Who Benefits from Public Education Provision? Evidence from Italy

Francesco Andreoli (CEPS/INSTEAD, Luxembourg, and University of Verona, Italy)

Giorgia Casalone (University of Verona, Italy)

Daniela Sonedda (University of the Eastern Piedmont Amedeo Avogadro, Italy)

Paper Prepared for the IARIW 33rd General Conference

Rotterdam, the Netherlands, August 24-30, 2014

Session 6C

Time: Thursday, August 28, Afternoon

Who benefits from public education provision? Evidence from Italy.*

Francesco Andreoli[a,b], Giorgia Casalone[c], and Daniela Sonedda[c,†]

[a] *CEPS/INSTEAD 4, avenue de la Fonte, L-4364 Esch sur Alzette, Luxembourg*
[b] *University of Verona, Via dell'Artigliere 19, I-37129 Verona, Italy.*
[c] *University of the Eastern Piedmont Amedeo Avogadro, via Perrone 18, I-28100 Novara, Italy.*

July 2014

Abstract

Public education provision is redistributive when rich families, who contribute to its financing, find it optimal to sort out of the public system and buy the educational services on the private market. This may occur if the quality of the educational services is lower in the public sector than it is in the private. We estimate structural quantile treatment effects to analyze the mechanisms behind the redistributiveness of public education provision using Italian data. We exploit heterogeneity in expected tax deductions to exogenously manipulate the 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 the educational transfers in kind. 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 (ii) more for lower quantiles of the households' earning capacity. Our findings explain how, for compulsory schooling, the households' sorting into private education may motivate a government, that aims at redistributing resources from the rich to the poor, to use public education provision as transfers in-kind.

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

JEL Codes: H40, D30, I20.

---

*We are grateful to Rolf Aaberge, Erich Battistin, Lorenzo Cappellari, Daniele Checchi, Carlo Fiorio, Paolo Ghinetti, Arnaud Lefranc, Enrico Rettore, Francesca Zantomio and Claudio Zoli for valuable comments. We thank participants at conferences and seminars held at Aix-en-Provence (LAGV), Bari (ECINEQ), Canazei, IRVAPP, Novara, Pavia and Torino for useful comments. We also thank Carlo Fiorio for kindly providing us data on gross income and personal income taxes. We are fully responsible for any errors.

†Corresponding author.

Contacts: `francescondrl@gmail.com` (F. Andreoli), `giorgia.casalone@eco.unipmn.it` (G. Casalone) and `daniela.sonedda@eco.unipmn.it` (D. Sonedda).

1 Introduction

In Italy, as in many other countries, public education provision and free accessibility to compulsory education are fundamental constitutional rights. Determining the optimal amount of resources devoted to finance educational services is a relevant economic issue. As largely recognized, public education provision, together with health care, account for a substantial share of the public budget in countries with developed welfare states. Several reasons justify this spending: among them, a redistributive motive (see Aaberge, Langorgen and Lindgren 2013).

This paper aims at analyzing the mechanisms behind the redistributiveness of public education provision using Italian data. Public education provision is redistributive as far as more affluent families, who contribute to its financing, find it optimal to sort out of the public system, and buy the educational services on the private market. Different reasons may justify why families choose private schools. We will focus on the interplay between the family resources and school quality, although other factors such as the support of common values (e.g., religion (Sander 2001) and status symbol (Fershtman, Murphy and Weiss 1996)) also play a relevant role.

There is a long tradition within the human capital investment models (see for instance Stiglitz 1974) of claiming that the quality embedded in private schools is higher than in public schools. If this is the case, since quality is a normal good, rich households prefer an higher amount of this quality level, and they may opt out for private education even if having to pay for it. 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).

The choice of producing a lower quality level in the public sector is at the heart of the redistributive nature of educational transfers in-kind. This paper focuses on a specific mechanism operating through the quality of the education system, according to which the different sorting of the families into private schooling may motivate a government, that aims at redistributing resources from the rich to the poor, to use public education provision as transfers in-kind. 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).

The policymaker with redistributive intents imposes costs that may take the form of restrictions on the quality of the public educational service, or on the heterogeneity and personalization of the curricula. Such 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 of the households with higher earning 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). The quality of public education should be, however, high enough to insure an adequate service to low income families, who would otherwise bear only the cost associated to this mechanism. 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 service. Whether the mechanism also works in post-mandatory education (i.e. for families with kids 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 kid's education that are positively correlated with family income. Second, the quality of private schooling for upper secondary education is not necessarily higher than that related to public schools. This occurs, for instance, in Italy as a consequence of the demand for private education of less talented kids coming from rich households (Bertola, Checchi and Oppedisano 2007, Bertola and Checchi 2013).

This paper proposes to convert the quality of the public education provision, interpreted as educational transfers in-kind, 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 inexpensive public education. It represents a lower bound of the opportunity costs to choose private education. Following the standard practice, we assume that the value of the educational transfer in-kind received by each student is equal to the average cost of producing the services this student benefit from. Since one of the main component of this average cost of producing the public education services is the teacher-student ratio, our measure of the educational transfers in-kind reflects the objective quality of the public service.

One of the major difficulties in this type of analysis is related to data availability. 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. We make use of a study carried out exclusively for year 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. 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.

This paper contributes to the limited empirical evidence on the relationship between family income and educational transfers in-kind redistributiveness, by analyzing the premises of the mechanism driving the sorting process into public and private education among Italian households. At the heart of the sorting process into private education, there is the correlation between the unobservable family specific earning capacity and preference for quality of the education good. It is precisely their correlation that affects the incidence of the self-targeting mechanisms. To assign our results with a causal interpretation, we need to single out the exogenous effect of income. 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, the household's earning capacity determines the access into private education. We expect therefore that an increase in household income is associated with decreasing transfers in-kind that goes to the household with higher earning capacity. On the other hand, for a given degree of the household's earning capacity, proxied by the quantiles of the distribution of household earning capacity, the quality of public schools as measured by our transfers in-kind, may explain the sorting into private and public education. In this case, the magnitude of the negative relation between household income and the transfers in-kind she receives 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 large share of a marginal income gain into private education.

Our analysis 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 earning capacity. These results are strengthened when we confine our analysis to compulsory education only.

The rest of the paper is organized as follows. Section 2 sets the scene illustrating how and when public education provision is redistributive and describing the microsimulation exercise on the educational transfers in-kind. Section 3 describes the data, our instrument, and the method. Results and the discussion are reported in section 4. Finally, section 5 concludes.

2 Public education provision and in-kind transfers

2.1 Quality sorting and educational transfers in-kind

We illustrate through graphic analysis the mechanism connecting sorting on quality, household earning capacity, and private or public educational choices according to the model by Besley and Coate (1991), as presented by Gahvari and Mattos (2007). Assume that two goods are produced within the economy: a numeraire consumption good c and a publicly provided indivisible (education) good. Producers are assumed to behave competitively and p defines the price of quality at the margin under linear technology. There are two types of households: the poor households with low income y^P and the rich households with high income y^R, such that $y^P < y^R$. The publicly-provided educational services are financed by a personal tax T.

Households may choose to consume only one of the two variants of the education good produced in the sector while caring about its quality k (i.e. families may consume either private or public sector education) which is a normal good. The production of each variant of the educational services embodies a specific quality level. This implies that households with higher income levels may prefer to opt out for higher quality variants of the good even if this means having to support in full its cost in the private sector. To get redistribution through public education provision, however, the policymaker needs to implement a second or even third best allocation of resources.

Figure 1 allows to interpret the dynamic of the sorting mechanism. If household earning capacity was perfectly observable, AC would show the first-best frontier while the curve $DB'EF$ represents the utility feasibility frontier with public education provision. Let $\bar{k}$ be the value of the quality of educational services if publicly provided and let the point B correspond to a no transfer policies. In order to achieve redistribution, the Besley and Coate transfer scheme requires a separating equilibrium that satisfies the following incentive compatibility constraints:

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

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

where $u^R(y^R - T, \bar{k})$ and $u^P(y^P - T, \bar{k})$ denote the rich and poor households' utility if they were to consume the publicly provided educational services of quality $\bar{k}$; $V^R(p, y^R - T)$ and $V^P(p, y^P - T)$ define instead the indirect utility functions of the rich and the poor if they were to purchase the educational services from the market at price p. 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} (corresponding to point D) that

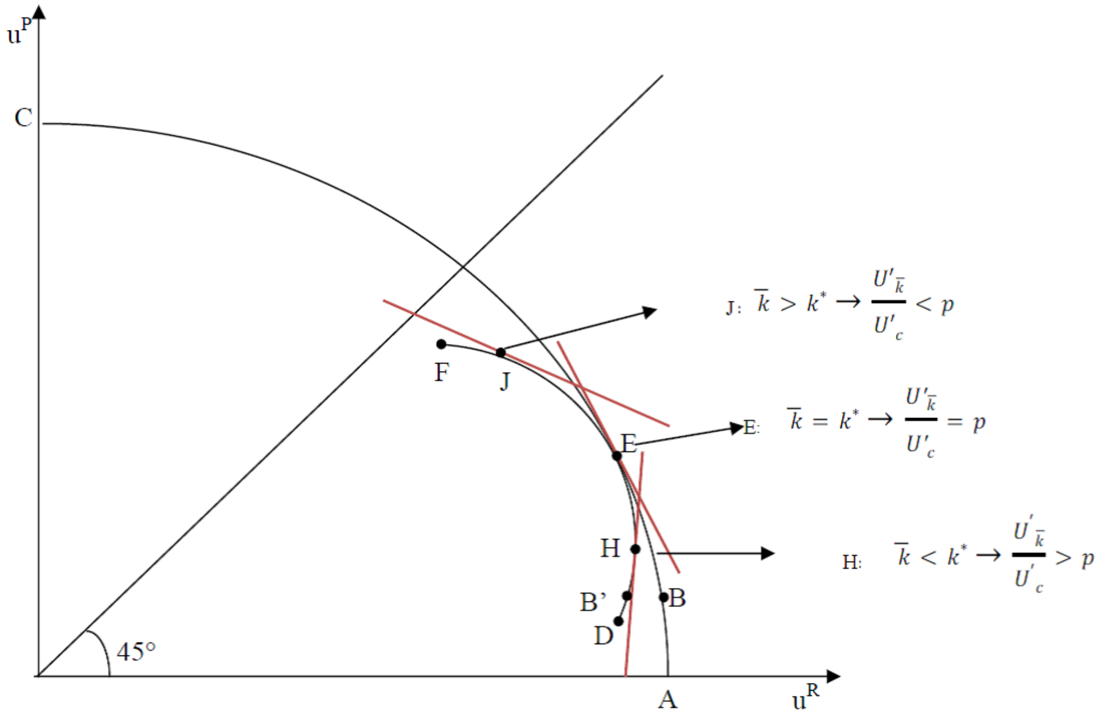


Figure 1: The Economy's Pareto Frontier (AC) and Utility Feasibility Frontier ($DB'EF$) with public education provision when $k_{max} > k^*$.

satisfies equation (1b), rich and poor families self-target with respect to participation to the program.

The same figure illustrates the deadweight loss associated to the program. Only point E is on the first best frontier corresponding to the efficient quality level k^* that makes the poor households indifferent between receiving one extra euro in cash and one extra euro worth of the publicly provided educational services such that $\frac{U'_{\bar{k}=k^*}}{U'_c} = p$.[1] 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.

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 redistributional packages. 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

[1] Figure 1 illustrates the case where $k_{max} \geq k^*$, when $k_{max} \leq k^*$ the utility feasibility frontier is everywhere inside the Pareto frontier.

receive its value in cash, remains unobservable. This implies a trade-off between the cost to the government to minimize the asymmetric information on the households' earning capacity and the deadweight loss inherent in an inefficient quality of the public provision of education.

2.2 Public educational services as transfers in-kind

The evaluation of educational transfers in-kind is an empirical demanding exercise whose difficulty motivates the little evidence about the behavior of the households in the sorting process into either private or public education.

One of the reason for this limitedness is data availability for educational transfers in-kind. 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 costs of producing it, denoted $AC(r, e)$, which is allowed to vary across Italian regions r and educational levels e.[2] 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 data collected by the Bank of Italy, SHIW (Survey on Households Income and Wealth) 2004 wave. We treat as recipients of the transfers all children in a family, aged between 3 and 5 years, and those aged from 6 to 23 years who classify themselves as *students* in the survey. Unfortunately, we do not observe the type (i.e. either private or public) of school attended by the students. Consequently, we assign to each student the cost of production of the education service he is consuming in his region of residence and for his educational level, discounted by the probability he has to benefit of public education. Denote this probability by $\omega(g)$, which is specific to a set g of household characteristics. It encapsulates the information on the school selection process from the side of the households. The monetary value of the educational transfer in-kind associated to each child c in family h of type g_h, who lives in region r_c and who is in educational level e_c is denoted:

$$k_c \;:=\; \omega(g_h) \cdot AC(r_c, e_c) \quad \text{for } c \in h. \tag{2}$$

To compute $\omega(g_h)$ we use ISTAT, Multiscopo Survey data for year 2005, the closest to year 2004, that provides information on whether the interviewed family has a child

[2] 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.

enrolled either in a private or in a public school.[3] We collapse those families with children in education into homogenous groups denoted by g according to 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.[4] For each group g, we use observed frequencies to determine the probabilities 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. The resulting distribution of in-kind transfers accruing to each child is heterogeneous across groups of families, regions and educational levels.[5]

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:

$$k_h = \sum_{c \in h} k_c. \tag{3}$$

The first source of heterogeneity in the distribution of k_h is related to the differences, across groups of households, in the preferences for quality of the educational services, which determines the choice of private versus public provision and to the variation in the public education priorities across educational levels of regional governments. The second source of heterogeneity is instead related to the tastes for education reflected in the number of children attending schools. The latter source plays a role only for kids in post-compulsory education.

To make comparable families with different educational needs, we scale k_h by the needs-adjusted equivalence scale (see Aaberge et al. 2013, Aaberge et al. 2010).[6] Nevertheless,

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

[4]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 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.

[5]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.

[6]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 kids a weight of 0.5, and to each kid 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.

the amount of educational transfers in-kind is per equivalent kid enrolled at schools since the equivalence scale neutralize for the households' size and composition conditional on the kid enrollment at school. All children in post-compulsory schooling age that do not attend any school take the value of educational transfers in-kind equal to zero.

2.3 Implications of the sorting mechanism

The household's sorting mechanism into private education may justify the existence of public education provision as a redistributive transfers program. Its premises can be formulated as hypothetical effects of household income on the in-kind transfer distribution. This paper uses an identification strategy that allows to estimate the marginal effect (i.e. the marginal benefit) of income on the amount of educational transfers in-kind chosen by the families across two relevant distributional dimensions.

For a given degree of quality, proxied by a finite quantile of the distribution of the educational transfers in-kind, household's earning capacity can be one of the main determinant of the access into private education. The model by Besley and Coate (1991) clarifies the concepts showing that when the households' earning capacity is unobservable, restrictions on the quality of the public educational service may deter rich households from mimicking the poor ones. Together with household earning capacity, quality is, therefore, the other relevant dimension.

For a degree of the household's earning capacity, proxied by a finite quantile of the distribution of the household earning capacity, the quality of public schools as measured by our transfers in-kind, may explain the type of school chosen. As long as households give up the quality of public schools freely provided they are revealing a preference for the quality of private schools.

Our empirical exercise measures the extent to which households income influences the benefit received by the public education provision across families, characterized by different earning capacities and different preferences for the quality of the educational services. Public education provision is redistributive if families sort themselves into private education as the government expect them to. This occurs if households that benefit less from public education are those families, for a given quality level, who have an higher earning capacity, and who have higher preferences for quality, for a given earning capacity. The empirical analysis detailed below follows these arguments in order to assess whether redistributionally motivated public education provision is justified.

3 Empirical strategy

3.1 SHIW Data: 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.[7] Individual data are collapsed into family income, providing a sample of 8,012 families of which eight of them are dropped since their income was either negative or zero.

The sample selection process is based on two data cuts. The Italian educational system has three main levels which start at the age of six. Before compulsory schooling, from the age of three, children attend the kindergarten which is generally publicly financed either by the State or by the local communities. Since families with children at kindergarten benefit from public education expenditures we include them in the main analysis. Consequently, we restrict our main sample to families that are *potentially* entitled to benefit from public spending on education, namely families with school-age children aged from 3 to 23 years old.[8] This amounts to run our estimates on families with children born between 1981 and 2001. The sample is then reduced to 2,495 households, 271 of which 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 that we use as covariate.[9]

The social structure of an economy changes over time generating potentially, for a given survey wave, a composition effect related to different age composition of the family heads coming from different grandparental backgrounds and living different moments of the life cycle. To prevent this composition effect we cut the lower and the upper 5% of the distribution of the age of the head of the family restricting our sample to families whose head aged from 33 to 60 years old at the time of the survey (i.e. individuals born between 1944 and 1971) ending up with 2,030 observations for whom descriptive statistics is reported in Table 1.

To account for scale economies within the household, we equalize household income using the EU equivalence scale which we consider to be the more appropriate scale since

[7] 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.

[8] 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.

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

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			

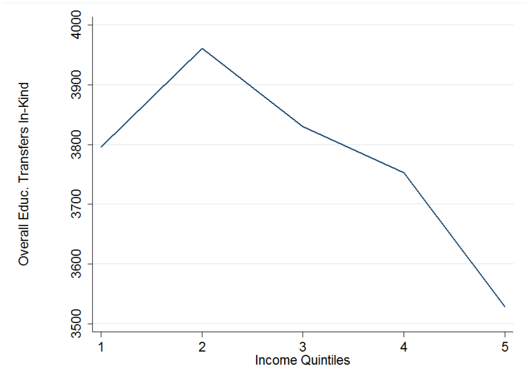
Sources: Microsimulated income data by C. Fiorio; Microsimulated educational transfers in-kind using INVALSI-MIPA data, 2003; SHIW, Bank of Italy, wave 2004.

it employs different scale factors for children and adults. In particular, it weights the head of the household, 1; children under 14 years old, 0.3, and other household components, including the spouse and other children older than 14 years old, 0.5.

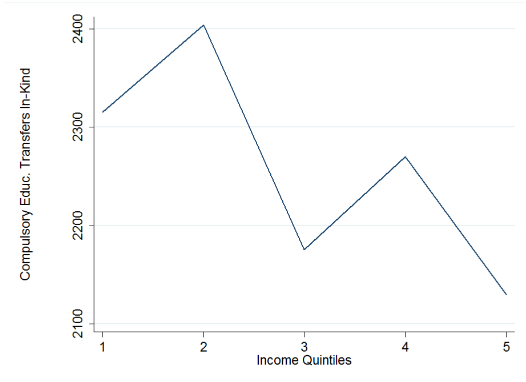
The average equivalent (net) income is 13,164 euro and ranges from 94.8 to more than 360,000 euro. About 80% of incomes are concentrated between 4,500 and 23,000 euro. The overall average educational transfers in-kind received is 3,774 euro but the average amount received is decreasing in the educational level ranging from 2,239 euro for compulsory education (including kindergarten) to 371.5 euro for tertiary 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.

On the one hand, panels (a), (b) and (c) of figure 2 illustrate an increasing relationship between the amount of the educational transfers in-kind and income in the lowest income quintile only. This relationship then turns out to be decreasing in all the other income quintiles. On the other hand, panel (d) of the same figure show that the probability of attending public schools is decreasing across income quartiles.

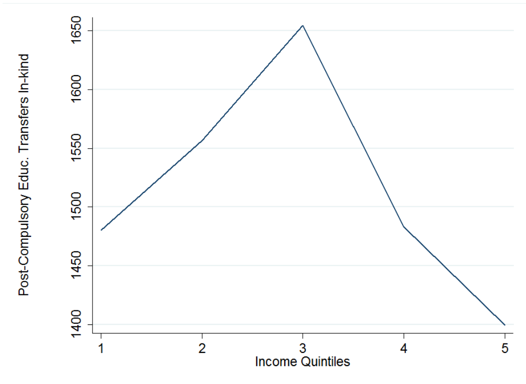
The relationships shown in these figures may be spurious. Observable and unobservable heterogeneity is likely to correlate with family specific skills determining both income and quality preferences. Controls for various characteristics of the household allow to account



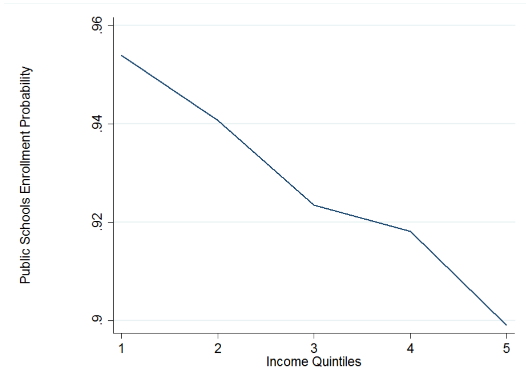
(a) Overall Educ. Transfers In-Kind



(b) Compulsory Educ. Transfers In-Kind



(c) Post Compulsory Educ. Transfers In-Kind



(d) Public Schools: Enrollment Probability

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

for observable heterogeneity. We adopt a control variate approach to sort out exogenous income variations, and to see their effects along both the household earning capacity and the educational transfers in-kind distributions. Alongside, we also consider the background of origin of the households, available in the dataset, to control for part of the families' unobservable characteristics.

3.2 Identification strategy: instrumenting income with expected tax deductions

At the heart of the sorting process into private education there is the correlation between the unobservable family specific earning capacity, that remain largely unobservable (i.e. the error terms of the income quantile equation which will follow), and the family specific preference for quality of the education good (i.e. the error term of the educational transfers in-kind quantile equation which will follow). It is precisely this correlation that affects the incidence of the self-targeting mechanisms.

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.

For each household member[10], independently on his working condition and on the true occupational status if working, 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 (denoted d_i with $i = 1, \ldots, 4$). These correspond to four conditions: 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.

The probability that the family h claims any of the four deductions depends on the probability that this family can be associated to each of the income sources. We assign to each member $m = 1, \ldots, M_h$ of the household h a profile of probabilities that m has to benefit of the deduction d_i. Denote this profile $\psi_i(a_m, s_m)$. We use data drawn from ISTAT (2003), to compute these probabilities which depend on two exogenous variables, age a_m and gender s_m of the household member m, and are estimated using the one-year lagged value of the observed frequencies of employees, retired persons and self-employed over the relevant Italian population for a given age class and gender.[11] At household member level, the instrument is exogenous since it combines the four maximum tax deductions determined by the law with the pre-determined (one-year lagged value) national frequency of the potential claimants that, to exploit the heterogeneity of the maximum tax deductions across income sources, is related to age and gender of each household member.

The overall amount of deductions accruing to the household is the sum of these benefits that each member of the household is entitled to. These potential deductions in each household is scaled by the household h specific size M_h, corresponding to:

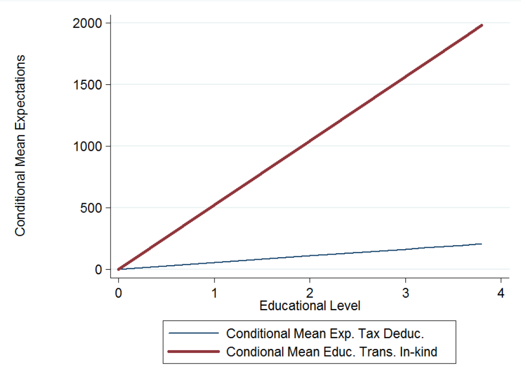
$$z_h := \sum_{m \in h} \frac{1}{M_h} \sum_{i=1}^{4} \psi_i(a_m, s_m) \cdot d_i \tag{4}$$

At household level, the instrument is exogenous since we assume that the age and gender composition within the household is orthogonal to the unobservable characteristics that may affect the households' sorting process into private/public education.

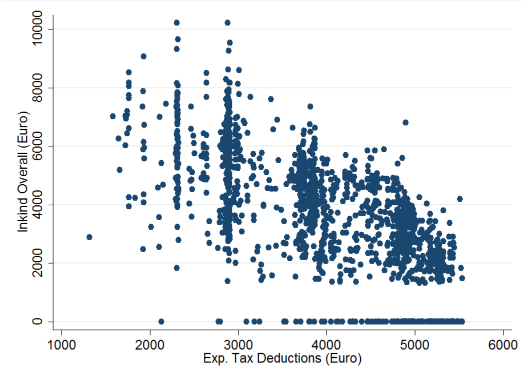
The key maintained exclusion restriction is that a manipulation of the distribution of

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

[11]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.



(a) Conditional Mean Exp. given Educ. Levels



(b) Scatter Educ. In-kind on Exp. Tax Ded.

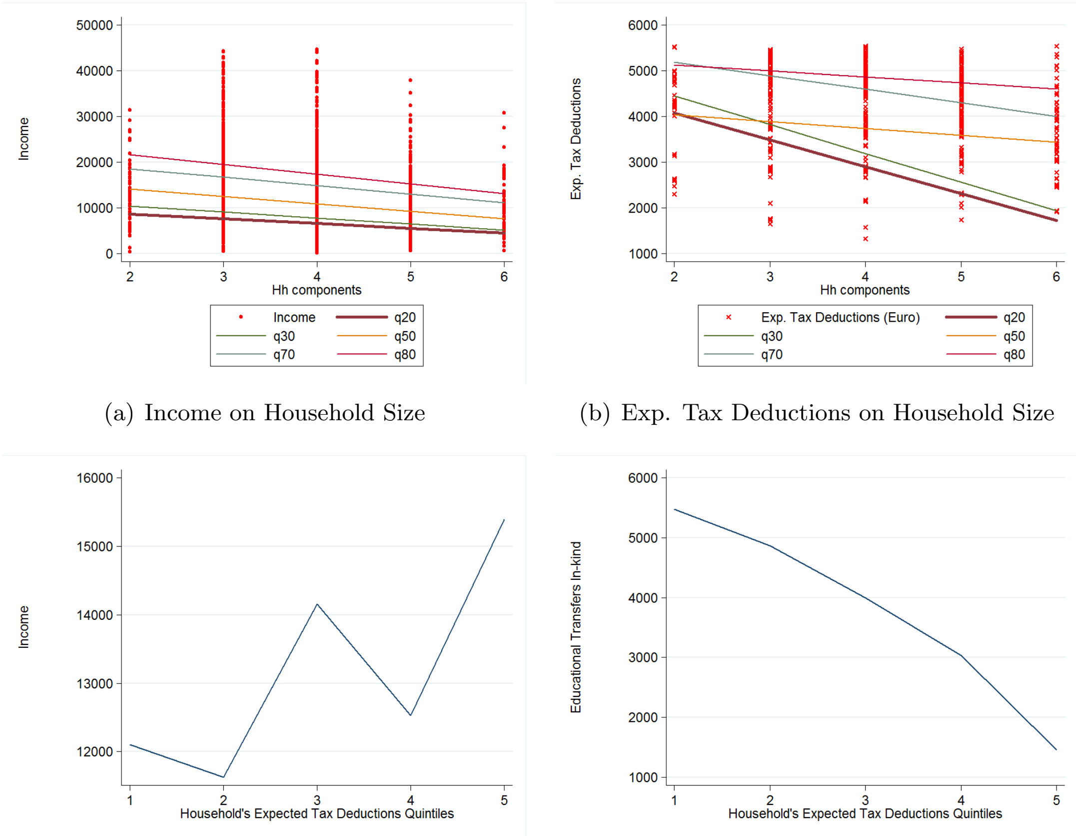
Figure 3: Validating the Exclusion Restriction.

Note: Educational levels are calculated as follows: the value of zero corresponds to any educational level attended (households with children in post-compulsory schooling age that stopped studying); the values of 1, 2, and 3 correspond to all household with at least one child in compulsory (1), upper secondary (2) and tertiary education (3). Household with more than one child are categorized as 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 level.

the expected tax deductions Z affects the quantiles of the distribution of the educational transfers in kind K only because it acts on the prevailing 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 from which the household benefit.

The instrumental variable z_h might be correlated with children age, thus rising potential concerns about the validity of the exclusion restriction. The expected tax deductions do not have, however, an 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 receives a fixed amount of benefits 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 of the family to which the household belongs. Also for children in post-compulsory schooling age the IV has not a direct effect on the transfer in-kind, because it is 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 provides graphical evidence on the validity of the exclusion restriction. Expected tax deductions are quite flat across educational levels but slightly increasing for households with children older than 14 years old since the national frequencies of employees and self-employees is positive for them. At any rate, even if there might exist a



(a) Income on Household Size (b) Exp. Tax Deductions on Household Size

(c) Income (d) Educational Transfers In-Kind

Figure 4: Tax deductions heterogeneity for household's income and educational transfers in-kind.

correlation between expected tax deductions and educational transfers in-kind related to the educational level of the kid, this correlation would result to be positive while the data show a reverted pattern, (see figure 3(b)).

Our second concern is that we are just using household size as the instrumental variable. The variation in the instrument, however, is substantially uncorrelated with household size. This is because z_h varies within household size according to the age class and the gender of each household member. Moreover, the within household size variability of our instrument does differ from the within household's size variability of income. Finally, the Y and Z distributions have also different between household's size variability as shown by the different slopes of the conditional quantile functions given household size. All these facts are well motivated in figures 4(a) and 4(b).

Our third and last concerns is whether the instrumental variable is relevant for generating sufficiently large exogenous changes in income to affect the transfers in-kind distribution. Figure 4 shows that household incomes increase, although not monotonically, along the distribution of the family's expected tax deductions. This is not surprising, given the regressive nature of income tax deductions in presence of increasing marginal personal income tax rates. In such a case, higher (net) income quintiles benefit more from tax deductions. The amount of educational transfers in-kind is lower for higher quintiles of the expected tax deductions (figure 4(d)). 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.

3.3 Structural quantile treatment effect estimation method

Making use of a particular feature of the 1993 SHIW wave, Checchi and Jappelli (2007) estimate the conditional mean probability of enrollment in private schools controlling for income quartile, both a subjective and an objective quality indicators and other covariates. Their empirical evidence suggests that rich households are more likely to use private education while the perceived quality of public schools measured by a self-reported quality score is negatively correlated with the probability of attending private schools. The selection mechanism presented in section 2.1 suggests that public education provision is redistributive if households that benefit less from public education are those with higher earning capacity, for a given degree of quality level, and those who have higher preferences for quality, for a given degree of earning capacity.[12]

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 transfer in-kind received by the families. This method is the most appropriate to measure the extent to which households income influences the benefit received by the public education provision heterogeneously across families earning capacity and preferences for the quality of the educational services. This double heterogeneity in the income effects allows to assess the implications of the sorting mechanisms on the distribution of transfers in-kind across families with children in education.

Consider the following 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. The analysis is at the household level and the subscript h is dropped for expositional purposes. We

[12]According to the Besley and Coate (1991) model, the probability of attending private education is negatively correlated with low income quantiles but positively correlated with high income quantiles. It is therefore likely that the conditional mean effect could be precisely zero.

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 effects of the variables of interest at different quantiles of income and transfers in-kind distributions. The instrument z allows to disentangle the exogenous variations in income from the unobserved components that jointly determined incomes and transfers in-kind accruing to the household.

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

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

where σ_K are strictly positive weights and the function ρ_{τ_Y} 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:

$$K = \alpha_0 + \alpha_1 Y + \mathbf{X}_h \cdot \alpha_2 + \mathbf{X}_{hh} \cdot \alpha_3 + \mathbf{X}_r \cdot \alpha_4 + \alpha_5 FB1 + \alpha_6 FB2 + u \qquad (5)$$

$$Y = \beta_0 + \beta_1 Z + \mathbf{X}_h \cdot \beta_2 + \mathbf{X}_{hh} \cdot \beta_3 + \mathbf{X}_r \cdot \beta_4 + \beta_5 FB1 + \beta_6 FB2 + U \qquad (6)$$

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 family including gender (i.e. if female), age, age squared, years of schooling[13]; $\mathbf{X}_r$ are local market conditions measured by the regional GDP per head and unemployment rate; $FB1$ and $FB2$ denote the distribution of family background differential in incomes made conditional on the degree of abilities of the households and on the two background measures employed in this analysis (socioeconomic background of the grand-fathers and the educational background of all grandparents). As shown in appendix B, these variables are estimated as transformation of the quantiles of the distributions of incomes made conditional on the background of origin of the observed households. They are interpreted as proxies of families' unobserv-

[13]For 12 observations only, we replace missing data with the years of schooling of the spouse.

able characteristics generated by the family background, since the household's rank in her family background group-specific income distribution is close to be a sufficient statistic for her unobservable abilities (Acemoglu and Pischke 2001).

We make use of a flexible specification of the error term u in equation (5) where income is allowed to influence both the location and scale of the educational transfers in-kind distribution. We also take under consideration the possibility that the location and scale effect might be heterogeneous across families with different background of origin, while holding their rank position in the income distribution as fixed. These considerations amount to formulating the error term in equation (5) as a linear transformation of income: $u = (\lambda\nu_Y + \nu_K + \text{FB1} + \text{FB2})(Y\psi + 1)$ and $U = \nu_K$ where ν_K and ν_Y are independent of one another and *i.i.d.* over households. The errors structure shows that the unobservable family specific earning capacity and preference for quality of the education good are correlated. This correlation then affects the self targeting mechanism.

Estimation of the model evolves in a two steps procedure. The first step consists in running a set of quantile regressions of equation (6) at finite quantiles of Y. The set of estimates $\widehat{\beta}$ identifies the distribution of $\nu_Y(\tau_Y)$ for every reference quantile τ_Y. The realizations of the variables $\widehat{\nu}_Y(\tau_Y)$ represent the unexplained part of the gap between the income of a given household and the income quantile corresponding to τ_Y. The second step consists in running a set of quantile regressions of equation (5) 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 relationship only for a selected number of quantiles corresponding to 20%, 30%, 50%, 70% and 80% of both the household earning capacity and the educational transfers in-kind distributions. The analysis starts at the 2nd decile because in the main sample households sitting at the 1st 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.[14] For sake of symmetry, we do not consider the 9th decile, either.

4 Results

4.1 Benchmark

We report in the first line of table 2 the benchmark estimates of OLS and quantile regression effects of income, treated as exogenous. The OLS income coefficient amounts to a negligible but significant -0.02. This might be the consequence of averaging benefits associated to a reductions in income for families who sit in the upper quantiles of the educational transfers

[14]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.

Table 2: OLS, Control Function and Quantile Regression Estimates

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

Note: The table reports OLS, Control Function and Quantile Regression 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 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; 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. Control function model 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 (6). Robust standard errors are reported in parentheses for OLS and CF estimates while bootstrapped standard errors are reported in parentheses for quantile regression estimates.

in-kind distribution with benefits from increases in income for families who sit in the lower quantiles of the educational transfers in-kind distribution. Columns (3) to (7) of the Table show that the income effect is negative and significant only for the higher quantiles of the educational transfers in-kind (i.e. quantiles equal to the median or above). The estimated coefficients are quite small and indistinguishable from the OLS estimates.

Like the OLS, the quantile regression coefficients do not have a causal interpretation in presence of heterogenous effects. If the effects of income are not a single parameter in the population but rather random variables that may vary with other observable and unobservable characteristics of the households, OLS and quantile regression estimates are biased. This is made clear when comparing the OLS and control function estimates, reported in the second column of table 2.

The control function estimates account for heterogeneity in income effects by conditioning on residuals and the interaction between income and these residuals estimated in a first stage where we use expected household tax deductions as instrument. The coefficient of the estimated residuals determines an intercept shift effect due to households' self-selection. Households have heterogeneous unobservable characteristics that influence permanently the amount of educational transfers in-kind received by affecting the intercept of the educational transfers in-kind equation. The interaction term captures, instead, the slope shift effect on the marginal effect of income on the amount of the educational transfers in-kind which is associated to the unobservable heterogeneity in household characteristics. This interaction term, however, is not statistically significant.

Under plausible assumptions,[15] the coefficient of the income variable of the control function estimates retrieves the *average marginal treatment effect* in the population. The control function can be conceived as an average structural relation that provides the counter-factual 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 (Blundell and Powell 2003). This average marginal treatment effect in the population, -0.73, is much higher (in absolute values) than the corresponding OLS estimate and represents the average marginal effect of income if the latter would be perfectly observable by the governments (i.e. if the income would be exogenous).

Although CF method considers both the intercept-slope shift assumptions on the way that covariates are allowed to influence the conditional distributions of the endogenous variables, it offers only a conditional mean view of the structural relationship. Structural quantile treatment effect estimation broadens this view, offering a more complete characterization of the stochastic relationship among income and educational transfers in-kind.

4.2 First stage

Table 3 reports quantile estimates of equation (6) for the main sample and for two subsamples used in the analyses that will follow. We interpret the estimated coefficients as the sum of two effects through which a change in our instrument exogenously manipulate the distribution of income Y. Let y_N be the net of taxes income, that is, by definition, equal to the gross income y_G minus the personal income tax liability T and $T = t(y_G - d)$, 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.

As a consequence, 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

[15]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.

indirect effect). In principle, this latter effect can be either negative or positive according to the labour supply change. It is negative, if the components of the household work less as the hourly net of taxes wage increases (i.e. an income effect). On the contrary, it is positive, if household earners respond to a raise in the net of taxes wage substituting leisure with work (i.e. a substitution effect).

Our estimated coefficients are always statistically significant at 1% and positive. Their values are almost always greater than the maximum marginal tax rate accruing to personal income taxes in Italy (43%), suggesting that the substitution effect dominates the income effect on the household labour supply.

4.3 Structural quantile treatment effects on the full sample

Figure 5 plots the marginal quantile treatment effects of income showing that an increase in households' income always lower the amount of educational transfers in-kind received. Our findings are robust to predetermined household heterogeneity captured, for a given family background, by the household's rank in the income distribution. The coefficients of these two variables, $FB1$ and $FB2$ have always the sign of the quantile residuals, positive in this case, 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. Our results are also qualitatively robust to a change in the equivalence scale, although the marginal effects of income are

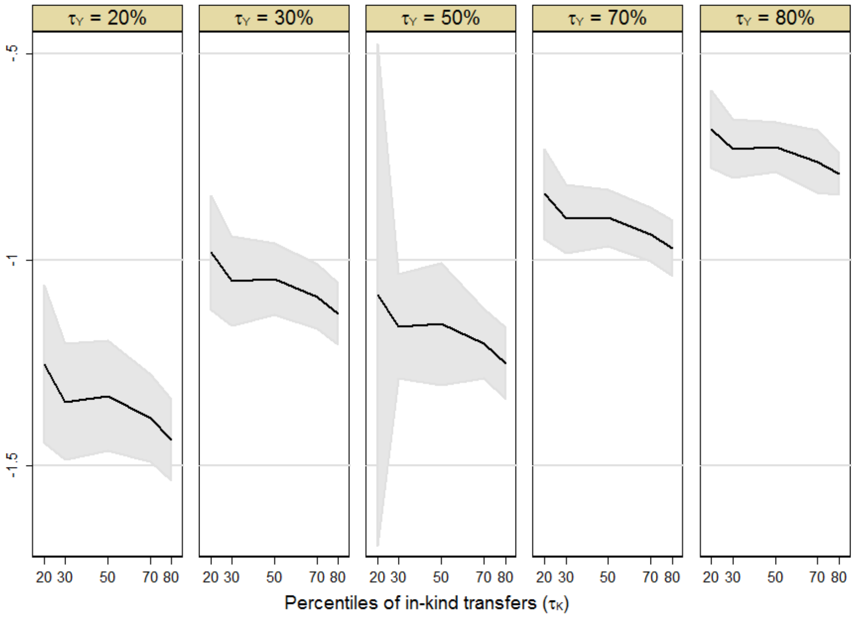


Figure 5: Marginal Quantile Treatment Effects of Income

Note: The figure plots the marginal quantile treatment effects of income for a given quantile of the household earning capacity. These marginal quantile treatment effects are calculated taking also into account the scale shift effect, measured by the interaction between income and the residuals of the given quantile of the household earning 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.

less heterogeneous.[16]

4.3.1 Fixing quantiles of the household earning capacity, τ_Y

A one euro increase in income reduces the amount of educational transfers in-kind more at the 80th quantile than at the 20th quantile of the K distribution. Table 4, panel (a), shows a battery of tests for the homogeneity of these marginal effects. The equality of the effects is rejected, in some cases at 10% level of significance, at all quantiles of the household earning capacity with the exception of the median. We interpret our findings as evidence that the opting out for private schools is higher for those households who value most the quality of the education good since sitting at the higher quantiles of the educational transfers in-kind distribution.[17]

[16] These results are reported in appendix C.

[17] We could have also compared other quantiles, for instance either the lowest and the median or the median and the highest. However, since in our case, the relationship of interest is almost monotone, heterogeneity of the effects is fully described by our Table 4 that compares the lowest and the highest quantiles.

Table 4: Homogeneity Tests: 20th and 80th quantiles of K fixing τ_Y

	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%
MQTEY	0.184*	0.149**	0.166	0.133**	0.108**
	(0.10)	(0.07)	(0.31)	(0.06)	(0.05)
	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%
MQTEY	-0.570***	-0.613***	-0.604***	-0.624***	-0.647***
	(0.11)	(0.08)	(0.07)	(0.07)	(0.06)

Note: The Table reports the homogeneity tests of marginal quantile treatment effects of income, in the main sample, at the 20th and the 80th quantiles of educational transfers in-kind distribution, fixing quantiles of the household earning capacity (panel (a)) and at the 20th and the 80th quantiles of the household earning capacity, fixing quantiles of the educational transfers in-kind distribution (panel (b)). Standard errors are reported in parentheses.

4.3.2 Fixing quantiles of the household preferences for quality, τ_K

Panel (b) of Table 4 reports the homogeneity test between the marginal effects of income at the 20th and the 80th quantiles of the household earning capacity. These differences are always negative and statistically significant at a 1% level, suggesting that a one euro increase in income reduces more the amount of educational transfers in-kind for the 20th quantile than for the 80th quantile of the household earning capacity. The marginal effect of income, if negative, can be interpreted in terms of a marginal benefit rate. Our income coefficients are, for instance, 1.437 and 0.79 for the 20th and 80 quantiles of the household earning capacity. This is evidence of the progressivity of the educational transfers in-kind since their benefit rate is decreasing, in absolute values, although not strictly monotonically in our case, in the income distribution.

4.3.3 Mean (quantile) treatment effects

The structural quantile treatment effect method allows to decompose the stochastic effect of the distribution of income on the distribution of the educational transfers in-kind into two distinct dimensions: the one related to the distribution of the household earning capacity and the one related to the distribution of the educational transfers in-kind proxing household preferences for the quality of the education good. Our assumption on the errors structure has provided structural insights into how these two dimensions 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 earning capacity, while the *mean treatment effect* results from averaging again, this time with respect to the quantiles of the distribution of the educational trans-

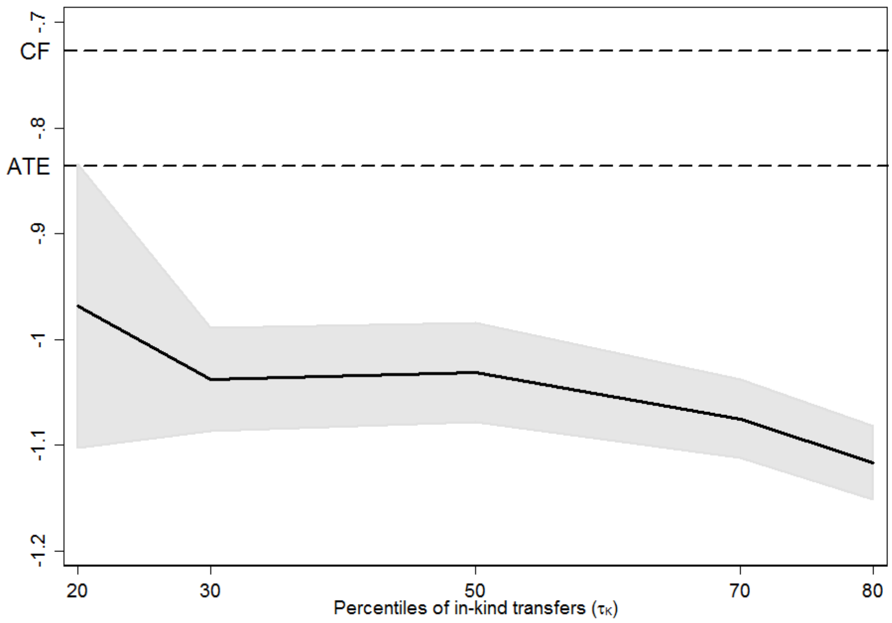


Figure 6: Average Quantile Treatment Effects of Income

Note: The figure plots the average quantile treatment effects, the mean treatment effect and the mean (average) treatment of income using control function method reported in Table 2. The mean treatment effect is calculated integrating out the distribution of the household earning capacity by assigning as weights the area under the distribution evaluated at the fix points of the 20th, 30th, 50th, 70th and 80th quantiles. The 20th bottom and upper part of the distribution are assumed to a have a weight equal to zero. The mean (average) treatment effect is obtained by averaging across the quantiles of the distribution of the educational transfers in-kind. Confidence bands at 99% level.

fers 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 might correspond to the average treatment effect estimated in section 4.1 using the control function method. Figure 6 supports our argument. The difference between the average treatment effect retrieved in control function CF and the mean treatment effect obtained starting from our structural quantile treatment effect estimates is likely to be due to our hypothesis on assigning a zero weight to the 20th and 80th quantiles of the distributions of the household earning capacity and the amount of educational transfers in-kind to compute the final effect.

4.4 Analysis across educational levels

The Besley and Coate (1991) model chiefly applies to compulsory education, where enrolment is mandatory to all children and parents only have to choose the type, private or public, of the school. 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 kid attends post-compulsory education, the household chooses between private and public education.

Furthermore, the two stages of the education system can be further differentiated according to the quality of the educational services they offer. Based on the Italian experience, Bertola et al. (2007) and Bertola and Checchi (2013) show that the quality of private schooling for upper secondary is lower than that related to public schools, inferring the "remedial role" played by upper secondary private education. To account for both 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 kids in upper secondary schooling age. Additional tables with robustness checks are reported in the appendix.

4.4.1 Compulsory education

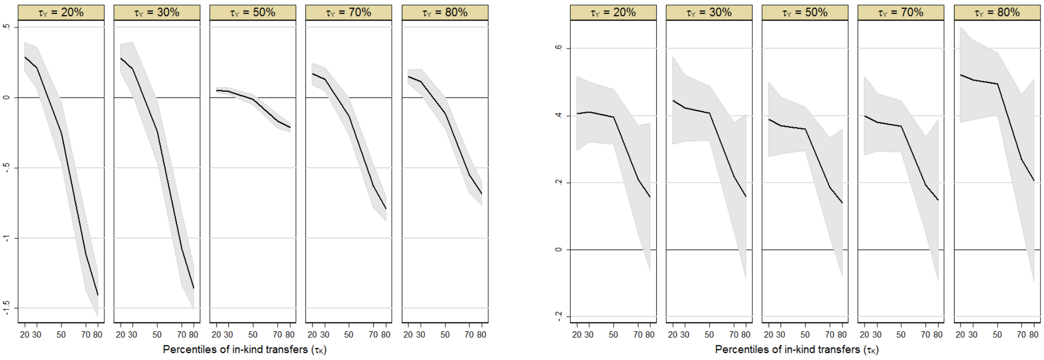
Panel (a) of figure 7 illustrates the marginal effect of income on the amount of educational transfers in-kind when we consider only families with at least one child in compulsory schooling age.[18] Estimates are based on a reduced sample of 888 households. We find that an increase in income affects positively the amount of educational transfers in-kind at the 20th and 30th quantiles of the K distribution but negatively at quantiles above the median.

The marginal impact of income on the median amount of educational transfers in-kind is negligible. At the lower quantiles of the educational transfers in-kind, this effect is low and, for a given earning capacity of the households, only families that value less the quality of the educational services consume the publicly provided education 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.

At higher quantiles of the educational transfers in-kind, households who value more the quality of the education good self-target themselves by opting out, gradually, towards private education. For this reason, at the higher quantiles of the educational transfers in-kind distribution, the sign of the marginal effect of income on the amount of educational transfers in-kind is negative. The differences in the marginal effect of income at the 20th and 80th quantiles of the educational transfers in-kind are higher at the lower quantiles of the household earning capacity. The households who value less the quality of the educational services and have a lower earning capacity are those who benefit more from the publicly provided mandatory education system.

Figure 7 provides also evidence of the progressivity of the educational transfers in-

[18] Here we are not considering families with children at kindergarten. This is because kindergarten is not compulsory in Italy. Results are qualitatively robust when we consider kindergarten. These results are reported in appendix C.



(a) Compulsory Education (b) Upper Secondary Education

Figure 7: Marginal Quantile Treatment Effects of Income: Sub-Samples

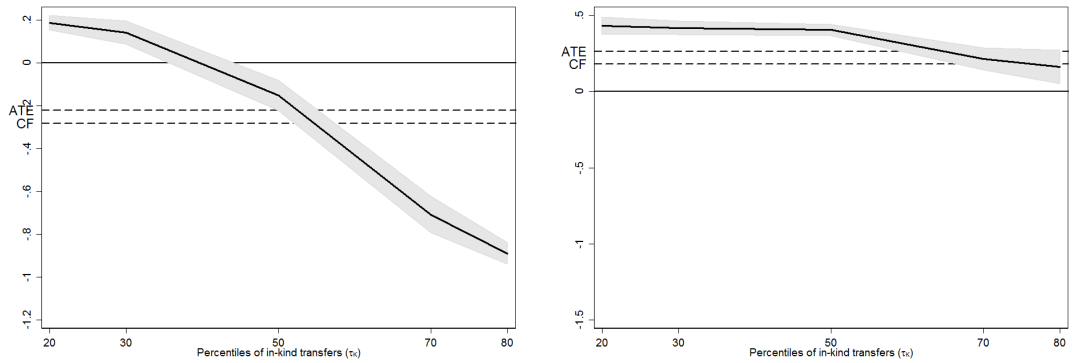
Note: The figure plots the marginal quantile treatment effects of income for a given quantile of the household earning capacity for the sub-samples of compulsory education, Panel 7(a), and upper secondary education, Panel 7(b). These marginal quantile treatment effects are calculated taking also into account the scale shift effect, measured by the interaction between income and the residuals of the given quantile of the household earning 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.

kind since the marginal benefit rate, i.e. the marginal effect of income, is decreasing, in absolute values, in the household earning capacity distribution. At the 30th and the 50th (the median) quantiles of the K distribution, however, the equality between these marginal effects at the lowest and highest quantiles of the household earning capacity cannot be rejected.

4.4.2 Upper secondary education

Panel (b) of figure 7 shows a different picture when the analysis is restricted to families with at least one child in upper secondary schooling age.[19] In this case, the marginal effects of income are always positive. In upper secondary education, the mechanisms through which families self-select themselves are, therefore, different, possibly because of the sequentiality of the choice. We cannot directly prove it since we do not observe kid's future income. However, under the assumption that the expected returns of education of the offsprings are positively correlated with the realized return in income of the family (i.e. the realized returns can be forecast by observed family income), one can speculate that families are self-selecting themselves into private post-compulsory education according to the expected returns to kid's education. Households are more likely to choose higher levels of education

[19] Our sample is now made of 767 families. We have also considered the subsamples comprising all 1182 households with at least one kid in either (both) upper secondary or (and) tertiary schooling age and that including only 564 families with at least one child potentially at university.



(a) Compulsory Education

(b) Upper Secondary Education

Figure 8: Average Quantile Treatment Effects of Income: Sub-Samples

Note: The figure plots the average quantile treatment effects of income for the sub-samples of compulsory education, Panel 8(a), and upper secondary education, Panel 8(b). The mean treatment effect is calculated integrating out the distribution of the household earning capacity by assigning as weights the area under the distribution evaluated at the fix points of the 20th, 30th, 50th, 70th and 80th quantiles. The 20th bottom and upper part of the distribution are assumed to a have a weight equal to zero. The mean (average) treatment effect is obtained by averaging with respect to the quantiles of the distribution of the educational transfers in-kind. Confidence bands at 99% level.

if the return to education is higher.

The positive marginal effect of income at the 20th quantile of educational transfers in-kind distribution are always statistically different and higher than those at 80th quantiles across all the quantiles distribution of the household earning capacity. It is interesting that the income coefficients are positive but never statistically significant at the 80th quantile of the educational transfers in-kind distribution, the quantile in which sit the households who value most the quality of the educational good. This results is consistent with the findings presented by Bertola et al. (2007) and Bertola and Checchi (2013), who suggest that the quality of private schooling for upper secondary education is lower, or at least not higher, than that related to public schools.[20] If this the case, the incentive compatibility constraints of rich households cannot be satisfied and the assumptions behind the Besley and Coate (1991) required to achieve redistribution through public education provision are clearly violated.

A one euro increase of income is more beneficial to the 20th than it is to the 80th quantiles of the household earning capacity distribution. We suspect that rich households whose children are not highly talented choose to buy private post-compulsory educational services as a "remedial" for reaching the educational objectives of the children. In contrast,

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

kids coming from the poor household that are not talented should stop studying since for them the opportunity costs of attending schools is too high. It follows for upper secondary education, that public schools should attract proportionally more skilled individuals, both from rich and poor households, as shown by Bertola et al. (2007).

Panels (a) and (b) of figure 8 plot the average quantile treatment effects and the average treatment effects for compulsory and upper secondary education. These parameters are retrieved from our structural quantile treatment effects estimates integrating over the two relevant dimensions, the household earning capacity and the educational transfers in-kind distributions. In both cases the average treatment effects almost coincide with the parameters estimated using control function method. Consequently, on average, public education provision is redistributive for compulsory education but it is not redistributive for post-compulsory education.

5 Conclusions

This paper investigated the mechanisms behind the redistributiveness of public education provision using Italian data. We interpret almost free public educational services as transfers in-kind received by families who do not choose private education. The monetary equivalent value of the transfers in-kind is measured by the expected cost supported by the government to provide the service for free, reflecting the quality of the service provided.

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 (ii) more for lower quantiles of the household earning capacity. We interpret our results as evidence of a self-targeting device through which rich households sort themselves into private education. Our results explain how, for compulsory schooling, the households' sorting into private education may motivate a government, that aims at redistributing resources from the rich to the poor, to use public education provision as transfers in-kind.

Our results suggest that reforms of the public education system that aim at changing the quality of the publicly provided education services might alter the self-targeting mechanism premises. This does not necessarily implies 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 will not necessarily be part of an optimal designed redistributional package. The deadweight loss associated with universal education provision suggests that the same distributional goals could be achieved more efficiently through other feasible policies. There is a clear trade-off between the cost to the government to minimize the asymmetric information on the households' earning capacity and the deadweight loss inherent in an inefficient quality of the public provision of education. The higher the cost to the government of observing its citizens' earning capacity the higher the necessity of an inefficient self-targeting device.

The empirical investigation shows that different self-selection processes apply at upper secondary education level where there also is evidence of a violation of one of the main assumption behind the self-targeting mechanism. On the one hand, for post-compulsory education families sort themselves according to the expected returns to kid's education. On the other hand, we find that the marginal effect of income is never statistically significant at the 80th quantile of the educational transfers in-kind distribution, the quantile in which sit the households who value most the quality of the educational good. This result suggests that the quality of private schooling for upper secondary education, is lower or at least not higher than that related to public schools as a consequence of the demand of less talented kids coming from rich households as also proved by Bertola et al. (2007) and Bertola and Checchi (2013). If this is the case, the incentive compatibility constraints of rich households cannot be satisfied since the quality of the publicly provided education good is not lower than that characterizing the private schools. Since only talented children coming from poor households do not stop studying and they are enrolled at public schools, for upper secondary education, public schools should attract proportionally more skilled individuals. Nevertheless, public education is not redistributive since for poor household with less talented kids the opportunity cost school of attending schools is too high.

References

Aaberge, R., Bhuller, M., Langørgen, A. and Mogstad, M. (2010). The distributional impact of public services when needs differ, *Journal of Public Economics* **94**(9-10): 549–562.

Aaberge, R., Langorgen, A. and Lindgren, P. (2013). The distributional impact of public services in european countries,, **476**.

Acemoglu, D. and Pischke, J. S. (2001). Changes in the wage structure, family income, and children's education, *European Economic Review* **45**(4-6): 890–904.

Asquini, G. and Bettoni, C. (eds) (2003). *Analisi delle spese per istruzione*, Franco Angeli.

Bertola, G. and Checchi, D. (2013). Who chooses which private education? theory and international evidence, *LABOUR* **27**(3): 249–271.

Bertola, G., Checchi, D. and Oppedisano, V. (2007). Private school quality in italy, *Giornale degli Economisti* **66**(3): 375–400.

Besley, T. and Coate, S. (1991). Public provision of private goods and the redistribution of income, *American Economic Review* **81**(4): 979–84.

Blackorby, C. and Donaldson, D. (1988). Cash versus kind, self-selection, and efficient transfers, *American Economic Review* **78**(4): 691–700.

Blundell, R. and Powell, J. (2003). Endogeneity in nonparametric and semiparametric regression models, *in* L. H. M. Dewatripont and e. S.J. Turnovsky (eds), *Advances in Economics and Econonometrics: Theory and Applications*, Vol. II, Eighth World Congress, Cambridge: Cambridge University Press.

Checchi, D. and Jappelli, T. (2003). School choice and quality, *IZA Discussion Papers 828*, Institute for the Study of Labor (IZA).

Checchi, D. and Jappelli, T. (2007). The impact of perceived public school quality on private school choice in italy, *in* L. Woessman and e. Petersen, P. (eds), *Schools and the equal of opportunity problem*, MIT.

Currie, J. and Gahvari, F. (2008). Transfers in cash and in-kind: Theory meets the data, *Journal of Economic Literature* **46**(2): 333–83.

Fershtman, C., Murphy, K. M. and Weiss, Y. (1996). Social status, education, and growth, *Journal of Political Economy* **104**(1): 108–32.

Gahvari, F. and Mattos, E. (2007). Conditional cash transfers, public provision of private goods, and income redistribution, *American Economic Review* **97**(1): 491–502.

INVALSI-MIPA (2005). Aspis iii - linea di ricerca sull'analisi della spesa per istruzione, *Technical report*, INVALSI-MIPA.

ISTAT (2003). Labour for surv, *Technical report*, ISTAT.

Koenker, R. and Bassett, Gilbert, J. (1978). Regression quantiles, *Econometrica* **46**(1): pp. 33–50.

Lefranc, A., Pistolesi, N. and Trannoy, A. (2009). Equality of opportunity and luck: Definitions and testable conditions, with an application to income in France, *Journal of Public Economics* **93**(11-12): 1189 – 1207.

Ma, L. and Koenker, R. (2006). Quantile regression methods for recursive structural equation models, *Journal of Econometrics* **134**(2): 471 – 506.

Roemer, J. (1998). *Equality of Opportunity*, Harvard University Press, Cambridge.

Sander, W. (2001). The effects of catholic schools on religiosity, education and competition, *Technical report*, National Center for the Study of Privatization in Education, Occasional Paper n.32.

Stiglitz, J. E. (1974). The demand for education in public and private school systems, *Journal of Public Economics* **3**(4): 349–385.

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

In Italy, the educational public system is managed by local authorities (regions, provinces and municipalities), although most of the financial resources arises from the central state. 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. Although competencies on public education in Italy are spread across several authorities, 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). Third, the only - at the best of our knowledge - detailed analysis on spending on education carried out in Italy by INVALSI-MIPA (2005) emphasizes the regional (together with the educational level) dimension, implicitly recognizing a primary source of variation at this level. Moreover, even within regions there is variation in local government spending across educational levels that correspond to primary (*scuola elementare*), compulsory secondary school (*scuole medie inferiori*), post-compulsory secondary school (*scuole superiori*) and tertiary education. We interpret this region by education level variability as a result of heterogenous spending priorities on different target (income) groups.

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), a document which records the expenditures on public education, has an aggregate perspective and the reported figures do not allow to calculate the expenditures along both dimensions (regions and educational levels) at the same time. However, for all education levels up to upper secondary school (including then pre-primary and excluding tertiary education) we take advantage of the results of a unique study named ASPIS III realised in 2005 (with data referring to 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). 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. In the following section we briefly 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 followed to estimate the average cost of tertiary education.

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

The Financial Statement of the Italian Ministry of Education 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. In order to attribute central government expenditures by educational levels to regions and, viceversa, region-specific expenditures to different educational levels, ASPIS III exploits a number of so called *drivers*. Drivers are indicators that depend on the specific expenditure. 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. To some extent using as a weighting factor the number of students and teachers, data provided by ASPIS III are taking account of differences in quality and efficiency in the public service production across regions and level of education. A further advantage of using ASPIS III is that data arise from a consolidated financial statement of central government and local authorities, avoiding the risk of double counting the value of expenditures which are financed by transfers from higher to lower levels of government.

ASPIS data provide us with a $r \times e$ matrix of data 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_{re}.[21] We finally apply regional-specific general indexes of consumer prices to inflate these average costs to 2004.

A.2 Tertiary education

To estimate the average costs of providing public tertiary education in Italy, we adopt a different strategy. 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 (state or regional) provided by 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 households, i.e. 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.[22]

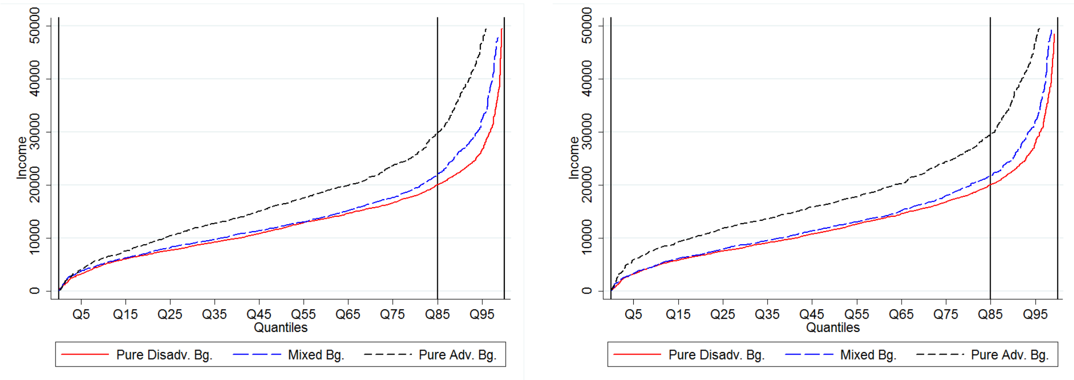
[21] Data estimated are net public expenditures on education, as households' out-of-pocket payments and other financial sources beyond government are excluded.

[22] SHIW 2004 data do not provide information on the university attended by the kids. 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.

B Assessing family background to control for household heterogeneity

We use family background indicators for either education or socio-economic position of the grand-parents provided by SHIW data,[23] We can partition the observed families into groups that are homogeneous with respect to the backgrounds of origin each of them considered separately. This is because different kind of household unobserved characteristics maybe associated to different family background indicators.

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 2030 families with children in education age. We, thus, employ 3651 and 3698 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.



(a) Grandparents' Occupational Conditions

(b) Grandparents' Level of Education

Figure 9: Measuring Household Unobservable Characteristics Related to Family Backgrounds.

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.[24] 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 advantage or disadvantage parental background from the side of both spouses, we consider a three family background groups, defined according to the socioeconomic position of the

[23]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)"*.

[24]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 income acquisition. Following them, we consider only the grandfather's occupational background since a large part of the grandmothers were housewives.

fathers of both spouses. The first purely disadvantaged background group comprises all the families for which both grandfathers were disadvantaged. The second purely advantaged group comprises all the families where both spouses' fathers were advantaged. Finally, the third residual group identifies a mixed background of origin.[25]

We repeat the classification also according to level of education of the grandparents. In this case, the purely disadvantaged background group includes all the households for which both spouses' parents had on average 5 years of education or lower.[26] The advantaged and the mixed group are defined using the residual classes.

For each of the groups generated by each of the two background characteristics of interest, we rank them within each group according to their income. To isolate the contribution of the group of origin at fixed degree of ability, 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 would have reached if the background of origin were equalized across all families. This 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 [27]. for the household unobservable characteristics related to each of the two family background, the estimated residual $\widehat{\varepsilon}$ of the following regression model:

$$y_h \ = \ \sum_{j=1}^{100} \gamma_j \cdot \mathbf{1}\left[h \in P(p_j)\right] \ + \ \varepsilon_h, \tag{7}$$

where $\mathbf{1}[.]$ is an indicator function for the condition expressed in its argument to be satisfied.

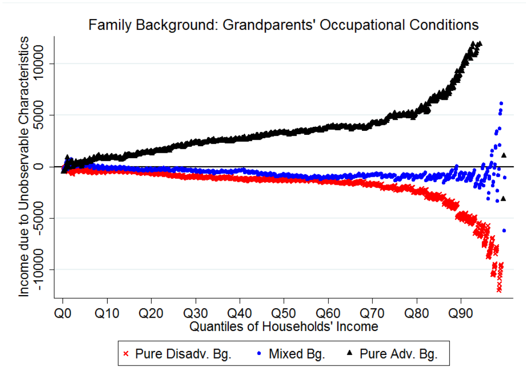
These residuals can be conceived as the empirical counterpart of the vertical distance between the family background specific quantile functions $F_t^{-1}(p)$, shown in figure 9.

To clarify the concept, families with positive residuals are those which have skills 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' skills with respect to any of the two (or both) grandparental background when the corresponding residuals are equal to zero for each percentile of the income distribution

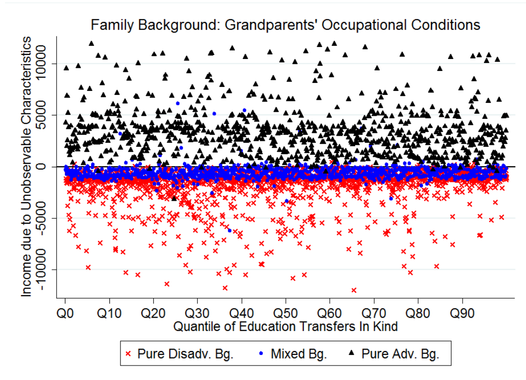
[25] In this type we include also those families with missing information on the occupational background of the father of one of the two spouses.

[26] 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 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.

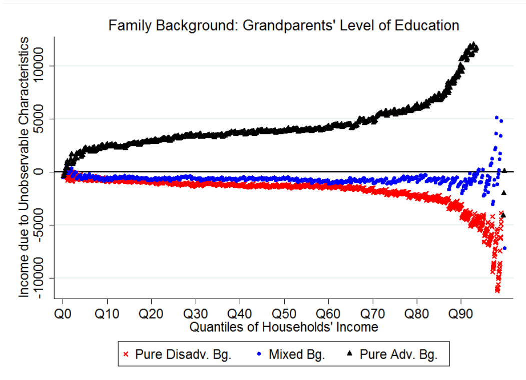
[27] We construct this sufficient statistics exploiting what is known in the Equality of Opportunity literature as the Roemer Identification Assumption (RIA) to accounting for effort in income, (see Roemer 1998)



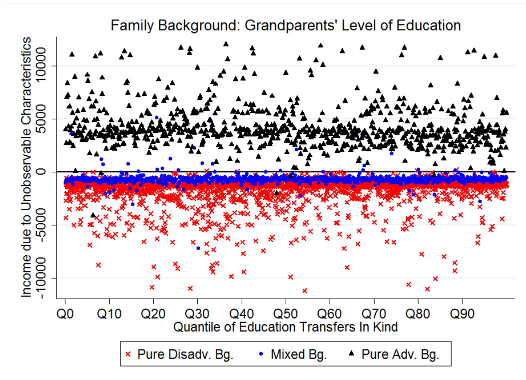
(a) Income Quantiles



(b) Educational Transfers In-Kind Quantiles



(c) Income Quantiles



(d) Educational Transfers In-Kind Quantiles

Figure 10: Deviations from Quantile Specific Average at Family Level, by Grandparental Background.

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

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.

C Tables

Table 5: Structural Quantile Treatment Effect Estimation: Main Sample

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	-1.252***	-1.343***	-1.330***	-1.385***	-1.437***
	(0.10)	(0.07)	(0.07)	(0.05)	(0.05)
Location shift	1.267***	1.358***	1.322***	1.375***	1.418***
	(0.10)	(0.08)	(0.07)	(0.06)	(0.05)
τ_Y: 30%					
Income	-0.982***	-1.050***	-1.046***	-1.089***	-1.132***
	(0.07)	(0.05)	(0.04)	(0.04)	(0.04)
Location shift	0.994***	1.064***	1.037***	1.079***	1.113***
	(0.07)	(0.06)	(0.05)	(0.04)	(0.04)
τ_Y: 50%					
Income	-1.084***	-1.161***	-1.156***	-1.203***	-1.251***
	(0.31)	(0.06)	(0.08)	(0.04)	(0.04)
Location shift	1.096***	1.172***	1.147***	1.193***	1.232***
	(0.28)	(0.07)	(0.09)	(0.04)	(0.05)
τ_Y: 70%					
Income	-0.840***	-0.900***	-0.898***	-0.937***	-0.972***
	(0.06)	(0.04)	(0.04)	(0.03)	(0.03)
Location shift	0.849***	0.908***	0.889***	0.925***	0.954***
	(0.06)	(0.05)	(0.04)	(0.03)	(0.03)
τ_Y: 80%					
Income	-0.683***	-0.730***	-0.726***	-0.761***	-0.790***
	(0.05)	(0.04)	(0.03)	(0.04)	(0.03)
Location shift	0.690***	0.737***	0.718***	0.749***	0.772***
	(0.05)	(0.04)	(0.03)	(0.04)	(0.03)

Note: Bootstrapped standard errors are reported in parentheses.

T

Ind. va
τ_Y: 20
FB1
FB2
τ_Y: 30
FB1
FB2
τ_Y: 50
FB1
FB2
τ_Y: 70
FB1
FB2
τ_Y: 80
FB1
FB2

Note: Bootstrappe

Table 6: Structural Quantile Treatment Effect Estimation: Main Sample

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	0.628***	0.698***	0.675***	0.713***	0.724***
	(0.08)	(0.06)	(0.05)	(0.04)	(0.04)
FB2	0.399***	0.396***	0.413***	0.423***	0.434***
	(0.06)	(0.04)	(0.04)	(0.04)	(0.04)
τ_Y: 30%					
FB1	0.613***	0.682***	0.661***	0.698***	0.709***
	(0.07)	(0.06)	(0.04)	(0.04)	(0.04)
FB2	0.332***	0.321***	0.341***	0.347***	0.355***
	(0.05)	(0.04)	(0.04)	(0.03)	(0.03)
τ_Y: 50%					
FB1	0.839***	0.924***	0.899***	0.945***	0.965***
	(0.10)	(0.07)	(0.09)	(0.04)	(0.04)
FB2	0.404***	0.400***	0.416***	0.425***	0.436***
	(0.13)	(0.04)	(0.04)	(0.04)	(0.04)
τ_Y: 70%					
FB1	0.713***	0.790***	0.764***	0.806***	0.820***
	(0.07)	(0.05)	(0.05)	(0.04)	(0.05)
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)	(0.07)	(0.04)
FB2	0.337***	0.333***	0.346***	0.354***	0.362***
	(0.05)	(0.04)	(0.04)	(0.07)	(0.04)

Note: Bootstrapped standard errors are reported in parentheses.

Table 7: Structural Quantile Treatment Effect Estimation: Compulsory 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	0.289***	0.211***	-0.251**	-1.114***	-1.403***
	(0.05)	(0.07)	(0.11)	(0.13)	(0.08)
Location shift	-0.276***	-0.194**	0.291**	1.131***	1.424***
	(0.05)	(0.08)	(0.11)	(0.13)	(0.08)
τ_Y: 30%					
Income	0.279***	0.205**	-0.241**	-1.075***	-1.353***
	(0.05)	(0.10)	(0.11)	(0.13)	(0.08)
Location shift	-0.267***	-0.188*	0.280**	1.091***	1.373***
	(0.05)	(0.10)	(0.11)	(0.13)	(0.08)
τ_Y: 50%					
Income	0.055***	0.046***	-0.014	-0.168***	-0.214***
	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)
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***
	(0.04)	(0.04)	(0.07)	(0.08)	(0.04)
Location shift	-0.157***	-0.114***	0.169**	0.647***	0.810***
	(0.03)	(0.04)	(0.07)	(0.07)	(0.04)
τ_Y: 80%					
Income	0.149***	0.114**	-0.114**	-0.549***	-0.685***
	(0.02)	(0.05)	(0.05)	(0.06)	(0.04)
Location shift	-0.138***	-0.099*	0.149**	0.562***	0.702***
	(0.02)	(0.06)	(0.06)	(0.06)	(0.04)

Note: Bootstrapped standard errors are reported in parentheses.

Table 8: Structural Quantile Treatment Effect Estimation: Compulsory 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	-0.150***	-0.113**	0.030	0.278***	0.395***
	(0.04)	(0.04)	(0.07)	(0.07)	(0.06)
FB2	-0.121**	-0.066	0.220**	0.735***	0.867***
	(0.05)	(0.06)	(0.09)	(0.09)	(0.06)
τ_Y*: 30%*					
FB1	-0.171***	-0.129	0.058	0.365***	0.508***
	(0.04)	(0.09)	(0.08)	(0.08)	(0.06)
FB2	-0.095**	-0.047	0.187**	0.625***	0.727***
	(0.05)	(0.05)	(0.09)	(0.09)	(0.07)
τ_Y*: 50%*					
FB1	-0.001	-0.009	-0.105	-0.305**	-0.361***
	(0.04)	(0.04)	(0.07)	(0.12)	(0.05)
FB2	-0.026	0.007	0.097	0.307**	0.340***
	(0.04)	(0.04)	(0.07)	(0.12)	(0.05)
τ_Y*: 70%*					
FB1	-0.186***	-0.140***	0.086	0.436***	0.582***
	(0.05)	(0.05)	(0.08)	(0.09)	(0.06)
FB2	-0.076*	-0.036	0.161**	0.545***	0.629***
	(0.04)	(0.05)	(0.07)	(0.07)	(0.06)
τ_Y*: 80%*					
FB1	-0.147***	-0.110	0.049	0.276***	0.385***
	(0.04)	(0.11)	(0.07)	(0.07)	(0.06)
FB2	-0.082**	-0.040	0.167**	0.568***	0.653***
	(0.04)	(0.06)	(0.08)	(0.08)	(0.06)

Note: Bootstrapped standard errors are reported in parentheses.

Table 9: Homogeneity Tests: 20th and 80th quantiles of K fixing τ_Y

	Panel (a): 20th and 80th quantiles of K, given τ_Y				
	$\tau_Y : 20\%$	$\tau_Y : 30\%$	$\tau_Y : 50\%$	$\tau_Y : 70\%$	$\tau_Y : 80\%$
$MQTEY$	1.692***	1.633***	0.268***	0.960***	0.833***
	(0.09)	(0.08)	(0.02)	(0.05)	(0.04)
	Panel (b): 20th and 80th quantiles of Y, given τ_K				
	$\tau_K : 20\%$	$\tau_K : 30\%$	$\tau_K : 50\%$	$\tau_K : 70\%$	$\tau_K : 80\%$
$MQTEY$	0.140**	0.098	-0.137	-0.565***	-0.717***
	(0.06)	(0.09)	(0.12)	(0.15)	(0.09)

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

Table 10: Structural Quantile Treatment Effect Estimation
Upper Secondary 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	0.409***	0.412***	0.397***	0.206**	0.152
	(0.06)	(0.05)	(0.04)	(0.08)	(0.11)
Location shift	-0.386***	-0.391***	-0.384***	-0.223***	-0.174
	(0.06)	(0.05)	(0.04)	(0.08)	(0.12)
τ_Y: 30%					
Income	0.446***	0.424***	0.409***	0.215***	0.154
	(0.07)	(0.05)	(0.04)	(0.08)	(0.12)
Location shift	-0.427***	-0.403***	-0.396***	-0.232***	-0.176
	(0.07)	(0.05)	(0.04)	(0.08)	(0.13)
τ_Y: 50%					
Income	0.390***	0.371***	0.360***	0.183**	0.138
	(0.06)	(0.04)	(0.03)	(0.08)	(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)	(0.04)	(0.04)	(0.07)	(0.12)
Location shift	-0.382***	-0.365***	-0.361***	-0.209***	-0.169
	(0.06)	(0.05)	(0.04)	(0.07)	(0.13)
τ_Y: 80%					
Income	0.521***	0.506***	0.495***	0.273***	0.210
	(0.07)	(0.06)	(0.05)	(0.10)	(0.15)
Location shift	-0.506***	-0.491***	-0.492***	-0.287***	-0.231
	(0.07)	(0.06)	(0.05)	(0.10)	(0.16)

Note: Bootstrapped standard errors are reported in parentheses.

Table 11: Structural Quantile Treatment Effect Estimation
Upper Secondary 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	-0.127***	-0.118***	-0.114**	-0.020	0.010
	(0.04)	(0.04)	(0.05)	(0.06)	(0.08)
FB2	0.133***	0.134***	0.154***	0.138**	0.104
	(0.03)	(0.03)	(0.05)	(0.07)	(0.09)
τ_Y: 30%					
FB1	-0.174***	-0.156***	-0.150***	-0.038	-0.004
	(0.04)	(0.03)	(0.04)	(0.07)	(0.08)
FB2	0.004	-0.004	0.018	0.058	0.048
	(0.03)	(0.03)	(0.03)	(0.06)	(0.08)
τ_Y: 50%					
FB1	-0.202***	-0.189***	-0.181***	-0.051	-0.013
	(0.04)	(0.04)	(0.04)	(0.07)	(0.10)
FB2	0.027	0.028	0.040	0.067	0.057
	(0.03)	(0.03)	(0.04)	(0.06)	(0.09)
τ_Y: 70%					
FB1	-0.233***	-0.223***	-0.205***	-0.070	-0.018
	(0.05)	(0.03)	(0.04)	(0.07)	(0.10)
FB2	-0.016	-0.007	0.004	0.056	0.034
	(0.04)	(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)	(0.12)
FB2	0.003	0.006	0.015	0.070	0.041
	(0.03)	(0.04)	(0.04)	(0.06)	(0.08)

Note: Bootstrapped standard errors are reported in parentheses.

Table 12: Homogeneity Tests: 20th and 80th quantiles of K fixing τ_Y

	Panel (a): 20th and 80th quantiles of K, given τ_Y				
	$\tau_Y : 20\%$	$\tau_Y : 30\%$	$\tau_Y : 50\%$	$\tau_Y : 70\%$	$\tau_Y : 80\%$
MQTEY	0.249**	0.287**	0.249**	0.252*	0.316**
	(0.12)	(0.13)	(0.12)	(0.13)	(0.15)
	Panel (b): 20th and 80th quantiles of Y, given τ_K				
	$\tau_K : 20\%$	$\tau_K : 30\%$	$\tau_K : 50\%$	$\tau_K : 70\%$	$\tau_K : 80\%$
MQTEY	-0.113	-0.094	-0.098	-0.067	-0.057
	(0.09)	(0.08)	(0.06)	(0.13)	(0.19)

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

Table 13: Structural Quantile Treatment Effect Estimation: Main Sample
Household Size as Equivalence Scale

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	-0.851***	-0.872***	-0.882***	-0.839***	-0.858***
	(0.05)	(0.08)	(0.04)	(0.03)	(0.03)
Location shift	0.862***	0.875***	0.885***	0.833***	0.849***
	(0.05)	(0.08)	(0.04)	(0.03)	(0.03)
τ_Y: 30%					
Income	-0.664***	-0.685***	-0.691***	-0.660***	-0.675***
	(0.04)	(0.04)	(0.03)	(0.02)	(0.03)
Location shift	0.675***	0.687***	0.694***	0.654***	0.666***
	(0.04)	(0.04)	(0.03)	(0.02)	(0.03)
τ_Y: 50%					
Income	-0.736***	-0.753***	-0.765***	-0.731***	-0.745***
	(0.05)	(0.05)	(0.03)	(0.03)	(0.04)
Location shift	0.745***	0.754***	0.768***	0.724***	0.737***
	(0.05)	(0.05)	(0.03)	(0.03)	(0.04)
τ_Y: 70%					
Income	-0.567***	-0.583***	-0.593***	-0.568***	-0.579***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
Location shift	0.574***	0.583***	0.596***	0.561***	0.571***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.04)
τ_Y: 80%					
Income	-0.458***	-0.475***	-0.480***	-0.461***	-0.470***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Location shift	0.465***	0.474***	0.483***	0.454***	0.461***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)

Note: Bootstrapped standard errors are reported in parentheses.

Table 14: Structural Quantile Treatment Effect Estimation: Main Sample
Household Size as Equivalence Scale

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	0.435***	0.454***	0.451***	0.432***	0.440***
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
FB2	0.261***	0.259***	0.275***	0.253***	0.257***
	(0.04)	(0.05)	(0.03)	(0.02)	(0.02)
τ_Y: 30%					
FB1	0.424***	0.445***	0.441***	0.423***	0.431***
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
FB2	0.213***	0.212***	0.227***	0.208***	0.211***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
τ_Y: 50%					
FB1	0.577***	0.591***	0.601***	0.574***	0.584***
	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)
FB2	0.263***	0.270***	0.277***	0.256***	0.259***
	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)
τ_Y: 70%					
FB1	0.486***	0.499***	0.511***	0.488***	0.497***
	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)
FB2	0.242***	0.247***	0.251***	0.231***	0.234***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)
τ_Y: 80%					
FB1	0.376***	0.389***	0.398***	0.380***	0.388***
	(0.04)	(0.04)	(0.03)	(0.03)	(0.02)
FB2	0.225***	0.231***	0.232***	0.213***	0.215***
	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)

Note: Bootstrapped standard errors are reported in parentheses.

Table 15: Homogeneity Tests: 20th and 80th quantiles of K fixing τ_Y
Household Size as Equivalence Scale

	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%
MQTEY	0.006	0.010	0.009	0.013	0.012
	(0.06)	(0.04)	(0.05)	(0.04)	(0.03)
	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%
MQTEY	-0.393***	-0.398***	-0.402***	-0.379***	-0.388***
	(0.06)	(0.08)	(0.04)	(0.04)	(0.04)

Note: The Table reports the homogeneity tests of marginal quantile treatment effects of income, main sample, at the 20th and the 80th quantiles of educational transfers in-kind distribution fixing quantiles of the household earning capacity (panel (a)) and at the 20th and the 80th quantiles of quantiles of the household earning capacity fixing quantiles of the educational transfers in-kind distribution (panel (b)). Standard errors are reported in parentheses.

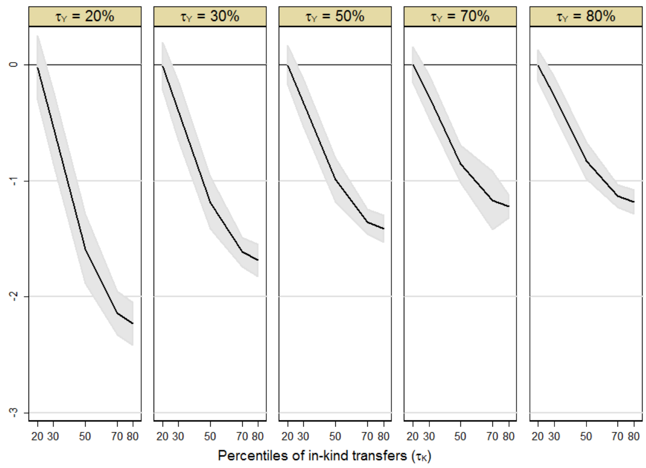


Figure 11: Marginal Quantile Treatment Effects of Income
Compulsory Education Including Kindergarten

Note: The figure plots the marginal quantile treatment effects of income for a given quantile of the household earning capacity. These marginal quantile treatment effects are calculated taking into account the scale shift effect, measured by the interaction between income and the residuals of the given quantile of the household earning capacity, and the interactions between income and our two variables of family background, each of them considered separately. Confidence bands at 99% level.

Table 16: Structural Quantile Treatment Effect Estimation
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***
	(0.14)	(0.16)	(0.15)	(0.09)	(0.09)
Location shift	0.053	0.567***	1.608***	2.148***	2.223***
	(0.14)	(0.16)	(0.15)	(0.09)	(0.10)
τ_Y: 30%					
Income	-0.008	-0.394***	-1.187***	-1.613***	-1.685***
	(0.10)	(0.13)	(0.12)	(0.06)	(0.07)
Location shift	0.041	0.430***	1.213***	1.621***	1.675***
	(0.11)	(0.13)	(0.11)	(0.07)	(0.07)
τ_Y: 50%					
Income	-0.001	-0.323***	-0.990***	-1.352***	-1.412***
	(0.09)	(0.11)	(0.10)	(0.05)	(0.06)
Location shift	0.033	0.358***	1.015***	1.359***	1.402***
	(0.09)	(0.11)	(0.10)	(0.05)	(0.06)
τ_Y: 70%					
Income	0.000	-0.275***	-0.852***	-1.166***	-1.218***
	(0.08)	(0.09)	(0.08)	(0.13)	(0.05)
Location shift	0.031	0.308***	0.874***	1.172***	1.209***
	(0.08)	(0.09)	(0.08)	(0.12)	(0.05)
τ_Y: 80%					
Income	-0.002	-0.266***	-0.828***	-1.129***	-1.181***
	(0.07)	(0.08)	(0.08)	(0.05)	(0.05)
Location shift	0.033	0.298***	0.849***	1.135***	1.173***
	(0.07)	(0.09)	(0.08)	(0.05)	(0.05)

Note: Bootstrapped standard errors are reported in parentheses.

Table 17: Structural Quantile Treatment Effect Estimation
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***
	(0.07)	(0.07)	(0.06)	(0.06)	(0.08)
FB2	0.022	0.303***	0.862***	1.203***	1.235***
	(0.08)	(0.10)	(0.10)	(0.06)	(0.06)
τ_Y: 30%					
FB1	-0.009	0.150**	0.460***	0.581***	0.630***
	(0.06)	(0.07)	(0.06)	(0.05)	(0.06)
FB2	0.013	0.204***	0.573***	0.819***	0.837***
	(0.06)	(0.08)	(0.08)	(0.05)	(0.06)
τ_Y: 50%					
FB1	-0.002	0.249***	0.735***	0.954***	1.015***
	(0.08)	(0.10)	(0.08)	(0.06)	(0.07)
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)	(0.07)	(0.17)	(0.08)
FB2	0.008	0.124**	0.360***	0.537***	0.542***
	(0.04)	(0.06)	(0.06)	(0.11)	(0.05)
τ_Y: 80%					
FB1	-0.006	0.193**	0.576***	0.736***	0.792***
	(0.07)	(0.08)	(0.07)	(0.06)	(0.07)
FB2	0.011	0.125**	0.363***	0.541***	0.547***
	(0.04)	(0.06)	(0.06)	(0.04)	(0.05)

Note: Bootstrapped standard errors are reported in parentheses.

Table 18: Homogeneity Tests: 20th and 80th quantiles of K fixing τ_Y
Compulsory Education Including Kindergarten

	Panel (a): 20th and 80th quantiles of K, given τ_Y				
	$\tau_Y : 20\%$	$\tau_Y : 30\%$	$\tau_Y : 50\%$	$\tau_Y : 70\%$	$\tau_Y : 80\%$
$MQTEY$	2.211***	1.676***	1.410***	1.220***	1.181***
	(0.15)	(0.12)	(0.10)	(0.09)	(0.08)
	Panel (b): 20th and 80th quantiles of Y, given τ_K				
	$\tau_K : 20\%$	$\tau_K : 30\%$	$\tau_K : 50\%$	$\tau_K : 70\%$	$\tau_K : 80\%$
$MQTEY$	-0.017	-0.264	-0.755***	-1.011***	-1.052***
	(0.16)	(0.18)	(0.17)	(0.11)	(0.11)

Note: The Table reports the homogeneity tests of marginal quantile treatment effects of income at the 20th and the 80th quantiles of educational transfers in-kind distribution fixing quantiles of the household earning capacity (panel (a)) and at the 20th and the 80th quantiles of quantiles of the household earning capacity fixing quantiles of the educational transfers in-kind distribution (panel (b)). Standard errors are reported in parentheses.

Table 19: Structural Quantile Treatment Effect Estimation
Tertiary 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	0.049	0.153**	0.217***	0.286***	0.339***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)
Location shift	-0.024	-0.149**	-0.205***	-0.279***	-0.332***
	(0.06)	(0.07)	(0.06)	(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)	(0.08)
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***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)
Location shift	-0.010	-0.127**	-0.180***	-0.248***	-0.314***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)
τ_Y: 70%					
Income	0.023	0.090**	0.142***	0.185***	0.234***
	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
Location shift	-0.007	-0.094**	-0.140***	-0.185***	-0.237***
	(0.05)	(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)	(0.04)	(0.05)
Location shift	-0.005	-0.093**	-0.146***	-0.195***	-0.250***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)

Note: Bootstrapped standard errors are reported in parentheses.

Table 20: Structural Quantile Treatment Effect Estimation
Tertiary 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	-0.102	-0.213**	-0.232***	-0.305***	-0.390***
	(0.09)	(0.10)	(0.08)	(0.08)	(0.08)
FB2	0.151**	0.077	0.003	-0.042	-0.038
	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)
τ_Y: 30%					
FB1	-0.095	-0.236**	-0.266***	-0.352***	-0.443***
	(0.10)	(0.11)	(0.09)	(0.09)	(0.10)
FB2	0.154*	0.101	0.035	0.005	0.020
	(0.08)	(0.08)	(0.06)	(0.08)	(0.08)
τ_Y: 50%					
FB1	-0.082	-0.197*	-0.220**	-0.290***	-0.374***
	(0.09)	(0.11)	(0.09)	(0.08)	(0.09)
FB2	0.151*	0.096	0.025	-0.010	-0.012
	(0.08)	(0.08)	(0.05)	(0.07)	(0.09)
τ_Y: 70%					
FB1	-0.070	-0.149*	-0.160**	-0.199***	-0.256***
	(0.08)	(0.09)	(0.07)	(0.07)	(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)	(0.09)	(0.08)	(0.08)	(0.08)
FB2	0.152**	0.119*	0.059	0.040	0.043
	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)

Note: Bootstrapped standard errors are reported in parentheses.

Table 21: Homogeneity Tests: 20th and 80th quantiles of K fixing τ_Y
Tertiary Education

	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%
MQTEY	-0.291***	-0.299***	-0.280***	-0.209***	-0.220***
	(0.09)	(0.09)	(0.08)	(0.05)	(0.06)
	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%
MQTEY	0.027	0.064	0.071	0.093	0.097
	(0.07)	(0.08)	(0.07)	(0.08)	(0.09)

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