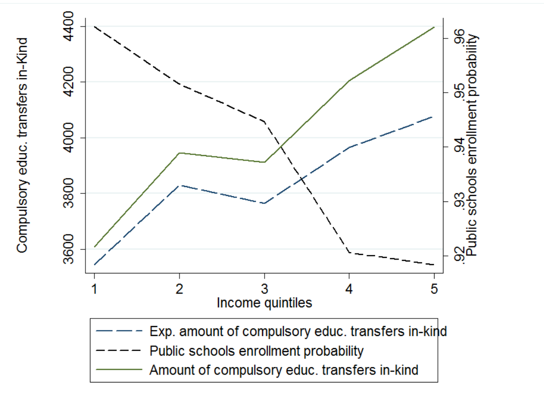
	Mean	sd	Min	Max
Income	13,164.43	12,723.53	94.76	360,002.56
Hh components	3.87	0.91	2.00	9.00
Income recipients	1.77	0.67	1.00	3.00
Prob. enroll. pub. sch.	0.93	0.08	0.51	1.00
Inkind Overall (Euro)	3,773.80	2,009.94	0.00	10,214.27
Inkind Comp. (Euro)	2,238.59	2,463.00	0.00	10,214.27
Inkind Sec. (Euro)	1,067.57	1,559.96	0.00	6,747.55
Inkind Univ. (Euro)	371.53	843.99	0.00	6,806.01
Exp. Max. Tax Deductions	3,926.52	949.91	1,318.83	5,537.73
Children, tot	1.90	0.79	1.00	7.00
Children studying (Comp.)	0.58	0.72	0.00	3.00
Children studying (Sec.)	0.44	0.62	0.00	4.00
Children studying (Univ.)	0.20	0.45	0.00	2.00
Hh head, female	0.33	0.47	0.00	1.00
Hh education (years)	10.58	3.75	5.00	19.00
Hh head, age	46.08	6.82	33.00	60.00
Family Back. Occ. (Euro)	120.91	7,342.07	-44,247.34	259,669.67
Family Back. Educ. (Euro)	-16.03	7,438.38	-47,840.55	258,711.23
Sample Size	2,030			

Sources: SHIW, Bank of Italy, wave 2004; microsimulated educational transfers in-kind using *INVALSI-MIPA* data, 2003; household gross income and personal income taxes kindly provided by C. Fiorio.

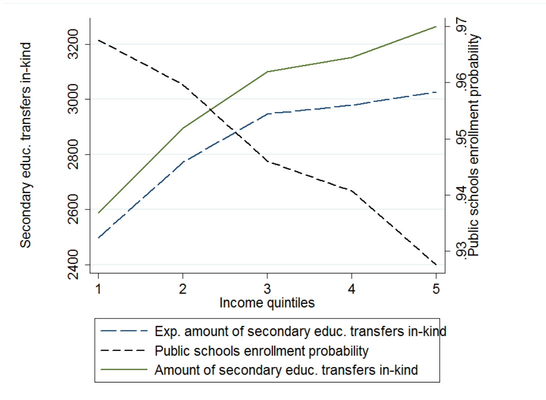
The dashed line in Figure 2 shows the distribution of *expected* transfers in kind (i.e., weighted by the probability of attending public schools) while the solid line in the same figure reports the distribution of *un-weighted* transfers in-kind, both plotted against the household income quintiles. For households with children in compulsory and secondary education, the figure shows that in-kind transfers received by the household increase with the household's income (panels (a) and (b) of the figure). This pattern is less neat when the focus is shifted to families with children enrolled in tertiary education (panel (c)). Overall, the relation between transfers in kind and income turns out to be inverted u-shaped, as shown by panel (d) in the figure. The discrepancy between expected and un-weighted transfers in-kind distributions is explained by the probability of enrolling into public schools (dot line), which is always decreasing in household income.

The relations shown in Figure 2 are likely to be spurious. We account for household observable heterogeneity, which potentially affects the selection process, by controlling for observable characteristics, as well as for the background of origin of the household. Furthermore, we adopt a control variate approach, illustrated above, to sort out exogenous income variations, and to see their effects along both the household income capacity and the educational transfers in-kind distributions. To achieve this goal we need an exclusion restriction, discussed in the following section.

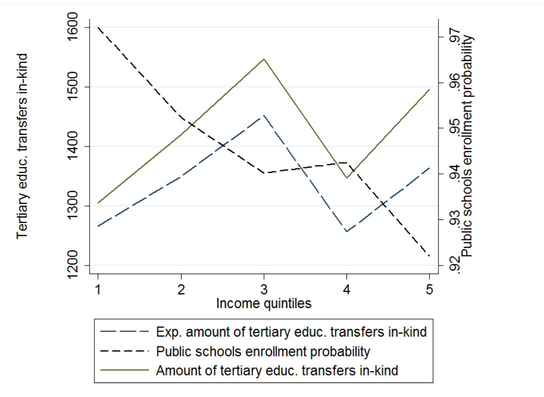
Figure 2: Income profiles for the amount, the expected amount of educational transfers in-kind and the probability of attending public schools.



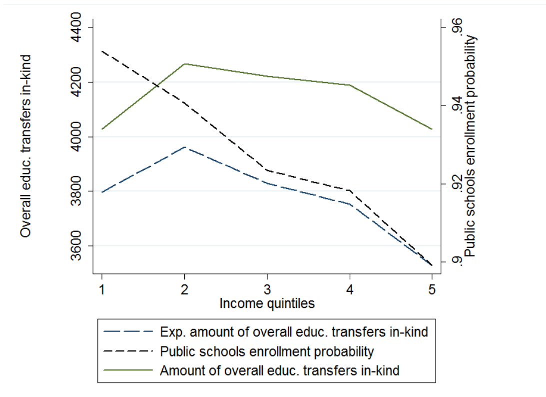
(a) Compulsory educ. transfers in-kind.



(b) Secondary educ. transfers in-kind.



(c) Tertiary educ. transfers in-kind.



(d) Overall educ. transfers in-kind.

Sources: SHIW, Bank of Italy, wave 2004; microsimulated educational transfers in-kind using *INVALSI-MIPA* data, 2003; ISTAT, *multiscopo survey* (2005).

3.5 Identification strategy: instrumenting income with expected tax deductions

The incidence of the self-targeting mechanism described in Besley and Coate (1991) is driven by the correlation between the unobservable family specific income capacity (i.e. the error term of equation (2b)) and the family specific preference for quality of the educational good (i.e. the error term of equation (2a)). Hence, to assess the impact of household income on in-kind transfers distribution it is necessary to single out a variation in income that is orthogonal to the household income capacity and tastes for quality. Our identification strategy does so by controlling for the these two components, and for their correlation, in a control variate setting. We exploit heterogeneity in expected tax deductions accruing to the household h, denoted z_h, to exogenously manipulate the distribution of income to disentangle the effect of such manipulation from the co-movements of the errors distribution.

Description of the instrument For each household member[15] $m = 1, \ldots, M_h$ of the household h, we calculate the expected value of the maximum tax deductions he is entitled to as a weighted average of the four maximum tax deductions fixed by the law in 2004 (denoted d_i with $i = 1, \ldots, 4$). These correspond to four levels: 7,500 euro for employed workers, 4,500 euro for self-employed workers, 7,000 euro for retired workers and 3,000 euro for the residual category, comprising for instance children in education.[16] The probability that family h claims any of the four deductions depends on two exogenous characteristics, the age a_m and gender s_m of the household member m, and is denoted $\psi_i(a_m, s_m)$. We compute these probabilities from ISTAT (2003) using the one-year lagged value of the observed frequencies of the distributions of the Italian population of employees, retired persons and self-employed workers given age class and gender.[17] The overall expected amount of deductions accruing to the household is the sum of the benefits that each member of the household is entitled to. These potential deductions at the household level are then scaled by the household h size M_h, giving:

$$z_h \; := \; \sum_{m \in h} \frac{1}{M_h} \sum_{i=1}^{4} \psi_i(a_m, s_m) \cdot d_i \tag{5}$$

Equation (5) defines the instrument for income. At household's member level, the instrument is exogenous since it combines the four maximum tax deductions determined by the law with the exogenous probabilities of claiming these deductions. At household level, the instrument is exogenous under the assumption that the age and gender composition of the household is orthogonal to the unobservable characteristics that may affect the households' sorting process into private/public education.

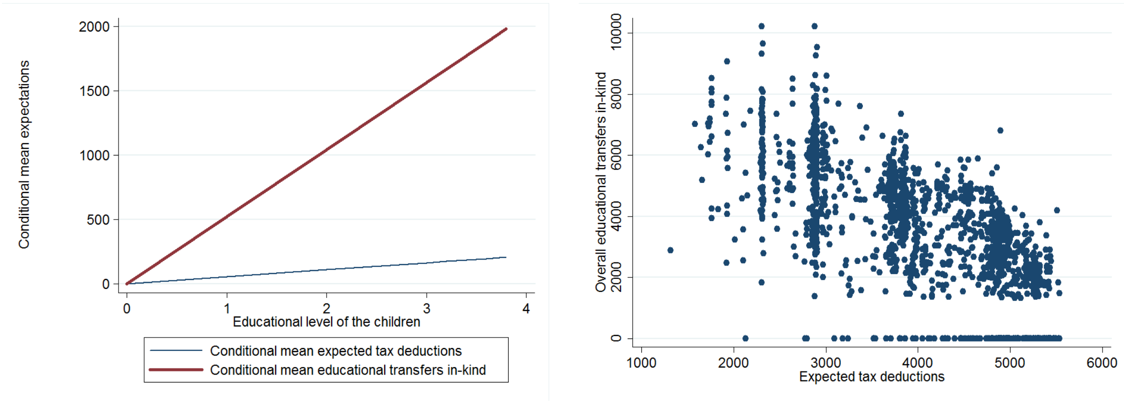
The exclusion restriction The key maintained exclusion restriction for identification is that a manipulation of the distribution of the expected tax deductions Z affects the quantiles of the distribution of the educational transfers in kind K only through its effect

[15] We consider here only the parents and the offspring as household members. We disregard other relatives living within the family even if they could potentially contribute to generate the income of the household.

[16] According to the Italian personal income system in 2004 the effective tax deduction accruing to each taxpayer was related to two parameters: the source of income, and the amount of gross income. The tax deduction system was designed to assure an exemption threshold (heterogeneous across sources of income), and to reinforce the progressivity of the personal income tax. The direct link between the tax deduction and the gross income explains why we do not use the effective tax deductions but rather an expected amount as an instrument for net income.

[17] We consider 18 age classes made of 5 years each with the exception of the lowest (age$\leq$ 14) and the highest (age$\geq$ 95). For instance, this amount to say that for all children aged less than 15 years old, the expected maximum tax deduction amounts to 3000 euros taken with probability equal to one since, for this age class and for both gender, the national frequencies of employees, retired persons and self-employees are equal to zero.

Figure 3: Validating the exclusion restriction.



(a) Conditional means given education levels.

(b) Educational transfers in-kind on expected tax deductions.

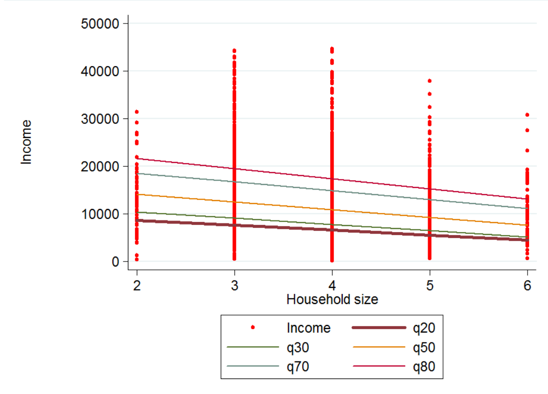
Note: We assign the following ordinal values to the educational levels of the children: the value of zero corresponds to any educational level attended (i.e. households with children in post-compulsory schooling age that stopped studying); to those households who have one or more children in the same educational level, we assign the values of 1 for compulsory, 2 for upper secondary and 3 for tertiary education; we impute to households with more than one child in different educational levels the values of 3.2 if having at least one child in compulsory and one in secondary education, 3.4 if having at least one child in compulsory and tertiary education, 3.6 if having at least one child in secondary and tertiary education and finally 3.8 if having at least one child in all educational levels.

on the household's income distribution Y. This amounts to saying that the household structure, the age and gender composition within the household have no direct effect on the amount of educational transfers in-kind accruing to the household.

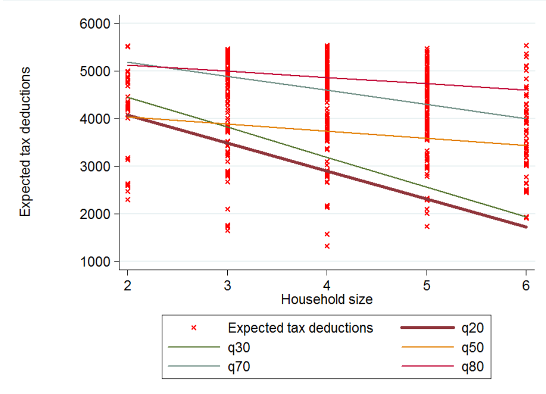
However, the instrumental variable z_h might be correlated with children's age, thus rising potential concerns about the validity of the exclusion restriction. The data show that the expected tax deductions do not have a direct impact on the transfers in-kind received by the household, when conditioned for the age profiles of the children. In fact, if the children is in compulsory schooling age, then he is entitled with a fixed deduction of 3,000 euros while the amount of educational transfers in-kind is always positive and heterogeneous according to the educational level (either primary or lower secondary), the region and the reference group to which the household belongs. The expected tax deductions do not have a direct effect on the transfers in-kind also for children in post-compulsory schooling age, because they are independent of the true working condition of the child, while the amount of the educational transfers in-kind depends upon his educational status.

Figure 3 supports these considerations. Expected tax deductions are flat across educational levels of the children but slightly increasing for households with children aged 14 or above, since the national frequencies of the distributions of employees and self-employees is positive for them. At any rate, even if there might exist a correlation between expected tax deductions and educational transfers in-kind related to the educational level of the

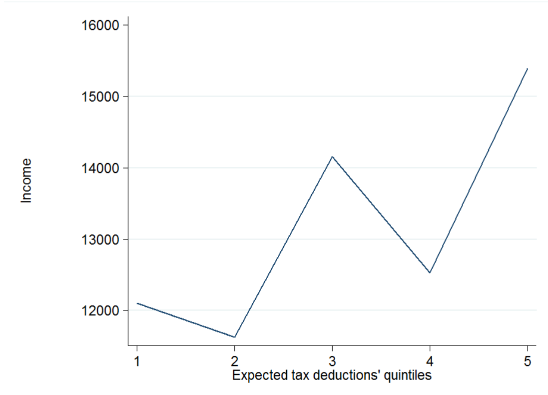
Figure 4: Expected tax deductions' variability for household's income and educational transfers in-kind.



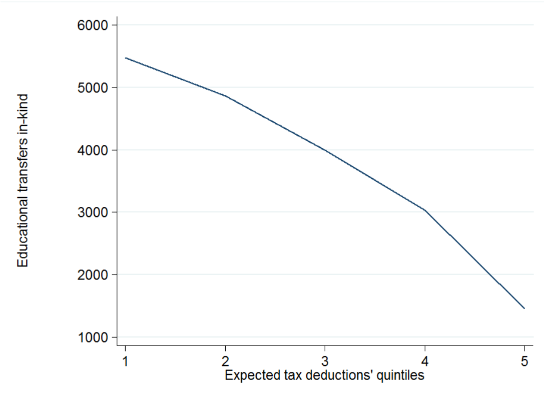
(a) Income on household size



(b) Expected tax deductions on household size



(c) Income on expected tax deductions



(d) Educ. transfers in-kind on exp. tax deductions

Sources: SHIW, Bank of Italy, wave 2004; microsimulated educational transfers in-kind using *INVALSI-MIPA* data, 2003; household gross income and personal income taxes kindly provided by C. Fiorio.

children, this correlation would result to be positive while the data in figure 3 (b) show a reverted pattern.

Our second concern is whether we are just using household size as the instrumental variable. We clearly document in panels (a) and (b) of figure 4 that the instrument variability is substantially uncorrelated with household size. In fact, z_h varies within household size according to the age class and the gender of each household member. Moreover, across household size, variability of our instrument does differ substantially from the variability of income registered for both the location and the scale as shown by the different slopes of the conditional quantile functions given household size.

Our third and last concern is whether the instrumental variable is relevant for generating sufficiently large exogenous changes in income to affect the transfers in-kind distribution. Panel (c) of figure 4 shows that household incomes increase along the distribution of the family's expected tax deductions. Consequently, our instrument behaves consistently with effective tax deductions that are regressive in presence of marginal personal income

Table 2: OLS, quantile regression and control function estimates.

	OLS	Quantiles educational transfers in-kind					CF
		20%	30%	50%	70%	80%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Income	-0.02***	-0.00	-0.01	-0.03***	-0.02*	-0.02***	-0.73***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
FB1	0.04**	0.01	0.03	0.07**	0.08*	0.07	0.58***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.05)	(0.06)	(0.03)
FB2	-0.02	0.00	-0.01	-0.05*	-0.05	-0.03	0.31***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.05)	(0.06)	(0.02)
Intercept shift							0.73***
							(0.03)

Note: The table reports OLS, quantile regression and control function estimates of the effect of income on educational transfers in-kind. The specification also includes an indicator for the number of earning recipients, dummies for the area of residence; cohort of birth of the first child of the household; gender (i.e. if female), age, age squared, years of schooling of the family's head; regional GDP per head and unemployment rate; interaction terms between income and the two measures of household unobserved characteristics related to the grandfathers occupational status and the level of education of the grandparents. These interaction terms are not statistically different from zero. The control function specification further includes the residuals of the first stage regression and their interaction with income. The first stage regression corresponds to OLS estimates of equation (2b). Robust standard errors are reported in parentheses for OLS and control function estimates while bootstrapped standard errors are reported in parentheses for quantile regression estimates.

taxes. The amount of educational transfers in-kind is lower for higher quintiles of the expected tax deductions (panel (d) of figure 4). These two graphs hint that the reduced form regression of an exogenous manipulation of the prevailing distribution of incomes on various quantiles of educational transfers in-kind distribution would estimate a negative effect of the former on the latter variable.

4 Results

4.1 Benchmark

Table 2 illustrates some benchmark results. The income coefficient from an OLS regression, reported in column (1), is negligible but significant, which might be the consequence of averaging the heterogeneity in the income effects along the distribution of transfers in-kind.[18] Columns (2) to (6) reject this conjecture, by showing that the income effect is generally negative and close to zero, and it turns out to be significant only above the median of the educational transfers in-kind distribution.

[18] If educational transfers in-kind are redistributive, it might be the case that the marginal effect of income is negative in the upper part but positive in the lower part of the educational transfers in-kind distribution.

Like the OLS, the quantile regression coefficients do not have a causal interpretation when there are unobservable dimensions that simultaneously affect both income and in-kind transfers. We use a control function (denoted CF) approach to cope with this form of endogeneity of income. The CF estimates account for heterogeneity in income effects by conditioning on residuals of a first stage income regression, where we use expected household tax deductions as an instrument, and the interaction between income and these residuals. The coefficient of the estimated residuals determines the shift of the intercept of the educational transfers in-kind function associated to households' self-selection. The interaction term captures, instead, the slope shift effect of the marginal change of income, which is associated to the unobservable heterogeneity in household characteristics. As reported in column (7) of table 2 , this interaction terms is not statistically significant.[19]

The CF estimate of the marginal effect of income corresponds to -0.73, confirming an upward bias of the OLS estimate equal to -0.02. Under plausible assumptions,[20] this coefficient measures the *average marginal treatment effect* of income in the population. In fact, the control function can be conceived as a structural relation that provides the counterfactual conditional expectations of k given y (and other covariates), if y could be manipulated independently of the errors as if the endogeneity of y was absent and household income capacity would be perfectly observable by the government implementing the mechanism (Blundell and Powell 2003).

The CF method incorporates assumptions on the intercept-slope shift effects of income on the conditional distributions of the endogenous variables, offering only a conditional mean perspective of the underlying structural relations. In fact, it does not allow to verify how and whether the marginal effect of income varies across both the income capacity and preferences for the quality of the educational good distributions. Structural quantile treatment effect estimation broadens this view, offering a more complete characterization of the stochastic relationship between income and educational transfers in-kind.

4.2 First stage

Table 3 reports quantile estimates of equation (2b) for the working sample, and for two subsamples of households with at least one child in compulsory and upper secondary schooling age. We interpret the estimated coefficients as the sum of two effects through which a change in the instrument affects the distribution of income, as outlined below.

Let y_N be the net of taxes income, corresponding to the gross income y_G minus the

[19] Given the linear model specification and the insignificance of the interaction term between the first stage residuals and the income variable, IV and control function estimates are here equivalent.

[20] Our two measures of unobservable household characteristics related to the grandfathers occupational conditions and grandparents' level of education and other household specific heterogeneity components unrelated to these two family background variables are all mean independent of the instrument z in such a way that the instrument is *as good as randomly assigned*.

Table 3: Structural quantile treatment effect estimation: first stage.

	Quantile of income				
	20%	30%	50%	70%	80%
	(1)	(2)	(3)	(4)	(5)
Main sample					
Exp. tax deductions	0.907***	1.156**	1.045***	1.348***	1.665***
	(0.17)	(0.56)	(0.18)	(0.21)	(0.38)
Comp. education					
Exp. tax deductions	1.069***	1.109***	6.853***	1.879***	2.166***
	(0.28)	(0.28)	(0.37)	(0.48)	(0.50)
Upper sec. education					
Exp. tax deductions	1.049***	1.015**	1.168***	1.138***	0.846
	(0.32)	(0.47)	(0.30)	(0.43)	(0.52)

Note: The table reports the first stage of the structural quantile treatment effect estimates. The specification also includes an indicator for the number of earning recipients, dummies for the area of residence and a polynomial of degree one in the cohort of birth of the first child of the household; gender (i.e. if female), age, age squared, years of schooling of the family's head; regional GDP per head and unemployment rate and the two measures of household unobserved characteristics related to the grandfathers occupational status and the level of education of the grandparents. Bootstrapped standard errors are reported in parentheses.

personal income tax liability T, with $T = t(y_G - d)$ where t represents the average tax rate and d a tax deduction. We can decompose the overall effect of a change of (expected) tax deductions on net of taxes income as follows:

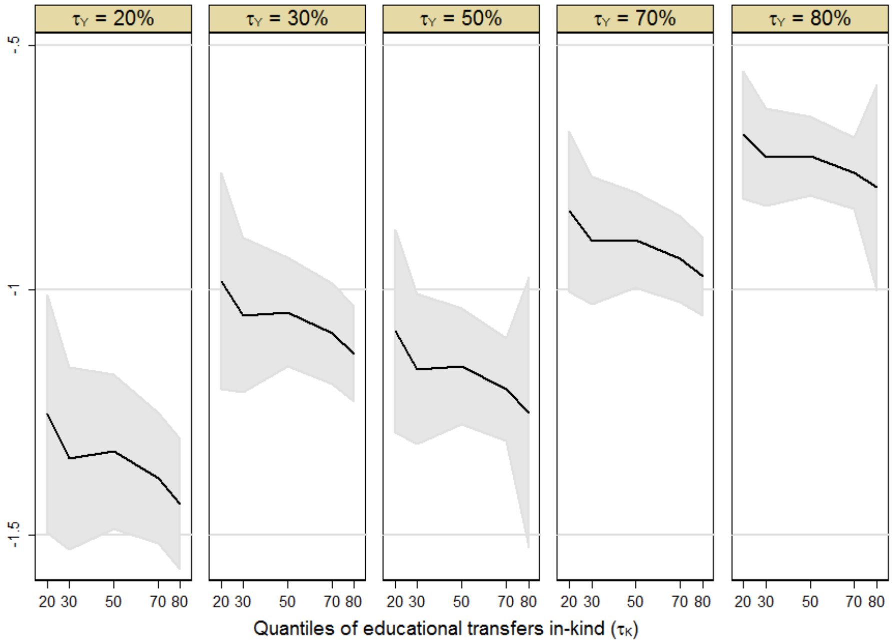
$$\frac{\partial y_N}{\partial d} = t' + \frac{\partial y_G}{\partial d}(1 - t')$$

where t' stands for marginal personal income tax rate. Recall that in Italy the taxation system is individualized, hence the effects of a change in (expected) tax deductions affect primarily the income of each household member.

The variation of (net of taxes) income due to a one euro increase of (expected) tax deductions is the sum of the tax cut equal to the marginal tax rate (the direct effect), and of the variation of the gross income net of the marginal tax rate (the indirect effect). In principle, the latter effect can be either negative or positive depending on the behavioral labor supply response of each household member. It is negative if an income effect prevails, while it is positive if the response to the increase in net income amounts to substituting leisure with labour. At the household level, the effect of expected tax deductions on income corresponds to the sum of the effects estimated for each component of the family.

The estimates of the first stage regression, reported in table 3, highlight the pattern of the variation of the coefficient of the expected tax deductions across the selected quantiles of the income distribution. These coefficients are always statistically significant at 1% in the working sample and positive, with values always greater than the maximum marginal tax

Figure 5: Marginal quantile treatment effects of income.



Note: The figure plots the marginal quantile treatment effects of income for a given quantile of the household income capacity. These marginal quantile treatment effects are calculated taking also into account the interaction between income and the residuals of the given quantile of the household income capacity, and the interactions between income and our two measures of household unobserved characteristics related to the grandfathers occupational status and the level of education of the grandparents, each of them considered separately. Confidence bands at 99% level.

rate accruing to personal income taxes in Italy (45%). This suggests that the substitution effect dominates the income effect on the household labor supply.

4.3 Structural quantile treatment effects on the working sample

Figure 5 plots the marginal quantile treatment effects of income on the quantiles of the transfers in-kind distribution, at selected income capacity levels, for the working sample. Overall, an exogenous increase in income is always associated to a decrease in transfers in-kind accruing to the households. These coefficients are obtained after controlling for family background characteristics, captured by $FB1$ and $FB2$. The signs of the effects of these variables coincide with the signs of the quantile residuals, are positive, and statistically significant at 1% level. Hence, the two variables are capturing different household unobservable characteristics that have an independent effect on the amount of the educational transfers in-kind distribution.

To properly interpret the figure and to assess the premises of the sorting mechanism, it is necessary to fix one of the two dimensions of heterogeneity at a time.

Fixing quantiles τ_Y of the household income capacity. For a given quantile of the income capacity, identified by each of the five panels in figure 5, we find that the magnitude of the (negative) effect of household income on the transfers in-kind distribution increases with the taste for educational quality, identified by the quantiles of transfers in-kind reported in the horizontal axis in each of the panels of the figure. Table 4, panel (a), reports the statistical test for the difference between the impact of income on the lowest level of quality tastes ($\tau_K = 20\%$) and the same effect at high level of quality tastes ($\tau_K = 80\%$), respectively for each panel in figure 5. These differences are always positive and in most of the cases significant, indicating that the negative effect of income on the transfers distribution is attenuated at the bottom of the distribution compared to what happens at the top. This result is consistent with the view that, given income capacity τ_Y, households with higher tastes for educational quality are more keen to sacrifice an higher marginal benefit of income and opting out from the public education system to buy higher quality schooling, compared to households with lower tastes for the quality of the educational good.

Fixing quantiles τ_K of the household preferences for quality. For a given quantile of the preferences for quality, we find that the magnitude of the negative effect of household income on the transfers in-kind decreases across the quantiles of income capacity. To see this pattern, it is necessary to keep track of the effect of income on the same quantile of the transfers in-kind distribution across the five panels in figure 5. Table 4, panel (b), reports the statistical test for the difference between the impact of income on transfers in-kind at low income capacity ($\tau_Y = 20\%$) and high income capacity ($\tau_Y = 80\%$), respectively for each level of preferences for education. These differences are always negative and significant, and their magnitude is increasing with τ_K. This result is consistent with the view that, given preferences for education, households with higher income capacity face larger incentives to opt out from the public education system compared to families with low income capacity. That is, when the household income capacity increases, the marginal effect of income becomes smaller in absolute value since more families sort themselves into private education gaining a zero marginal benefit from public education provision.

Mean (quantile) treatment effects. The assumptions made on the structure of errors in the structural quantile treatment effect model have provided insights into how the dimensions of income capacity and preferences for education are connected. As suggested by Ma and Koenker (2006), there are other relevant but more aggregated evaluation parameters that can be retrieved from structural quantile treatment effects estimation. The *mean quantile treatment effect* is obtained by integrating out the distribution of the household income capacity, while the *mean treatment effect* results from averaging these last

Table 4: Homogeneity tests.

Panel (a): 20th and 80th quantiles of K, given τ_Y				
τ_Y : 20%	τ_Y : 30%	τ_Y : 50%	τ_Y : 70%	τ_Y : 80%
0.184*	0.149*	0.166	0.133**	0.108
(0.10)	(0.09)	(0.13)	(0.07)	(0.09)
Panel (b): 20th and 80th quantiles of Y, given τ_K				
τ_K : 20%	τ_K : 30%	τ_K : 50%	τ_K : 70%	τ_K : 80%
-0.570***	-0.613***	-0.604***	-0.624***	-0.647***
(0.11)	(0.08)	(0.07)	(0.06)	(0.10)

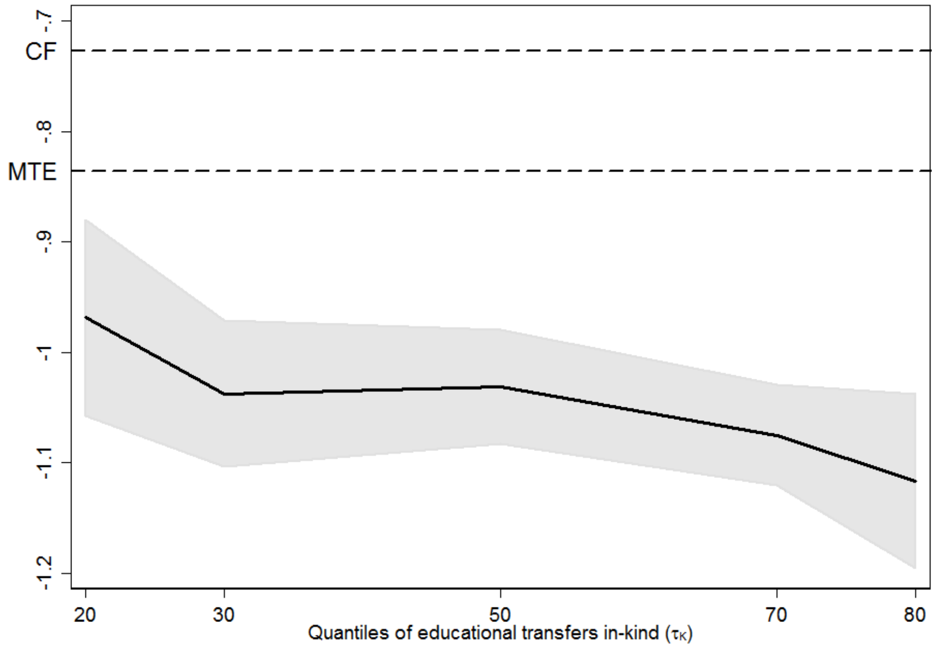
Note: The table reports the homogeneity tests of the marginal quantile treatment effects of income. Panel (a) displays the difference between the marginal income effects estimated at the 20th and the 80th quantiles of educational transfers in-kind distribution, fixing quantiles of the household income capacity. Panel (b) displays instead the difference between the marginal income effects estimated at the 20th and the 80th quantiles of the household income capacity, fixing quantiles of the educational transfers in-kind distribution. Standard errors are reported in parentheses.

effects with respect to the quantiles of the distribution of the educational transfers in-kind. The mean treatment effect theoretically coincides with what is estimated by the two-stage least-squares estimator in the pure location shift version of the model, and in our case, where the interactions terms are not significant, it should correspond to the *average treatment effect* estimated in section 4.1 using control function method. Figure 6 supports this argument. The difference between the average treatment effect retrieved in the CF setting and the mean treatment effect obtained from our structural quantile treatment effect estimates is small and perhaps related to our hypothesis to assign a zero weight to the poorest and richest quintiles of the distributions of both the household income capacity and of the amount of educational transfers in-kind, in order to compute the final mean treatment effect. Patterns in the figures support the internal consistency of the structural model estimates.

4.4 Analysis across educational levels

The Besley and Coate (1991) mechanism applies to compulsory education provision, where enrolment is mandatory to all children and parents only have to choose between private or public schooling. The households' choice for post-compulsory education is, instead, sequential. First, the household decides whether or not to enroll the child at school. Only in the event that the child attends post-compulsory education, the household chooses between private and public education. To account for these issues, this section deals with replicating our main analysis for two subsamples that distinguish between families with children in compulsory schooling age and those with children in upper secondary schooling

Figure 6: Mean quantile treatment effects of income.



Note: The figure plots the mean quantile treatment effects, the mean treatment effect of income and the coefficient estimated using control function method reported in Table 2. The mean quantile treatment effects are calculated integrating out the distribution of the household income capacity. To each of the point of the structural quantile treatment effects' estimates (i.e. the 20th, 30th, 50th, 70th and 80th quantile estimates), we assign as weight the area under the distribution of the household income capacity calculated at the corresponding fixed point. The lowest and the highest quintiles of the distribution of the household income capacity are assumed to a have a weight equal to zero. The mean treatment effect is obtained by averaging again, using the same procedure, this time, across the quantiles of the distribution of the educational transfers in-kind. Confidence bands at 99% level.

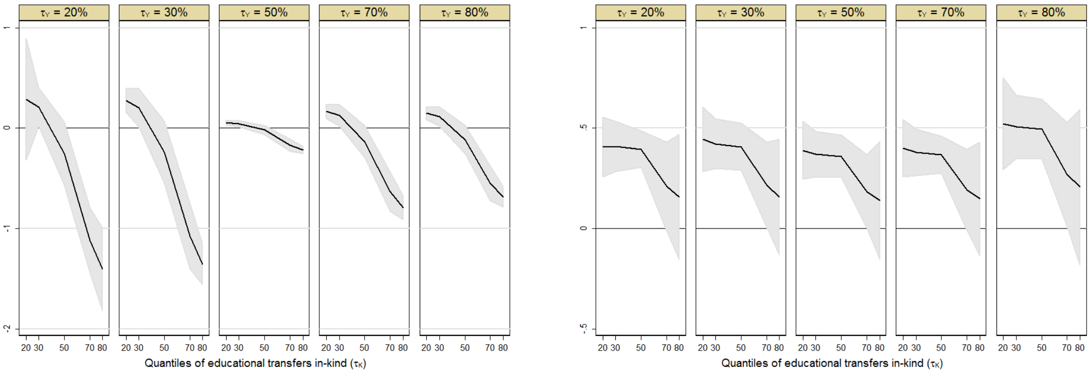
age. Additional tables with robustness checks are reported in the appendix.[21]

Compulsory education. Panel (a) of figure 7 illustrates the marginal effect of income on the amount of educational transfers in-kind when the empirical assessment is restricted to families with at least one child in compulsory schooling age.[22] Estimates are based on a reduced sample of 888 households. We find that an increase in income affects positively the 20th and 30th quantiles of educational transfers in-kind distribution, while the effect turns out to be significant and negative at quantiles above the median. The marginal impact of income on the median amount of educational transfers in-kind is negligible and insignificant when evaluated at the median level of the household income capacity.

[21] In appendix C, we report estimates for a variety of subsamples: households with children in compulsory schooling age including kindergarten; households with children in both secondary and tertiary schooling age; households with children in tertiary schooling age.

[22] Here, we are not including families with children at kindergarten since kindergarten is not compulsory in Italy.

Figure 7: Marginal quantile treatment effects of income: sub-samples.



(a) Compulsory education (b) Upper secondary education

Note: The figure plots the marginal quantile treatment effects of income for a given quantile of the household income capacity for the sub-samples of compulsory education, (panel (a)), and upper secondary education, (panel (b)). These marginal quantile treatment effects are calculated taking also into account the interaction between income and the residuals of the given quantile of the household income capacity, and the interactions between income and our two measures of household unobserved characteristics related to the grandfathers occupational status and the level of education of the grandparents, each of them considered separately. Confidence bands at 99% level.

At the lower quantiles of the educational transfers in-kind distribution and for a given income capacity of the households, only families that value less the quality of the educational services consume the publicly provided educational good. Since quality is a normal good, the marginal effect of an increase in income on the amount of educational transfers in-kind is positive for them.

Given household income capacity, at higher quantiles of the educational transfers in-kind, households who value more the quality of the educational good reveal their preferences being ready to give away an higher marginal income gain from public education provision. For this reason, the sign of the marginal effect of income on the amount of educational transfers in-kind turns out to be negative. Moreover, the higher the quantile of the educational transfers in-kind distribution, the higher the magnitude of the marginal income gain these families are willing to give up. Overall, the households valuing less the quality of the educational services and having a lower income capacity are those who benefit more from the publicly provided mandatory education system.

Figure 7 provides also evidence of the self-targeting mechanism showing that the educational transfers in-kind is redistributive. In fact, the magnitude of the negative marginal effect of income attenuates along the household income capacity distribution, holding tastes for quality as fixed. This suggests that for a given quality level of the public educational good, the higher the household income capacity, the higher the proportion of families who opt out to private education and gain consequently a zero marginal benefit from public education provision.[23] Overall, the households who value more the quality of the educational services and have an higher income capacity are those who benefit less from the public mandatory education provision.

Upper secondary education. Panel (b) of figure 7 shows a different picture, obtained from repeating the analysis on the 767 families with at least one child in upper secondary schooling age. In this case, the marginal effects of income on transfers in-kind are always positive. In upper secondary education, the mechanisms through which families self-select into private and public education are, therefore, different from the mechanisms underlying compulsory education. However, under the assumption that the expected returns to education of the offspring are positively correlated with the realized return in income of the family of origin (i.e. the realized returns can be forecast by observed family income), one can speculate that families are self-selecting into post-compulsory education, independently on whether public or private, according to the expected returns to children education compared to the costs of attending education. Keeping educational costs as fixed, households are more likely to choose higher levels of education if the returns to education of the children is higher. For given expected returns, households are more likely to choose higher level of education if the costs, including the opportunity costs in terms of forgone wage, are lower.

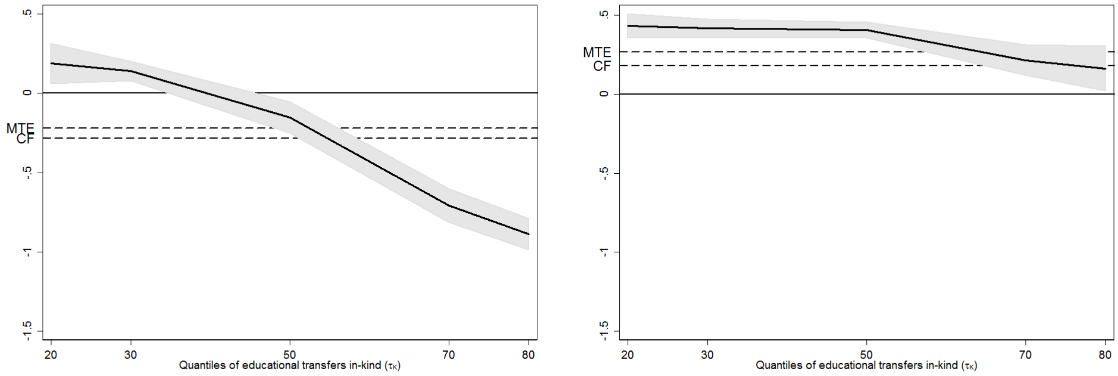
The marginal effects of income at the 20th quantile of educational transfers in-kind distribution are always statistically positive and larger than the same effects calculated at the 80th quantile, irrespectively of household income capacity. On the contrary, the effects at the 80th quantile of the educational transfers in-kind distribution (indicating high level of preferences for education quality) are never significant. This result is consistent with the findings presented by Bertola et al. (2007) and Bertola and Checchi (2013), who suggest that the teaching quality of private schooling for upper secondary education is not higher than the quality of public schools, suggesting a remedial scope for private education in Italy.[24] If this is the case, the incentive compatibility constraints of rich households cannot be satisfied and the assumptions behind the Besley and Coate (1991) mechanism, required to achieve redistribution through public education provision, are clearly violated.

Finally, panels (a) and (b) of figure 8 plot the mean quantile treatment effects and the

[23]For quantiles either lower or equal to the median of K's distribution, however, the equality between these marginal effects at the lowest and highest quantiles of the household income capacity cannot be rejected. As discussed above, this is likely to be the consequence of the fact that the households who value less the quality of the schooling system consume the publicly provided educational good independently of their income.

[24]The same qualitatively result can be found when we use the subsample of families with children in post-compulsory schooling. There is instead no evidence of either a remedial role for private universities or self-targeting of the families into tertiary education. These results are shown in the appendix.

Figure 8: Mean quantile treatment effects of income: sub-samples.



(a) Compulsory education (b) Upper secondary education

Note: The figure plots the mean quantile treatment effects of income for the sub-samples of compulsory education, (panel (a)), and upper secondary education, (panel (b)). The mean quantile treatment effects are calculated integrating out the distribution of the household income capacity. To each of the point of the structural quantile treatment effects' estimates (i.e. the 20th, 30th, 50th, 70th and 80th quantile estimates), we assign as weight the area under the distribution of the household income capacity calculated at the corresponding fixed point. The lowest and the highest quintiles of the distribution of the household income capacity are assumed to a have a weight equal to zero. The mean treatment effect is obtained by averaging again, using the same procedure, this time, across the quantiles of the distribution of the educational transfers in-kind. Confidence bands at 99% level.

mean treatment effect for compulsory and upper secondary education. These parameters are retrieved from the structural quantile treatment effects estimates integrated over the dimensions of the household income capacity and tastes for education quality. In both cases, this validation check confirms the consistency of the structural quantile treatment estimates with the average treatment effect of income on transfers in-kind estimated using control function method. Consequently, data seem to reject the premises of self-targeting into private and public post-compulsory education.

5 Conclusions

This paper tests one of the mechanisms behind the redistributiveness of public education provision, by analyzing the sorting process into public and private education among Italian households. We quantify the value of public educational services received by an household with children in education as the monetary equivalent transfer in-kind received by the household opting for public education. Operationally, the in-kind transfer is measured by the expected cost supported by the government to provide the service almost inexpensively for the families. This is an objective measure of the quality of the educational services provided by the public sector.

We show that an increase in income reduces the amount of educational transfers in-kind (i) more for higher quantiles of the educational transfers in-kind, keeping income capacity as fixed, (ii) more for lower quantiles of the household income capacity, holding tastes for education quality as constant. Overall, the households who value less the quality of the educational services and have a lower income capacity are those who benefit more from compulsory educational services provided by the public sector. We interpret these results as evidence that public education provision can be assimilated to a progressive transfer of income because rich households with high preferences for the quality of the educational good sort themselves into private education, while contributing to its financing. This is consistent with the premises of the Besley and Coate (1991) mechanism.

Our results suggest that reforms of the public education system that aim at altering the quality of the publicly provided education services are expected to alter this self-targeting mechanism. However, this does not necessarily imply that such reforms would lead to a loss in either efficiency or equity terms. In their conclusions, Besley and Coate (1991) underline that public education provision might not necessarily be part of an optimally designed redistributional package. The deadweight loss associated with universal education provision suggests that similar distributional goals could be achieved more efficiently through other feasible policies.

Moreover, our empirical investigation shows that the premises of the Besley and Coate (1991) mechanism applies to compulsory schooling but not at post-compulsory education level where families likely sort into the education system according to the expected returns to their children education compared to the costs of attending schooling. For given costs, if the expected returns to education of the offspring are positively correlated with the (realized return in) income of the family, children coming from rich families attend proportionally more post-compulsory education. For given expected returns, children coming from rich households face a lower opportunity cost of enrolling at schools. These considerations seem to hold for Italian data independently of the type of school chosen and pave the way to argue that publicly provided post-compulsory education is not redistributive.

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Appendices

A Assessing the average costs per student at regional and educational level

The estimation of the average cost of public education *by* region *and* educational level is a difficult exercise. The Financial Statement (*Rendiconto Generale*) of the Italian Ministry of Education (MIUR) records public spending on education according to two classifications. One aggregates data at the central government level, distinguishing across different levels of education but not across different regions. The other organizes data by regions but does not distinguish across different educational levels. For all education levels up to upper secondary school (including pre-primary and excluding tertiary education) we take advantage of ASPIS III carried out by the Italian National Institute for the Evaluation of Education System (INVALSI) and the Consortium for the Development of the Methodologies and Innovations of the Public Administrations (MIPA) exclusively for the year 2003. This study draws together information arising from several sources (Ministry of Economy, Ministry of Education, Italian Institute of Statistics) to develop a matrix of public expenditures on education based on both the regional and the educational level dimensions.

Although competencies on public education in Italy are spread across several authorities[25], in this paper we use regions as the unit of analysis for three main reasons. First, the main source of variation in educational expenditures in Italy is at the local level, as 95% of the central government spending on education finances the salaries of the teaching and non teaching staff. Second, regions (which territory is then organized into provinces and municipalities) can be considered as 'whole units' due to the complex system of financial transfers from higher to lower levels of governments (mainly from regions to province and municipalities). ASPIS III collects data from a consolidated financial statement of central government and local authorities, and avoids the risk of double counting the value of expenditures which are financed by transfers from higher to lower levels of government. Third, INVALSI-MIPA (2005) emphasizes the regional (together with the educational level) dimension, implicitly recognizing a primary source of variation at this level.

In what follows, we describe the main features of the methodology developed by ASPIS III. All details (only in Italian) can be found in the accompanying reports Asquini and Bettoni (2003) and INVALSI-MIPA (2005). Finally, a specific section describes the methodology used to calculate the average cost of tertiary education.

A.1 Pre-primary, primary, lower and upper secondary school

In order to attribute central government expenditures by educational levels to regions and, conversely, region-specific expenditures to different educational levels, ASPIS III exploits a number of so called *drivers*. For instance, the main driver is represented by the number of students and of teaching and non-teaching staff in each region and educational level. For

[25] According to INVALSI-MIPA (2005) 71% of the public expenditures for education (from pre-primary to upper secondary) is financed by the central state, while regions account for 6%, provinces for 5.5% and the remaining, 17.5%, is financed by municipalities.

this reason, these data take account, at least in part, of differences in quality and efficiency in the public service production across regions and levels of education.

ASPIS III data can be organized in a $r \times e$ matrix whose cells record the public spending (total costs) on education for 20 Italian regions (r) and 4 educational levels (e) for year 2003. We divide each of these total costs by the total number of students enrolled at school reported in the corresponding cell of an analogue $r \times e$ matrix. We end up with a $r \times e$ matrix providing the average spending per student by region and educational level indicated in the main text as $AC(r, e)$.[26] We finally apply regional-specific general indexes of consumer prices to inflate these average costs to 2004.

A.2 Tertiary education

We adopt a different strategy to estimate the average costs of providing public tertiary education. We calculate the overall amount of resources that each Italian university receives from the central government and the local public authorities from the reclassified financial statements of Italian public universities (either state or regional) provided by the national committee for the evaluation of the Italian tertiary education system (CNVSU) for year 2004. This overall amount of resources measures the total costs of producing tertiary education at university level.

The regional total costs are obtained by summing up total costs accruing to all universities located in a given region. These regional total costs are then divided by the number of students enrolled in each region to end up with the average regional costs of providing public tertiary education. Notice that these average costs are net of the fees paid by the households and consequently they represent the costs actually borne by the government. We take account of students' mobility across regions by weighting each regional average costs by the probability that a student resident in a certain region is enrolled at a university in a different region. These probabilities are calculated using a 20×20 students' mobility matrix based on the enrollment statistics of MIUR.[27]

B Assessing family background to control for household heterogeneity

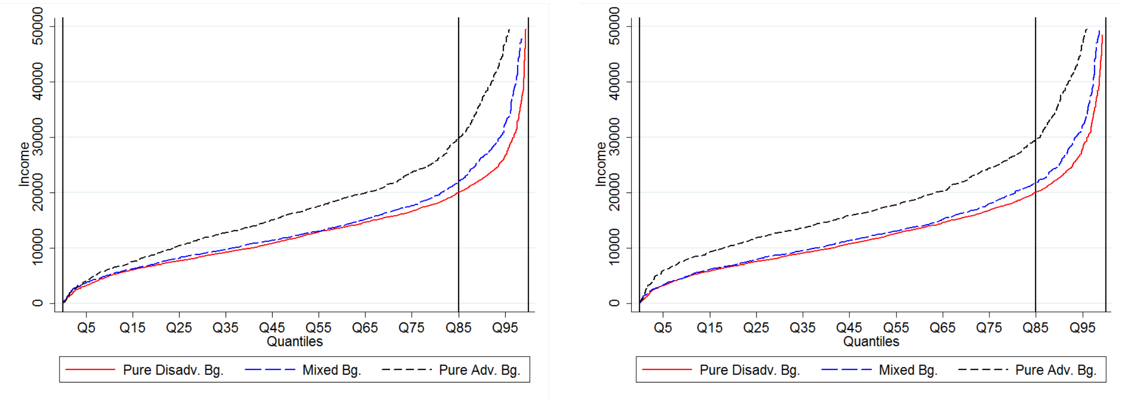
We use two family background indicators for either education or socio-economic position of the grand-parents to partition the observed families into homogeneous groups. These information can be found in SHIW.[28] We consider each of these two family background indicators separately to let different kinds of household unobserved characteristics be associated to different family background indicators.

[26]Households' out-of-pocket payments and other financial sources beyond government are excluded. Consequently, these average costs purely reflect public expenditures on education.

[27]SHIW 2004 data do not provide information on the university currently attended by the children. In Italy, generally, students enrolled at a university located in a region other than that of their parents' residence, use not to change their residence. In such a case, they would be surveyed by the Bank of Italy within the family.

[28]The 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 time preceding retirement or death)"*.

Figure 9: Measuring household unobservable characteristics related to family backgrounds.



(a) Grandparents' occupational conditions (b) Grandparents' level of education

We retain all households in the full dataset whose head aged from 33 to 60 years to avoid a fertility composition effect which may arise if we make use of our sample made of 2,030 families with children in education age. Then, we use 3,651 and 3,698 observations when referring to grandparental occupational conditions and level of education, respectively. The difference in observations between the two family background indicators is due to missing data.

We use a similar taxonomy as in Lefranc, Pistolesi and Trannoy (2009) to classify the grand-fathers (i.e. the fathers of both parents in an household) in the observed families according to their occupational status.[29] To maintain a parsimonious structure, we collapse grand-fathers' background information into two categories. The *disadvantaged grand-parental background* gathers the grand-fathers unemployed or employed either in agriculture or as an unskilled manual worker; and into an *advantaged grand-parental background*, comprising all the other cases. To account for the composite effect of having an advantaged or disadvantaged parental background from the side of both spouses, we consider three family background groups, defined according to the socioeconomic position of the fathers of both spouses. The first *purely disadvantaged background* group comprises all the families for which both grandfathers were disadvantaged. The second *purely advantaged background* group comprises all the families where both spouses' fathers were advantaged. Finally, the third residual group identifies a *mixed background* of origin.[30]

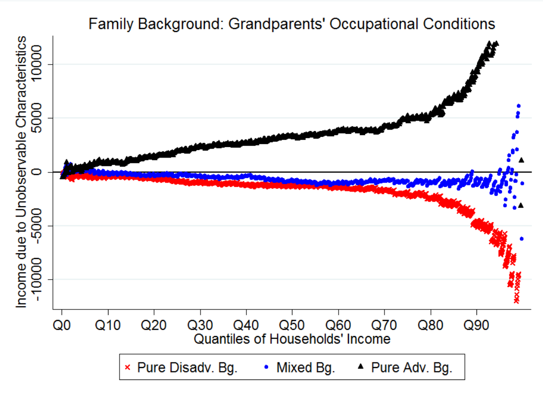
We repeat the classification also according to level of education of the grandparents. In this case, the purely disadvantaged (advantaged) background group includes all the households for which both spouses' parents had on average (more than) 5 years of education or lower.[31] The mixed group is defined by combining the two classes.

[29]Lefranc et al. (2009) apply this taxonomy to show that in France exists inequality of opportunities in income acquisition since individuals experiencing different social origins related to their father's occupation are not guaranteed an equal access to advantage in earning income. Following them, we consider only the grandfather's occupational background since a large part of the grandmothers were housewives.

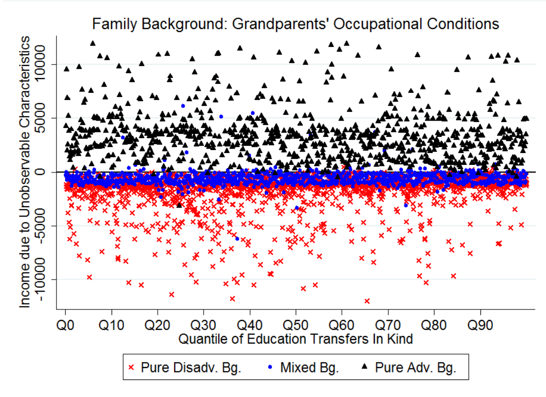
[30]In this group, we include also those families with missing information on the occupational background of the father of one of the two spouses.

[31]We fix the level of advantage to higher than 5 years of education level since enrollment in primary education reached 90% only in 1931. The presence of a double track schooling system weakened the enforceability of 8 years of compulsory education as dictated by both the Gentile's law and the article n.34

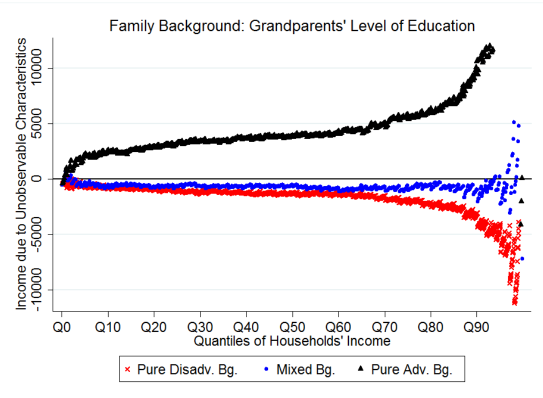
Figure 10: Deviations from quantile specific weighted average at family level, by grand-parental background.



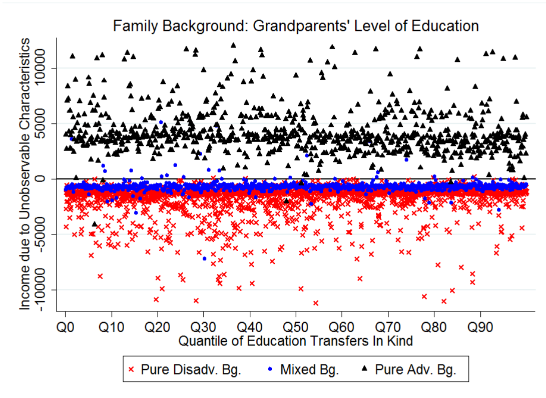
(a) Income quantiles



(b) Educational transfers in-kind quantiles



(c) Income quantiles



(d) Educational transfers in-Kind quantiles

Notes: Deviations from quantile specific incomes beyond the 1500 euros interval have been trimmed for presentation purposes.

For each of the three groups generated by each of the two backgrounds of interest, we rank households within each group according to their income. To isolate the contribution of the group of origin at fixed degree of unobservable characteristics (abilities), we compare for each background variable the income of a family at a given rank with the income that the family with the same abilities (identified by her position in the group specific distribution) would have reached if the background of origin were equalized across all families, thus expecting the average attainable income. This latter distribution would coincide with the distribution estimated from the whole sample. To obtain reliable estimates of this residual income measure, each group's population is partitioned into 100 percentiles according to the observed incomes of these households. The set of households in the same percentile relative to their group is denoted $P(p_j)$. This set gathers all families with similar abilities.

Using this set, we consider as a sufficient statistics [32] for the household unobservable

of the Italian Constitution (1948). It is only with Law n.1859, December 31st 1962, which abolished the second track (the *avviamento al lavoro*) of the schooling system, that all children were constrained until age 14 to follow a single program, encompassing primary education and lower secondary school.

[32] We construct this sufficient statistics exploiting what is known in the equality of opportunity literature

characteristics related to each of the two family background, the estimated residual $\widehat{\varepsilon}$ of the following regression model:

$$y_h = \sum_{j=1}^{100} \gamma_j \cdot \mathbf{1}\left[h \in P\left(p_j\right)\right] + \varepsilon_h, \tag{6}$$

where $\mathbf{1}[.]$ is an indicator function for the condition expressed in its argument to be satisfied. This indicator function is empirically captured by sets of dummies which take the value of 1 in correspondence of the rank occupied by the household in her group specific income distribution.

These residuals can be conceived as the empirical counterpart of the vertical distance between each family background specific quantile functions $F_t^{-1}(p)$, shown in figure 9, and the quantile functions of the whole sample income distribution.

To clarify the concept, families with positive residuals are those which have abilities that provide them an advantage in income with respect to the other households experiencing different family background but sitting in the same percentile. These disadvantaged households would counterfactually have the same income realization of the advantaged one if grown-up in a different family background. Given this setting, there are no differences in families' abilities with respect to any of the two (or both) grandparental backgrounds when the corresponding residuals are equal to zero for each percentile of the income distribution in such a way that the family background specific distributions are identical. In figure 10 we plot these residuals across the quantile distributions of both income and educational transfers in-kind.

as the Roemer Identification Assumption (RIA) to accounting for effort in income, (see Roemer 1998).

C Additional materials not intended for publication

Table 5: Structural quantile treatment effects: main sample.

Ind. variable:	**Quantiles Educational Transfers In-kind**				
	$\tau_K : 20\%$	$\tau_K : 30\%$	$\tau_K : 50\%$	$\tau_K : 70\%$	$\tau_K : 80\%$
	(1)	(2)	(3)	(4)	(5)
τ_Y: 20%					
Income	-1.252***	-1.343***	-1.330***	-1.385***	-1.437***
	(0.10)	(0.07)	(0.06)	(0.05)	(0.05)
Location shift	1.267***	1.358***	1.322***	1.375***	1.418***
	(0.10)	(0.07)	(0.06)	(0.05)	(0.05)
τ_Y: 30%					
Income	-0.982***	-1.050***	-1.046***	-1.089***	-1.132***
	(0.09)	(0.06)	(0.04)	(0.04)	(0.04)
Location shift	0.994***	1.064***	1.037***	1.079***	1.113***
	(0.09)	(0.06)	(0.04)	(0.04)	(0.04)
τ_Y: 50%					
Income	-1.084***	-1.161***	-1.156***	-1.203***	-1.251***
	(0.08)	(0.06)	(0.05)	(0.04)	(0.11)
Location shift	1.096***	1.172***	1.147***	1.193***	1.232***
	(0.08)	(0.06)	(0.05)	(0.04)	(0.10)
τ_Y: 70%					
Income	-0.840***	-0.900***	-0.898***	-0.937***	-0.972***
	(0.06)	(0.05)	(0.04)	(0.03)	(0.03)
Location shift	0.849***	0.908***	0.889***	0.925***	0.954***
	(0.07)	(0.05)	(0.04)	(0.04)	(0.03)
τ_Y: 80%					
Income	-0.683***	-0.730***	-0.726***	-0.761***	-0.790***
	(0.05)	(0.04)	(0.03)	(0.03)	(0.08)
Location shift	0.690***	0.737***	0.718***	0.749***	0.772***
	(0.05)	(0.04)	(0.03)	(0.03)	(0.09)

Note: Bootstrapped standard errors are reported in parentheses.

Table 6: Structural quantile treatment effects: main sample.

Ind. variable:	**Quantiles Educational Transfers In-kind**				
	$\tau_K : 20\%$	$\tau_K : 30\%$	$\tau_K : 50\%$	$\tau_K : 70\%$	$\tau_K : 80\%$
	(1)	(2)	(3)	(4)	(5)
τ_Y: 20%					
FB1	0.628***	0.698***	0.675***	0.713***	0.724***
	(0.07)	(0.06)	(0.04)	(0.04)	(0.04)
FB2	0.399***	0.396***	0.413***	0.423***	0.434***
	(0.06)	(0.04)	(0.04)	(0.03)	(0.04)
τ_Y: 30%					
FB1	0.613***	0.682***	0.661***	0.698***	0.709***
	(0.08)	(0.06)	(0.04)	(0.04)	(0.04)
FB2	0.332***	0.321***	0.341***	0.347***	0.355***
	(0.06)	(0.04)	(0.04)	(0.04)	(0.04)
τ_Y: 50%					
FB1	0.839***	0.924***	0.899***	0.945***	0.965***
	(0.08)	(0.06)	(0.05)	(0.04)	(0.05)
FB2	0.404***	0.400***	0.416***	0.425***	0.436***
	(0.06)	(0.04)	(0.04)	(0.04)	(0.08)
τ_Y: 70%					
FB1	0.713***	0.790***	0.764***	0.806***	0.820***
	(0.07)	(0.06)	(0.05)	(0.04)	(0.04)
FB2	0.365***	0.360***	0.377***	0.384***	0.394***
	(0.06)	(0.04)	(0.04)	(0.03)	(0.04)
τ_Y: 80%					
FB1	0.558***	0.620***	0.594***	0.629***	0.639***
	(0.06)	(0.05)	(0.04)	(0.03)	(0.13)
FB2	0.337***	0.333***	0.346***	0.354***	0.362***
	(0.05)	(0.04)	(0.04)	(0.03)	(0.04)

Note: Bootstrapped standard errors are reported in parentheses.

Table 7: Structural quantile treatment effects: compulsory education.

Ind. variable:	**Quantiles Educational Transfers In-kind**				
	τ_K : 20%	τ_K : 30%	τ_K : 50%	τ_K : 70%	τ_K : 80%
	(1)	(2)	(3)	(4)	(5)
τ_Y: 20%					
Income	0.289	0.211***	-0.251**	-1.114***	-1.403***
	(0.23)	(0.07)	(0.12)	(0.13)	(0.16)
Location shift	-0.276	-0.194***	0.291**	1.131***	1.424***
	(0.27)	(0.08)	(0.13)	(0.13)	(0.16)
τ_Y: 30%					
Income	0.279***	0.205***	-0.241**	-1.075***	-1.353***
	(0.05)	(0.07)	(0.12)	(0.13)	(0.08)
Location shift	-0.267***	-0.188**	0.280**	1.091***	1.373***
	(0.05)	(0.08)	(0.13)	(0.13)	(0.08)
τ_Y: 50%					
Income	0.055***	0.046***	-0.014	-0.168***	-0.214***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Location shift	-0.041***	-0.030**	0.048**	0.177***	0.226***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
τ_Y: 70%					
Income	0.169***	0.130***	-0.133**	-0.633***	-0.792***
	(0.03)	(0.04)	(0.06)	(0.08)	(0.05)
Location shift	-0.157***	-0.114***	0.169***	0.647***	0.810***
	(0.03)	(0.04)	(0.06)	(0.08)	(0.05)
τ_Y: 80%					
Income	0.149***	0.114***	-0.114**	-0.549***	-0.685***
	(0.02)	(0.04)	(0.05)	(0.07)	(0.04)
Location shift	-0.138***	-0.099**	0.149***	0.562***	0.702***
	(0.03)	(0.04)	(0.06)	(0.07)	(0.04)

Note: Bootstrapped standard errors are reported in parentheses.

Table 8: Structural quantile treatment effects: compulsory education.

Ind. variable:	**Quantiles Educational Transfers In-kind**				
	τ_K : 20%	τ_K : 30%	τ_K : 50%	τ_K : 70%	τ_K : 80%
	(1)	(2)	(3)	(4)	(5)
τ_Y: 20%					
FB1	-0.150	-0.113**	0.030	0.278***	0.395***
	(0.10)	(0.05)	(0.09)	(0.07)	(0.06)
FB2	-0.121	-0.066	0.220**	0.735***	0.867***
	(0.11)	(0.06)	(0.10)	(0.09)	(0.14)
τ_Y: 30%					
FB1	-0.171***	-0.129**	0.058	0.365***	0.508***
	(0.05)	(0.05)	(0.08)	(0.08)	(0.06)
FB2	-0.095**	-0.047	0.187**	0.625***	0.727***
	(0.05)	(0.06)	(0.09)	(0.07)	(0.06)
τ_Y: 50%					
FB1	-0.001	-0.009	-0.105*	-0.305***	-0.361***
	(0.03)	(0.04)	(0.06)	(0.06)	(0.05)
FB2	-0.026	0.007	0.097*	0.307***	0.340***
	(0.03)	(0.04)	(0.05)	(0.06)	(0.05)
τ_Y: 70%					
FB1	-0.186***	-0.140***	0.086	0.436***	0.582***
	(0.04)	(0.05)	(0.07)	(0.08)	(0.06)
FB2	-0.076	-0.036	0.161*	0.545***	0.629***
	(0.05)	(0.05)	(0.09)	(0.07)	(0.06)
τ_Y: 80%					
FB1	-0.147***	-0.110**	0.049	0.276***	0.385***
	(0.04)	(0.04)	(0.07)	(0.07)	(0.06)
FB2	-0.082*	-0.040	0.167*	0.568***	0.653***
	(0.05)	(0.05)	(0.09)	(0.07)	(0.06)

Note: Bootstrapped standard errors are reported in parentheses.

Table 9: Homogeneity tests.

Panel (a): 20th and 80th quantiles of K, given τ_Y				
τ_Y : 20%	τ_Y : 30%	τ_Y : 50%	τ_Y : 70%	τ_Y : 80%
1.692***	1.633***	0.268***	0.960***	0.833***
(0.28)	(0.09)	(0.02)	(0.05)	(0.04)
Panel (b): 20th and 80th quantiles of Y, given τ_K				
τ_K : 20%	τ_K : 30%	τ_K : 50%	τ_K : 70%	τ_K : 80%
0.140	0.098	-0.137	-0.565***	-0.717***
(0.24)	(0.08)	(0.13)	(0.14)	(0.17)

Note: The Table reports the homogeneity tests of marginal quantile treatment effects of income, for compulsory education. Panel (a) displays the difference between the marginal income effects estimated at the 20th and the 80th quantiles of educational transfers in-kind distribution, fixing quantiles of the household income capacity. Panel (b) displays instead the difference between the marginal income effects estimated at the 20th and the 80th quantiles of the household income capacity, fixing quantiles of the educational transfers in-kind distribution. Standard errors are reported in parentheses.

Table 10: Structural quantile treatment effects: upper secondary education.

Ind. variable:	**Quantiles Educational Transfers In-kind**				
	τ_K : 20%	τ_K : 30%	τ_K : 50%	τ_K : 70%	τ_K : 80%
	(1)	(2)	(3)	(4)	(5)
τ_Y: 20%					
Income	0.409***	0.412***	0.397***	0.206**	0.152
	(0.06)	(0.05)	(0.04)	(0.09)	(0.12)
Location shift	-0.386***	-0.391***	-0.384***	-0.223**	-0.174
	(0.06)	(0.05)	(0.04)	(0.09)	(0.13)
τ_Y: 30%					
Income	0.446***	0.424***	0.409***	0.215***	0.154
	(0.06)	(0.05)	(0.04)	(0.08)	(0.11)
Location shift	-0.427***	-0.403***	-0.396***	-0.232***	-0.176
	(0.07)	(0.05)	(0.05)	(0.08)	(0.12)
τ_Y: 50%					
Income	0.390***	0.371***	0.360***	0.183**	0.138
	(0.06)	(0.04)	(0.04)	(0.07)	(0.11)
Location shift	-0.371***	-0.353***	-0.351***	-0.199***	-0.158
	(0.06)	(0.05)	(0.04)	(0.07)	(0.12)
τ_Y: 70%					
Income	0.399***	0.380***	0.368***	0.194**	0.148
	(0.06)	(0.05)	(0.04)	(0.08)	(0.11)
Location shift	-0.382***	-0.365***	-0.361***	-0.209***	-0.169
	(0.06)	(0.05)	(0.04)	(0.08)	(0.12)
τ_Y: 80%					
Income	0.521***	0.506***	0.495***	0.273***	0.210
	(0.09)	(0.06)	(0.06)	(0.10)	(0.15)
Location shift	-0.506***	-0.491***	-0.492***	-0.287***	-0.231
	(0.09)	(0.07)	(0.06)	(0.10)	(0.16)

Note: Bootstrapped standard errors are reported in parentheses.

Table 11: Structural quantile treatment effects: upper secondary education.

Ind. variable:	**Quantiles Educational Transfers In-kind**				
	τ_K : 20%	τ_K : 30%	τ_K : 50%	τ_K : 70%	τ_K : 80%
	(1)	(2)	(3)	(4)	(5)
τ_Y: 20%					
FB1	-0.127***	-0.118***	-0.114***	-0.020	0.010
	(0.04)	(0.03)	(0.04)	(0.06)	(0.08)
FB2	0.133***	0.134***	0.154***	0.138**	0.104
	(0.04)	(0.03)	(0.04)	(0.07)	(0.09)
τ_Y: 30%					
FB1	-0.174***	-0.156***	-0.150***	-0.038	-0.004
	(0.04)	(0.03)	(0.05)	(0.07)	(0.09)
FB2	0.004	-0.004	0.018	0.058	0.048
	(0.03)	(0.03)	(0.04)	(0.06)	(0.08)
τ_Y: 50%					
FB1	-0.202***	-0.189***	-0.181***	-0.051	-0.013
	(0.04)	(0.04)	(0.04)	(0.06)	(0.09)
FB2	0.027	0.028	0.040	0.067	0.057
	(0.03)	(0.03)	(0.04)	(0.06)	(0.07)
τ_Y: 70%					
FB1	-0.233***	-0.223***	-0.205***	-0.070	-0.018
	(0.04)	(0.04)	(0.05)	(0.07)	(0.10)
FB2	-0.016	-0.007	0.004	0.056	0.034
	(0.03)	(0.03)	(0.04)	(0.06)	(0.08)
τ_Y: 80%					
FB1	-0.329***	-0.316***	-0.302***	-0.131	-0.061
	(0.05)	(0.05)	(0.05)	(0.08)	(0.11)
FB2	0.003	0.006	0.015	0.070	0.041
	(0.03)	(0.03)	(0.04)	(0.06)	(0.09)

Note: Bootstrapped standard errors are reported in parentheses.

Table 12: Homogeneity tests.

Panel (a): 20th and 80th quantiles of K, given τ_Y				
τ_Y : 20%	τ_Y : 30%	τ_Y : 50%	τ_Y : 70%	τ_Y : 80%
0.249**	0.287**	0.249**	0.252**	0.316*
(0.12)	(0.11)	(0.12)	(0.11)	(0.16)
Panel (b): 20th and 80th quantiles of Y, given τ_K				
τ_K : 20%	τ_K : 30%	τ_K : 50%	τ_K : 70%	τ_K : 80%
-0.113	-0.094	-0.098	-0.067	-0.057
(0.11)	(0.08)	(0.07)	(0.13)	(0.19)

Note: The Table reports the homogeneity tests of marginal quantile treatment effects of income, upper secondary education. Panel (a) displays the difference between the marginal income effects estimated at the 20th and the 80th quantiles of educational transfers in-kind distribution, fixing quantiles of the household income capacity. Panel (b) displays instead the difference between the marginal income effects estimated at the 20th and the 80th quantiles of the household income capacity, fixing quantiles of the educational transfers in-kind distribution. Standard errors are reported in parentheses.

Table 13: Structural quantile treatment effects.
Compulsory education including kindergarten.

Ind. variable:	**Quantiles Educational Transfers In-kind**				
	$\tau_K : 20\%$	$\tau_K : 30\%$	$\tau_K : 50\%$	$\tau_K : 70\%$	$\tau_K : 80\%$
	(1)	(2)	(3)	(4)	(5)
τ_Y: 20%					
Income	-0.019	-0.530***	-1.582***	-2.140***	-2.233***
	(0.13)	(0.16)	(0.21)	(0.18)	(0.10)
Location shift	0.053	0.567***	1.608***	2.148***	2.223***
	(0.14)	(0.16)	(0.21)	(0.18)	(0.10)
τ_Y: 30%					
Income	-0.008	-0.394***	-1.187***	-1.613***	-1.685***
	(0.11)	(0.13)	(0.12)	(0.07)	(0.07)
Location shift	0.041	0.430***	1.213***	1.621***	1.675***
	(0.11)	(0.13)	(0.12)	(0.07)	(0.07)
τ_Y: 50%					
Income	-0.001	-0.323***	-0.990***	-1.352***	-1.412***
	(0.09)	(0.11)	(0.10)	(0.06)	(0.07)
Location shift	0.033	0.358***	1.015***	1.359***	1.402***
	(0.10)	(0.11)	(0.10)	(0.06)	(0.07)
τ_Y: 70%					
Income	0.000	-0.275***	-0.852***	-1.166***	-1.218***
	(0.08)	(0.10)	(0.09)	(0.05)	(0.05)
Location shift	0.031	0.308***	0.874***	1.172***	1.209***
	(0.08)	(0.10)	(0.09)	(0.05)	(0.05)
τ_Y: 80%					
Income	-0.002	-0.266***	-0.828***	-1.129***	-1.181***
	(0.12)	(0.09)	(0.08)	(0.05)	(0.05)
Location shift	0.033	0.298***	0.849***	1.135***	1.173***
	(0.12)	(0.10)	(0.08)	(0.05)	(0.05)

Note: Bootstrapped standard errors are reported in parentheses.

Table 14: Structural quantile treatment effects.
Compulsory education including kindergarten.

Ind. variable:	**Quantiles Educational Transfers In-kind**				
	τ_K : 20%	τ_K : 30%	τ_K : 50%	τ_K : 70%	τ_K : 80%
	(1)	(2)	(3)	(4)	(5)
τ_Y: 20%					
FB1	-0.007	0.165**	0.500***	0.635***	0.687***
	(0.06)	(0.07)	(0.06)	(0.08)	(0.06)
FB2	0.022	0.303***	0.862***	1.203***	1.235***
	(0.08)	(0.10)	(0.13)	(0.11)	(0.07)
τ_Y: 30%					
FB1	-0.009	0.150**	0.460***	0.581***	0.630***
	(0.06)	(0.07)	(0.05)	(0.06)	(0.06)
FB2	0.013	0.204***	0.573***	0.819***	0.837***
	(0.06)	(0.08)	(0.08)	(0.05)	(0.05)
τ_Y: 50%					
FB1	-0.002	0.249***	0.735***	0.954***	1.015***
	(0.09)	(0.09)	(0.08)	(0.07)	(0.08)
FB2	0.014	0.197**	0.563***	0.805***	0.820***
	(0.06)	(0.08)	(0.08)	(0.05)	(0.06)
τ_Y: 70%					
FB1	-0.001	0.232**	0.683***	0.881***	0.941***
	(0.08)	(0.09)	(0.08)	(0.07)	(0.08)
FB2	0.008	0.124*	0.360***	0.537***	0.542***
	(0.05)	(0.07)	(0.08)	(0.05)	(0.05)
τ_Y: 80%					
FB1	-0.006	0.193**	0.576***	0.736***	0.792***
	(0.10)	(0.08)	(0.06)	(0.05)	(0.07)
FB2	0.011	0.125*	0.363***	0.541***	0.547***
	(0.07)	(0.07)	(0.07)	(0.04)	(0.05)

Note: Bootstrapped standard errors are reported in parentheses.

Table 15: Homogeneity tests.

Panel (a): 20th and 80th quantiles of K, given τ_Y				
$\tau_Y : 20\%$	$\tau_Y : 30\%$	$\tau_Y : 50\%$	$\tau_Y : 70\%$	$\tau_Y : 80\%$
2.211***	1.676***	1.410***	1.220***	1.181***
(0.16)	(0.12)	(0.11)	(0.09)	(0.13)
Panel (b): 20th and 80th quantiles of Y, given τ_K				
$\tau_K : 20\%$	$\tau_K : 30\%$	$\tau_K : 50\%$	$\tau_K : 70\%$	$\tau_K : 80\%$
-0.017	-0.264	-0.755***	-1.011***	-1.052***
(0.18)	(0.18)	(0.22)	(0.18)	(0.11)

Note: The Table reports the homogeneity tests of marginal quantile treatment effects of income, compulsory education including kindergarten. Panel (a) displays the difference between the marginal income effects estimated at the 20th and the 80th quantiles of educational transfers in-kind distribution, fixing quantiles of the household income capacity. Panel (b) displays instead the difference between the marginal income effects estimated at the 20th and the 80th quantiles of the household income capacity, fixing quantiles of the educational transfers in-kind distribution. Standard errors are reported in parentheses.

Table 16: Structural quantile treatment effects: tertiary education.

Ind. variable:	**Quantiles Educational Transfers In-kind**				
	$\tau_K : 20\%$	$\tau_K : 30\%$	$\tau_K : 50\%$	$\tau_K : 70\%$	$\tau_K : 80\%$
	(1)	(2)	(3)	(4)	(5)
τ_Y: 20%					
Income	0.049	0.153**	0.217***	0.286***	0.339***
	(0.06)	(0.07)	(0.05)	(0.06)	(0.08)
Location shift	-0.024	-0.149**	-0.205***	-0.279***	-0.332***
	(0.06)	(0.07)	(0.05)	(0.06)	(0.07)
τ_Y: 30%					
Income	0.041	0.152**	0.215***	0.286***	0.338***
	(0.06)	(0.06)	(0.05)	(0.06)	(0.07)
Location shift	-0.017	-0.150**	-0.205***	-0.281***	-0.337***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)
τ_Y: 50%					
Income	0.031	0.127**	0.189***	0.252***	0.311***
	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)
Location shift	-0.010	-0.127**	-0.180***	-0.248***	-0.314***
	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)
τ_Y: 70%					
Income	0.023	0.090**	0.142***	0.185***	0.234***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Location shift	-0.007	-0.094**	-0.140***	-0.185***	-0.237***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
τ_Y: 80%					
Income	0.021	0.088**	0.146***	0.193***	0.245***
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Location shift	-0.005	-0.093**	-0.146***	-0.195***	-0.250***
	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)

Note: Bootstrapped standard errors are reported in parentheses.

Table 17: Structural quantile treatment effects: tertiary education.

Ind. variable:	**Quantiles Educational Transfers In-kind**				
	$\tau_K : 20\%$	$\tau_K : 30\%$	$\tau_K : 50\%$	$\tau_K : 70\%$	$\tau_K : 80\%$
	(1)	(2)	(3)	(4)	(5)
τ_Y: 20%					
FB1	-0.102	-0.213**	-0.232***	-0.305***	-0.390***
	(0.10)	(0.11)	(0.08)	(0.09)	(0.08)
FB2	0.151*	0.077	0.003	-0.042	-0.038
	(0.08)	(0.08)	(0.05)	(0.08)	(0.09)
τ_Y: 30%					
FB1	-0.095	-0.236**	-0.266***	-0.352***	-0.443***
	(0.10)	(0.11)	(0.10)	(0.10)	(0.10)
FB2	0.154**	0.101	0.035	0.005	0.020
	(0.07)	(0.07)	(0.05)	(0.07)	(0.08)
τ_Y: 50%					
FB1	-0.082	-0.197**	-0.220**	-0.290***	-0.374***
	(0.10)	(0.10)	(0.09)	(0.08)	(0.08)
FB2	0.151**	0.096	0.025	-0.010	-0.012
	(0.08)	(0.08)	(0.07)	(0.07)	(0.08)
τ_Y: 70%					
FB1	-0.070	-0.149*	-0.160**	-0.199**	-0.256***
	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)
FB2	0.148*	0.092	0.018	-0.014	-0.021
	(0.08)	(0.07)	(0.05)	(0.07)	(0.08)
τ_Y: 80%					
FB1	-0.074	-0.174*	-0.208***	-0.262***	-0.335***
	(0.09)	(0.10)	(0.08)	(0.09)	(0.08)
FB2	0.152**	0.119	0.059	0.040	0.043
	(0.07)	(0.08)	(0.05)	(0.07)	(0.08)

Note: Bootstrapped standard errors are reported in parentheses.

Table 18: Homogeneity tests.

Panel (a): 20th and 80th quantiles of K, given τ_Y				
$\tau_Y : 20\%$	$\tau_Y : 30\%$	$\tau_Y : 50\%$	$\tau_Y : 70\%$	$\tau_Y : 80\%$
-0.291***	-0.299***	-0.280***	-0.209***	-0.220***
(0.09)	(0.08)	(0.07)	(0.06)	(0.06)
Panel (b): 20th and 80th quantiles of Y, given τ_K				
$\tau_K : 20\%$	$\tau_K : 30\%$	$\tau_K : 50\%$	$\tau_K : 70\%$	$\tau_K : 80\%$
0.027	0.064	0.071	0.093	0.097
(0.08)	(0.08)	(0.06)	(0.08)	(0.09)

Note: The Table reports the homogeneity tests of marginal quantile treatment effects of income, tertiary education. Panel (a) displays the difference between the marginal income effects estimated at the 20th and the 80th quantiles of educational transfers in-kind distribution, fixing quantiles of the household income capacity. Panel (b) displays instead the difference between the marginal income effects estimated at the 20th and the 80th quantiles of the household income capacity, fixing quantiles of the educational transfers in-kind distribution. Standard errors are reported in parentheses.

Table 19: Structural quantile treatment effects: post compulsory education.

Ind. variable:	**Quantiles Educational Transfers In-kind**				
	τ_K : 20%	τ_K : 30%	τ_K : 50%	τ_K : 70%	τ_K : 80%
	(1)	(2)	(3)	(4)	(5)
τ_Y: 20%					
Income	0.244**	0.365***	0.310***	0.008	-0.109
	(0.10)	(0.08)	(0.06)	(0.08)	(0.11)
Location shift	-0.222**	-0.360***	-0.319***	-0.031	0.075
	(0.11)	(0.08)	(0.06)	(0.09)	(0.12)
τ_Y: 30%					
Income	0.210***	0.305***	0.265***	0.004	-0.098
	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)
Location shift	-0.194**	-0.302***	-0.274***	-0.028	0.065
	(0.08)	(0.07)	(0.07)	(0.08)	(0.09)
τ_Y: 50%					
Income	0.210***	0.278***	0.248***	0.006	-0.092
	(0.07)	(0.06)	(0.05)	(0.07)	(0.08)
Location shift	-0.199**	-0.277***	-0.257***	-0.030	0.061
	(0.08)	(0.07)	(0.05)	(0.07)	(0.09)
τ_Y: 70%					
Income	0.151***	0.192***	0.168***	0.002	-0.067
	(0.05)	(0.05)	(0.04)	(0.04)	(0.06)
Location shift	-0.147***	-0.192***	-0.178***	-0.026	0.039
	(0.06)	(0.05)	(0.04)	(0.05)	(0.06)
τ_Y: 80%					
Income	0.147***	0.192***	0.166***	0.003	-0.065
	(0.05)	(0.04)	(0.04)	(0.05)	(0.06)
Location shift	-0.143**	-0.193***	-0.176***	-0.025	0.036
	(0.06)	(0.05)	(0.04)	(0.05)	(0.07)

Note: Bootstrapped standard errors are reported in parentheses.

Table 20: Structural quantile treatment effects: post compulsory education.

Ind. variable:	**Quantiles Educational Transfers In-kind**				
	τ_K : 20%	τ_K : 30%	τ_K : 50%	τ_K : 70%	τ_K : 80%
	(1)	(2)	(3)	(4)	(5)
τ_Y: 20%					
FB1	-0.111	-0.222***	-0.175***	-0.012	0.081
	(0.10)	(0.07)	(0.05)	(0.06)	(0.08)
FB2	-0.045	-0.050	-0.056	0.043	0.060
	(0.07)	(0.05)	(0.04)	(0.05)	(0.06)
τ_Y: 30%					
FB1	-0.122	-0.256***	-0.210***	-0.016	0.091
	(0.10)	(0.07)	(0.06)	(0.07)	(0.08)
FB2	-0.030	-0.010	-0.023	0.047	0.053
	(0.06)	(0.04)	(0.04)	(0.05)	(0.06)
τ_Y: 50%					
FB1	-0.138	-0.252***	-0.211***	-0.019	0.091
	(0.10)	(0.07)	(0.06)	(0.07)	(0.09)
FB2	-0.046	-0.034	-0.046	0.046	0.061
	(0.06)	(0.05)	(0.04)	(0.05)	(0.05)
τ_Y: 70%					
FB1	-0.094	-0.172**	-0.137***	-0.015	0.069
	(0.09)	(0.07)	(0.05)	(0.06)	(0.07)
FB2	-0.047	-0.040	-0.050	0.043	0.063
	(0.06)	(0.05)	(0.04)	(0.05)	(0.06)
τ_Y: 80%					
FB1	-0.092	-0.183***	-0.140***	-0.015	0.070
	(0.09)	(0.06)	(0.05)	(0.06)	(0.07)
FB2	-0.044	-0.031	-0.043	0.043	0.064
	(0.06)	(0.05)	(0.04)	(0.05)	(0.06)

Note: Bootstrapped standard errors are reported in parentheses.

Table 21: Homogeneity tests.

Panel (a): 20th and 80th quantiles of K, given τ_Y				
τ_Y : 20%	τ_Y : 30%	τ_Y : 50%	τ_Y : 70%	τ_Y : 80%
0.346***	0.304***	0.301***	0.219***	0.214***
(0.13)	(0.10)	(0.10)	(0.07)	(0.07)
Panel (b): 20th and 80th quantiles of Y, given τ_K				
τ_K : 20%	τ_K : 30%	τ_K : 50%	τ_K : 70%	τ_K : 80%
0.095	0.173*	0.143*	0.005	-0.044
(0.12)	(0.09)	(0.07)	(0.09)	(0.12)

Note: The Table reports the homogeneity tests of marginal quantile treatment effects of income, post-compulsory education. Panel (a) displays the difference between the marginal income effects estimated at the 20th and the 80th quantiles of educational transfers in-kind distribution, fixing quantiles of the household income capacity. Panel (b) displays instead the difference between the marginal income effects estimated at the 20th and the 80th quantiles of the household income capacity, fixing quantiles of the educational transfers in-kind distribution. Standard errors are reported in parentheses.