

Wage Functions and Rates of Return to Education in Italy

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Abstract

We study the return to education in Italy in the period 1995-2010 for a representative sample of Italian households. In line with previous literature, OLS under-estimate the return to schooling. When the endogeneity of schooling is taken into account, the return to an additional year in school increases. The evidence is that returns have not changed much over the considered period, varying between 5.9% and 7.9%. Looking to the different sector of employment, a relative convenience to work in the public sector emerges, but not significant for all the analyzed years. In addition, there is an evidence of a gender pay gap, in favor of men for all the period considered. When the type of school attended is taken into consideration, the returns to education increase with higher levels of educational attainment.

Keywords: education premium, Mincer equation, gender gap, public sector

JEL: I21; J24; J31; J45; J71

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1 Introduction

Education is one of the most important components of individual human capital (Becker 1993) thus a significant determinant of earnings. The estimation of the economic return to education has perhaps been one of the predominant areas of analysis in applied economics for over 50 years, in both micro and macroeconomics. The analysis of education has been driven by the concept of human capital, pioneered by Gary Becker, Jacob Mincer and Theodore Schultz. In human capital theory, education is an investment of current resources for future returns. The benchmark model for the development of empirical estimation of the returns to education is the relationship derived by Mincer (1974) between log hourly earnings and schooling. The original Mincer equation assumes linear effect on earnings of each year of education regardless of the attainment level.

The aim of this paper is to evaluate returns to education in Italy over time. In particular, we focus on education as a private decision to invest in human capital and we explore the internal rate of return to that private investment. Then, we take into account differential effects of different educational level (upper-secondary and tertiary education) and of different type of school (scientific, humanistic, technical) within each educational level. We use the SHIW conducted by the Bank of Italy, covering the period from 1995 to 2010 to estimate the returns to education.

The remainder of the paper is organized as follows. Section 2 provides some descriptive statistics on educational attainments in OECD Countries. Section 3 reviews previous works in the area. Section 4 presents the theoretical background of the earnings equation to be estimated. Section 5 describes the dataset used in the empirical estimation and the characteristics of the sample. Section 6 reports the estimates of the effect of schooling on individual wages. Finally, section 7 summarizes and concludes.

2 Education Attainments and Education Premium in OECD Countries

The current Italian education system is composed by primary, secondary, upper secondary and tertiary education. Primary school is compulsory for children aged between 6 and 11 years. Lower secondary education is also compulsory, free of charge and lasts three years. Post compulsory education is differentiated into the following categories: classical, scientific and pre-school teacher training, artistic education, technical school and vocational education. Upper secondary education lasts from three to five years, depending on the type of school. Since 1969, the selection of the type school does not preclude access to tertiary education. Graduation from upper secondary schools requires a leaving school certificate examination and access to tertiary education is only conditional on passing this exam.

In comparison with other OECD countries in 2009, average education attainments of the upper secondary education in Italy is substantially low as shown in Table 1. On average across OECD countries, the percentage of 25-34 year-olds with at least upper secondary education is 20 per cent higher than that among 55-64 year-olds (about 81.5 per cent against 61.3 per cent). This difference for cohort can be explained by the observed general decline in demand for manual labor and for basic cognitive skills (easily replicated by computers), in favor of a sharp increase in the demand for complex communication and advanced analytical skills, which require a more educated labor force.

Table 1 - Percentage of population that has attained at least upper secondary education, by age group.

	25-34 years old	55-64 years old
OECD average	81.5	61.3
Italy	70.3	36.7

Source: OECD (2011)

In Italy, just 70.3 per cent of the age-group 25-34 (versus an OECD average of 81.5 per cent) has attained at least upper secondary education; however, such a

percentage is much higher than the 36.7 per cent of the 55-64 age-group. Indeed, in Italy since 2000 to 2009 the percentage of population with upper secondary education increased by an average of 3 per cent, which represents an annual growth rate of 0.4 per cent. Extrapolating the current patterns of graduation, an average of 81 per cent of today's young people will complete upper secondary education over their lifetimes.

As regards tertiary education in OECD countries we observe the same upward trend of education attainment for younger cohorts of population as reported in Table 2 (from 22.4 per cent to 37 per cent).

Table 2 - Percentage of population that has attained tertiary education, by age group.

	25-34 years old	55-64 years old
OECD average	37.0	22.4
Italy	20.2	10.3

Source: OECD (2011)

In Italy in 2009 the percentage of population in the 25-34 years-olds cohort with a university degree is equal to 20.2 per cent, much lower than the OECD average of 37 per cent. Even though Italy shows a very significant increase over time of the percentage of the population attaining tertiary education (20.2 per cent of the 25-34 age group must be compared with 10.3 per cent of the 55-64 age group), we notice that such difference is well below that observed for OECD countries (from 22.4 per cent to 37 per cent).

Looking at gender in OECD and Italy, evident disparities in educational attainments between women and men are present in the older generations, but with a significant inversion in the more recent cohorts (see Tables 3 and 4). In particular, in OECD countries while for older generation (e.g. 55-64 age group) the percentage of people attaining upper secondary and tertiary education is significantly larger for men, for the 25-34 age group the educational level is significantly higher for women.

Table 3 - Percentage of population that has attained at least upper secondary education, by gender.

Women, by age group					
	25-64	25-34	35-44	45-54	55-64
OECD average	72	83	77	69	57
Italy	55	74	61	51	33

Men, by age group					
	25-64	25-34	35-44	45-54	55-64
OECD average	74	80	77	72	66
Italy	54	67	55	50	41

Source: OECD (2011)

The gender gap in education in favor of women is recorded also in Italy: 7 per cent higher for the same group for upper secondary education, and 9 per cent higher for women aged 25-34 for tertiary education.

Table 4 - Percentage of population that has attained tertiary education, by gender.

Women, by age group					
	25-64	25-34	35-44	45-54	55-64
OECD average	31	42	34	27	21
Italy	16	25	17	12	10

Men, by age group					
	25-64	25-34	35-44	45-54	55-64
OECD average	29	33	30	27	24
Italy	13	16	13	12	11

Source: OECD (2011)

Tertiary education brings substantial economic benefits for workers both in terms of higher earnings and lower probability to be fired. A person with a tertiary education can expect to earn over 50 per cent more than a person with an upper secondary or postsecondary non-tertiary education (OECD, 2011). In OECD countries, those who do not complete an upper secondary education could earn an average of 23 per cent less than their counterparts who do complete that level of education. The earnings advantage of having a tertiary degree increases with age (on average, the earnings of tertiary-educated 55-64 year-olds is larger than that for

25-64 year-olds: by 13 per cent for OECD countries, by 45 per cent for Italy) but across all educational levels women earn considerably less than men (in Italy, women who have obtained a tertiary degree earn 65 per cent or less of tertiary-educated men).

In all OECD countries, individuals with a tertiary-level degree have a greater chance of being employed than those without such a degree. In general, higher education improves job prospects and the likelihood of remaining employed in times. In 2009, in Italy 79 per cent of the population with a tertiary education is employed against 73 per cent with a upper secondary education (84 per cent against 74 per cent in OECD countries). Employment rates for workers with a tertiary education are higher of 28 per cent with respect to workers who have not completed an upper secondary education either for OECD countries and for Italy.

Finally, also the effect on earnings of an upper secondary education changed over time. Young individuals (25-34 year-olds) with a vocational² upper secondary education typically do well in the labor market when compared with the total 25-64 year-old population. In Italy, the unemployment rate for young individuals (25-34 year-olds) with vocational upper secondary education is 3 per cent points higher than that of the 25-64 year-old population (OECD, 2011).

3 Literature on the Estimated Returns to Schooling in Italy

The main features of empirical research on returns to education in Italy are shown in Table 5. The estimated rate of return to an additional year of schooling considerably vary across studies, also for the method used in the estimate. Antonelli (1985), who consider regional data, estimates that an additional year of schooling increases annual net earnings by 4.6 per cent. Cannari et al. (1989) use a larger sample from the 1986 wave of the Bank of Italy, finding a similar result of a return around 4 per cent. While Lucifora and Reilly (1990) estimate the mincerian earnings function using the ENI special survey on earning and they find that the

² Vocational or technical education is defined as education that is mainly designed to offer participants the opportunity to acquire

marginal return to schooling is slightly higher for men than for women but again around 4 per cent.

Table 5 – A summary of the estimated return to schooling of an additional year of schooling in Italy of a sample of empirical contributions.

Author	Method	Years of observations	Marginal return to education
Antonelli (1985)	OLS	1977	4.6
Cannari, Pellegrini, and Sestito (1989)	OLS	1986	4.0
Lucifora and Reilly (1990)	OLS	1985	4.0 (men) 3.6 (women)
Cannari and D'Alessio (1995)	IV	1993	7.0
Colussi (1996)	IV	1993	7.6
Flabbi (1997)	IV	1991	6.2 (men) 5.6 (women)
Brunello and Miniaci (1999)	IV	1993 and 1995	5.7
Brunello, Comi, and Lucifera (2000)	OLS	1995	6.2 (men) 7.7 (women)
Ciccone (2004)	OLS	1987-2000	6.1
Ciccone, Cingano, and Cipollone (2006)	OLS	1987-2000	6.9
Mendolicchio (2006)	PV	2002	5.3 (men) 6.5 (women)
Cingano and Cipollone (2009)	OLS	1987-2000	6.0

For the 1993 wave of Bank of Italy Cannari and D'Alessio (1995), using family background variables as instruments of educational outcomes, find that the marginal return to education is around 7 per cent, much higher than previous results. Also Colussi (1996) obtain a similar result, using the same wave and a similar set of instruments. For 1991 wave Flabbi (1997) calculates the returns to education separately for men and women with an instrumental variable approach based upon the identification of exogenous changes in the schooling system; he finds that the marginal effect of education is 6.2 per cent for men and 5.6 per cent for women, confirming the gender gap in earnings. For the 1993 and 1995 waves, Brunello and Miniaci (1999) estimate a return to education equal to 5.7 per cent (taking into account the endogeneity of schooling). The estimated coefficient on the mincerian rate of return to schooling is around 6 per cent in Ciccone (2004) and Cingano and Cipollone (2009).

Brunello, Comi and Lucifora (2000) find evidence of a greater return to schooling for women, that is also confirmed in the work of Mendolicchio (2006), in which proxy variables approach is applied to deal with the endogeneity of the schooling variable.

In summary, in the analysis the check for the endogeneity appears a crucial feature in order to avoid a likely downward bias in the estimate; furthermore, the estimated return appears to be varying over time, suggesting to separately consider the different waves; and, finally, gender gap should be take into consideration.

4 Theoretical Background Model and Empirical Strategy

The theoretical approach underlying most empirical studies of schooling attainment is the model of accumulation of human capital developed by Schultz (1961), Becker (1964) and Mincer (1958, 1974). In human capital theory, education is an investment of current resources in exchange of future returns. The benchmark model for the empirical estimation of the returns to education is the relationship developed by Mincer in a very celebrate model in 1974. This model focuses on the life-cycle dynamics of earnings and on the relationship between observed earnings, potential earnings and human capital investment, both in terms of formal schooling and on-the-job investment. No explicit assumption are made about the background economic environment. Observed earnings are a function of potential earnings net of human capital investment costs, where potential earnings in any time period depend on investments made in previous time periods. Let E_t be the potential earnings at time t . Investments in training can be expressed as a fraction of potential earnings invested, i.e. $C_t = k_t E_t$, where k_t is the fraction invested at time t . Let ρ_t be the return to training investments made at time t . Then:

$$E_{t+1} = E_t + C_t \rho_t = E_t(1 + k_t \rho_t) \quad (1)$$

Repeated substitution yields $E_t = \prod_{j=0}^{t-1} (1 + \rho_j k_j) E_0$.

Formal schooling is defined as years spent in full-time investment ($k_t = 1$). Assume that the rate of return on formal schooling is constant for all years of schooling ($\rho_t = \rho_s$) and that formal schooling takes place at the beginning of life. Then, assume that the rate of return to post-school investment, ρ_t is constant over time and equals ρ_0 . Then, we can write:

$$\ln E_t = \ln E_0 + s \ln(1 + \rho_s) + \sum_{j=s}^{t-1} \ln(1 + \rho_0 k_j) \quad (2)$$

which yields the approximate relationship (for small ρ_s and ρ_0)

$$\ln E_t \approx \ln E_0 + s\rho_s + \rho_0 \sum_{j=s}^{t-1} k_j \quad (3)$$

To establish a relationship between potential earnings and years of labor market experience, Mincer (1974) approximates the Ben-Porath (1967) model and further assumes a linearly declining rate of post-school investment:

$$k_{s+x} = \kappa \left(1 - \frac{x}{T}\right) \quad (4)$$

where $x_t = t - s \geq 0$ is the amount of work experience as of age t . The length of working life, T , is assumed to be independent of years of schooling. Under these assumptions, the relationship between potential earnings, schooling and experience is given by:

$$\ln E_{x+s} \approx [\ln E_0 - \kappa\rho_0] + \rho_s s + \left(\rho_0\kappa + \frac{\rho_0\kappa}{2T}\right)x - \frac{\rho_0\kappa}{2T}x^2 \quad (5)$$

Observed earnings equal potential earnings less investment costs, producing the following relationship for observed earnings:

$$\begin{aligned} \ln w(s, x) &\approx \ln E_{x+s} - \kappa \left(1 - \frac{x}{T}\right) = [\ln E_0 - \kappa\rho_0 - \kappa] \\ &\quad + \rho_s s + \left(\rho_0\kappa + \frac{\rho_0\kappa}{2T} + \frac{\kappa}{T}\right)x - \frac{\rho_0\kappa}{2T}x^2 \\ &= \alpha_0 + \rho_s s + \beta_0 x + \beta_1 x^2 \end{aligned} \quad (6)$$

Then, this is the standard form of the Mincer earnings model that regresses log earnings on a constant term, a linear term in years of schooling, and linear and quadratic term in years of labor market experience. In most of applications of the Mincer model, it is assumed that the intercept and slope coefficients are identical across persons. This implicitly assumes that E_0 , κ , ρ_0 and ρ_s are the same across persons and do not depend on the schooling level. However, Mincer formulates a

more general model that allows for the possibility that κ and ρ_s differ across persons, which produces a random coefficient model:

$$\ln w(s_i x_i) = \alpha_{0i} + \rho_{si} s_i + \beta_{0i} x_i + \beta_{1i} x_i^2 + \varepsilon_i \quad (7)$$

Assuming $\alpha_0 = E(\alpha_{0i}), \rho_s = E(\rho_{si}), \beta_0 = E(\beta_{0i}), \beta_1 = E(\beta_{1i})$, we can write this expression as:

$$\begin{aligned} \ln w(s, x) = & \alpha_0 + \rho_s s + \beta_0 x + \beta_1 x^2 + [(\alpha_{0i} - \alpha_0) + (\rho_{si} - \rho_s) s \\ & + (\beta_{0i} - \beta_0) x + (\beta_{1i} - \beta_1) x^2] \end{aligned} \quad (8)$$

where the terms in brackets are part of the error. Initially, Mincer assumes that $(\alpha_{0i} - \alpha_0), (\rho_{si} - \rho_s), (\beta_{0i} - \beta_0), (\beta_{1i} - \beta_1)$ are independent of (s, x) . In later work (Mincer, 1977), he relaxes this assumption.

Mincer derives several implications from the accounting identity model under different assumptions about the relationship between formal schooling and post-school investment patterns. Under the assumption that post-school investment patterns are identical across persons and do not depend on the schooling level, he shows that $\frac{\partial \ln w(s, x)}{\partial s \partial x} = 0$ and $\frac{\partial \ln w(s, x)}{\partial s \partial t} = \frac{\rho_0 \kappa}{T} > 0$. These two conditions imply:

- (i) log-earnings experience profiles are parallel across schooling levels
- (ii) log-earnings age profile diverge with age across schooling levels.

In the Mincer specification, the disturbance term captures unobservable individual effects, as unobserved ability, that may also influence schooling decision, and then induce a correlation between schooling and the error term in the earnings function. The correlation between schooling and error term means the former does not measure casual effects and thus schooling is endogenous. With endogeneity the returns to schooling estimated by the then estimation by ordinary least squares are biased. The solution to this problem has been addressed in different ways. Firstly, the measures of ability have been incorporated with a proxy variable for unobserved effects, in order to control separately the effect of education and ability. Secondly, one might exploit within-twins differences in wages and education,

assuming that unobserved effects are additive and common within twins so that they can be differentiated out by regressing the wage difference within twins against their education differences. Another approach deals with the simultaneous relationship between schooling and earnings by specifying a two-equation system, which is identified by exploiting instrumental variables that affect s but not w . Instrumental variables estimation, using family background as instruments for schooling, will be our strategy to deal with endogeneity.

The last approach is the most applied in the literature and it is what we applied in the following estimates.

5 The Dataset

The analysis is based on data provided by the Bank of Italy's Survey of Household Income and Wealth (SHIW), reporting several socio-economic characteristics of Italian households. The SHIW is a biannual survey on the microeconomic behavior of Italian families with a sample of approximately 8,000 household per year. The observations from eight subsequent surveys will be analyzed, from 1995 to 2010. In particular, the SHIW contains information both on households (family composition) and on individuals. Moreover, it provides detailed information on several characteristics of the worker, such as net yearly earnings, average weekly hours of work and number of months of employment per year³, educational attainment (the highest completed school degree⁴), job experience, gender, marital status, sector of employment, composition of his/her family, parents background, regions of residence, town size.

³ Our definition of the hourly wages is: yearly net earnings/(months worked*weekly hours worked*4)

⁴ Standard and not actual year of formal schooling are recorded. Since students who fail to reach a standard have to repeat the year, the actual number of years is likely to be underestimated.

We consider a sub-sample of men and women between 15-64 years old, full time and part time employees, working either in the public or in the private sector⁵ and such that information about earnings are available.

5.1 Variables Used in the Analysis

Earnings, schooling attainment, and working experience of every individual are the key variables in the estimate of Mincer equation.

In its original formulation, the Mincer equation refers to the hourly price of labor as correct measure of worker's earnings⁶. SHIW contains annual earnings net of taxes and social security contributions. Additional information on the average number of hours worked per week and on the number of months worked per year can be used to construct an estimate of the hourly net wage, the measure used by most empirical studies⁷.

Schooling attainment is generally measured by the number of years spent at school. SHIW does not contain information about this number of years, but only on the highest degree attained by individual. Following a common approach in literature (see, for instance, Vieira, 1999; Brunello and Miniaci, 1999) we calculate the educational attainment of the individual by imputing the number of years required to complete her/his reported level of educational attainment⁸. More precisely, we consider that the (statutory) numbers of years required to obtain a primary and a junior school certificate is 5 and 8 years respectively; instead, for the upper secondary school the number of years ranges from 11 (vocational or technical school) to 13 (classical or scientific studies); finally, for tertiary education, we

⁵ We exclude self-employed because of the low reliability of their declared earnings. As calculated by Brandolini and Cannari (1994) Bank of Italy's Survey of Household Income and Wealth (SHIW) seems to underestimate the self-employed earnings of about 50 percentage points.

⁶ Monthly or annual wages would in addition capture the effect of individual's decisions on working hours. Given the only weak positive correlation between working time and educational attainment it is reasonable to assume that the choice of hours worked reflects individual preferences rather than educational levels.

⁷ Notice that hourly measure of earnings can be affected by measurement errors due to the fact that we calculate hourly wages as total earnings divided by hours of work.

⁸ Standard, not actual, years of formal schooling are recorded. Since students who fail to reach a standard have to repeat the year, the actual number of years is likely to be underestimated.

consider 16, 18 and 21 years for the university diploma, the college degree, and the postgraduate degree (e.g. Ph.D.) respectively. In the analysis we will also treat education as a categorical variable divided into 6 categories: no education, primary school, junior high school, 3-year vocational school, upper secondary school, tertiary education (including university diploma, college and post-graduate education). It is important to stress that the statutory number of years can be significantly different from the actual number of years spent to obtain a degree, especially at college because of the high percentage of irregular student.

Many empirical studies use age as a proxy for the (working) experience of individuals. But this choice can be severely biased, especially for young cohorts. Other authors use potential experience, defined as the difference between the current age and the age at the labor market entry, but they ignore the possibility of unemployment or underemployment, again a crucial feature for young cohorts.

Here we use as proxy for experience the number of years for which a worker has been paid social security contribution; they should reflect the effective years of training on the job and learning-by-doing activities.

The control variables are as follows. A gender dummy (DUMMY_MALE) controls for different wage levels between men and women. Marital status also enter into the analysis as a dummy variable (DUMMY_MARRIED) taking the value 1 if the person is formally married and 0 otherwise. Over and above its effect via hours worked, part-time work is captured through a separate dummy variable (DUMMY_PART_TIME) since the assumption that each working hour makes the same contribution to weekly earnings (constancy of the hourly wage) may not hold across workers with different time status (part time versus full time).

We also introduce controls for family composition, as a proxy for the influence of housework, particularly important in the female labor supply (Heckman and Killingsworth, 1986). Indeed we control for the number of components of the family (NCOMP) and moreover, we add a dummy (DUMMY_HOUSEHOLD) to take into account the fact that the individual is the household of the family.

Controls for sector in the labor market (DUMMY_AGRICULTURAL for the agricultural sector, DUMMY_INDUSTRIAL for the industrial sector, DUMMY_PUBLIC for the public sector and D_OTHER_SECTOR for other sector different from the previous ones) concern the demand side factors that are not fully explained by human capital variables, and they allow reducing the bias arising from an imperfectly competitive labor market. Finally, the regression controls for the geographical area of residence: one dummy for the town of residence that has more than 500.000 inhabitants (DUMMY_TOWN), and three different dummies for the macro-regions: Nord, Center and South (DUMMY_NORTH, DUMMY_CENTER and DUMMY_SOUTH).

Table 6 reports the descriptive statistics of the main variables used in the empirical analysis for all the waves. Notice that the available measure of earnings is net of income taxes and social security contributions.

Table 6 - Means and standard deviations of the variables used in the empirical analysis for the entire sample (1995, 1998, 2000, 2002, 2004, 2006, 2008, 2010)

Variable	Mean	Stand. Dev.	Description
LOGY_H	2.210	0.439	Logarithm of the hourly real earnings less tax
SCHOOL	11.294	3.796	Schooling attainment, that is the number of years spent at school
COMP_SCHOOL	0.391	0.488	Compulsory school: no schooling, primary school and junior high school
VOCATIONAL	0.091	0.287	3-years Vocational degree
UPPER_SECONDARY	0.377	0.485	Upper secondary degree
DIPL_TECN	0.212	0.409	Technical school
DIPL_LIC	0.056	0.230	Liceo classico, scientifico, linguistico, artistico
DIPL_PROF	0.050	0.219	Vocational school
DIPL_MAG	0.050	0.217	Liceo magistrale
DIPL_OTHER	0.008	0.089	Other upper secondary degree
TERTIARY	0.141	0.348	Tertiary degree
L_LETT	0.039	0.195	Literature, Philosophy, Languages, Psychology
L_SCIEN	0.047	0.212	Mathematics, Physics, Chemistry, Biology, Medicine, Engineering, Agriculture, Veterinary
L_UMAN	0.038	0.190	Economics, Statistics, Architecture, Political Science, Sociology, Law
L_OTHER	0.017	0.128	Other tertiary degree
EXPERIENCE	17.480	10.616	Number of years for which it has been paid social security contributions, as a proxy for years of training on the job
DUMMY_MALE	0.581	0.493	Gender dummy
DUMMY_MARRIED	0.647	0.478	Dummy variable for marital status

NCOMP	3.343	1.179	Number of components of the family
DUMMY_HOUSEHOLD	0.473	0.499	Household dummy, that is equal to 1 if the individual is the household of the family
DUMMY_PART_TIME	0.087	0.281	Dummy variable for part time work
DUMMY_AGRICULTURAL	0.034	0.180	Dummy variable for agricultural sector
DUMMY_INDUSTRIAL	0.324	0.468	Dummy variable for industrial sector
DUMMY_PUBLIC	0.324	0.468	Dummy variable for public administration sector
DUMMY_OTHER_SECTOR	0.318	0.466	Dummy variable for other sector
DUMMY_TOWN	0.083	0.276	Dummy variable for the town of residence that has more than 500.000 inhabitants
DUMMY_NORTH	0.503	0.500	Dummy variable for North regions
DUMMY_CENTER	0.213	0.409	Dummy variable for Center regions
DUMMY_SOUTH	0.284	0.451	Dummy variable for South regions
DUMMY_SECT_PARENTS	0.379	0.485	Dummy variable equal to 1 if the individual works in the same sector of the father and/or of the mother
SCHOOL_F	6.040	4.095	Schooling attainment of the father's worker
SCHOOL_M	5.284	3.693	Schooling attainment of the mother's worker

6 Results

6.1 Estimation of Schooling

For each available year, a cross-sectional OLS regression of the Mincerian wage equation described in (6) is run to stress whether the estimated returns to education have varied significantly over time. Robust standard errors are computed, in order to control for the presence of outliers and heteroskedasticity (see the results in the appendix).

However, as discussed in a very large literature summarized by Card (1994), ordinary least squares estimates of the returns to education are not consistent either because of measurement errors in the schooling variable or because of the endogeneity of the schooling variable.

In particular, the measurement of years of schooling in our data is exposed to error because we lack information on completed years and observe only the last completed degree. But individuals with the same completed degree could have spent a significantly different number of years in education. Moreover, the endogeneity bias may arise either from unobserved variation in ability or from unobserved heterogeneity. If those who extended education beyond compulsory schooling have greater ability than other, then the estimated return to education is

biased upwards since part of the productivity differential is due to ability or skills acquired outside the school (ability bias). Thus, the ability bias may interact with heterogeneous subjective discount rates that result in under-estimating the true effect of schooling on earnings if the more impatient individuals happen to be the more able ones (heterogeneity bias). The total effect of the bias in the OLS estimates is ambiguous.

One way to deal with measurement errors and the endogeneity of schooling is to estimate the eq.(6) by using instrumental variables (IVs). The identification of a valid instrument is not easy work and has been reviewed among others by Card (1999) and Ashenfelter, Harmon and Oosterbeek (1999).

The requirements for an instruments to be valid are that it should be correlated with educational choice but not correlated with log wages conditional on schooling (Wooldridge, 2002). Candidates to be used as an instrument are only weakly correlated with the endogenous variable in question. It is well recognized that using such variables as instruments is likely to produce estimates with large standard errors. In particular, if the correlation between the instrument and the endogenous explanatory variable is weak, then even a small correlation between the instrument and the error can produce a larger inconsistency in the IV estimate of the coefficients than in the OLS estimates (Bound et al., 1995).

There is a long tradition in using family background variables, typically the level's of parent's schooling, as a valid instruments (Cannari and D'Alessio, 1995; Colussi, 1997; Card, 1999). The idea is based on the observation of persistence across generation about the level of schooling and it is theoretically justified by involuntary transmission of human capital.

Our instruments will be a set of variables that measure family background, including the highest completed educational level by the father and the mother of the interviewed individual. Then, more educated parents are likely to value education more and to fill better jobs.

However, the selection of family background variables as additional instruments has two potential problem. First, individual is asked to recall both the highest

educational level and the occupation held by his parents when they had his current age. Then, it is not clear whether information based on the same age as the respondent is always the most relevant. This is the case especially for the profession of the parents, that could have changed with respect to the profession held during the schooling period of the interviewed individual. Second, family characteristics could affect the returns to education, thus failing to satisfy the necessary condition for instruments validity. In our estimation strategy, the instrument validity are tested by computing Sargan test, which is an over-identification test with an asymptotic χ^2 distribution and degrees of freedom equal to the number of over-identifying restrictions. The test verifies whether the instruments play a direct role, through predicting educational attainment (Wooldridge, 2002). An important requirement in also that selected instrument should be correlated with the endogenous variable. The excluded instruments in the reduced form schooling equation are tested by computing the F-statistic on the excluded instruments in the reduced form schooling equation, experience and the square of experience equations as suggested by Bound et al. (1995).

Table 7 - IV estimates⁹. Dependent Variable: log of hourly earnings less tax. Omitted categories are: Center (DUMMY_CENTER); Industrial sector (DUMMY_INDUSTRIAL).

VARIABLES	1995	1998 ¹⁰	2000	2002	2004	2006	2008	2010
SCHOOL	0.0643*** (0.00368)	0.0619*** (0.00764)	0.0686*** (0.00477)	0.0712*** (0.00759)	0.0668*** (0.00678)	0.0786*** (0.00621)	0.0587*** (0.00613)	0.0685*** (0.00784)
EXPERIENCE	0.0189*** (0.00331)	0.0188*** (0.00671)	0.0206*** (0.00354)	0.0246*** (0.00530)	0.0144*** (0.00450)	0.0250*** (0.00375)	0.0227*** (0.00447)	0.0151*** (0.00439)
EXPERIENCE^2	-0.00014* (7.92e-05)	-0.00014 (0.000155)	-0.00019** (8.13e-05)	-0.000278** (0.000128)	-0.000149 (0.000115)	-0.000326*** (9.04e-05)	-0.000271** (0.000112)	-4.20e-05 (0.000100)
DUMMY_MALE	0.132*** (0.0250)	0.114*** (0.0354)	0.0940*** (0.0187)	0.0983*** (0.0252)	0.0812*** (0.0261)	0.109*** (0.0211)	0.157*** (0.0215)	0.154*** (0.0266)
DUMMY_MARRIED	0.00438 (0.0249)	0.0501 (0.0448)	0.0555** (0.0251)	0.00825 (0.0381)	0.0369 (0.0317)	-0.00941 (0.0235)	-0.0500* (0.0279)	0.0292 (0.0283)
NCOMP	0.0177** (0.00728)	0.0150 (0.0146)	-0.000804 (0.00781)	0.00124 (0.0101)	-0.00221 (0.00898)	0.0315*** (0.00896)	0.0275*** (0.00893)	-0.00232 (0.0110)
DUMMY_HOUSEHOLD	-0.00637 (0.0254)	-0.00119 (0.0369)	0.00604 (0.0184)	0.0224 (0.0247)	0.0188 (0.0245)	0.0306 (0.0200)	0.00901 (0.0237)	
DUMMY_TOWN	0.00582 (0.0210)	0.0310 (0.0405)	0.0128 (0.0215)	-0.0815** (0.0360)	-0.0184 (0.0447)	0.0423* (0.0242)	0.0166 (0.0305)	-0.0339 (0.0395)
DUMMY_NORTH	0.0378** (0.0167)	0.0671** (0.0286)	0.0464*** (0.0171)	0.0456* (0.0238)	0.0666** (0.0297)	-0.00828 (0.0193)	-0.00206 (0.0230)	0.0514* (0.0288)
DUMMY_SOUTH	-0.0239 (0.0185)	0.0634** (0.0319)	-0.00599 (0.0224)	0.00615 (0.0280)	0.0224 (0.0353)	-0.0493** (0.0230)	-0.0344 (0.0254)	0.0201 (0.0316)

⁹ In the SHIW waves, information about family background is available only for the households and for his/her spouse or cohabitant. For year 2008 for the households and for his/her spouse or cohabitant if the households is borne in an odd year, while for year 2010 only for the households.

¹⁰ The sample of the wave of year 1998 is smaller in comparison to other waves, because of the lack of data on the variable experience. This fact may affect the estimation.

DUMMY_AGRICULTURAL	-0.0394 (0.0703)	0.0210 (0.104)	-0.118* (0.0634)	-0.0405 (0.0578)	-0.0661 (0.0435)	-0.127* (0.0742)	-0.0606 (0.0481)	0.0278 (0.0692)
DUMMY_PUBLIC	0.109*** (0.0218)	0.0434 (0.0343)	0.0191 (0.0215)	0.00784 (0.0314)	0.0525* (0.0311)	0.0100 (0.0290)	0.0947*** (0.0288)	0.0677* (0.0356)
DUMMY_OTHER_SECTOR	0.0156 (0.0179)	-0.00719 (0.0397)	-0.00734 (0.0197)	-0.0140 (0.0232)	-0.0144 (0.0263)	-0.0298 (0.0204)	-0.00225 (0.0235)	0.00405 (0.0265)
DUMMY_SECT_PARENTS	-0.00735 (0.0182)	0.0422* (0.0250)	-0.0132 (0.0151)	-0.00237 (0.0186)	-0.0113 (0.0188)	-0.0150 (0.0172)	0.0306* (0.0186)	0.00793 (0.0224)
DUMMY_PART_TIME	0.0387 (0.0360)	0.0777 (0.0648)	0.0673*** (0.0340)	-0.0617 (0.0440)	-0.0124 (0.0386)	0.0180 (0.0415)	0.0186 (0.0367)	0.0444 (0.0333)
Constant	1.074*** (0.0596)	1.028*** (0.132)	1.061*** (0.0697)	1.033*** (0.0940)	1.183*** (0.0854)	0.923*** (0.0879)	1.115*** (0.0878)	1.026*** (0.112)
Observations	4,352	1,468	3,783	3,321	3,405	3,437	2,836	2,145
R-squared	0.403	0.308	0.293	0.261	0.206	0.268	0.331	0.250

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7 presents the IV estimates for the period 1995-2010. The Sargan test never rejects the null hypothesis of no miss specification (see the first stage estimation and all the tests in the appendix), so we cannot reject the validity of over-identifying restrictions. In addition the Bound test that always rejects the null hypothesis of no correlation between education and additional instruments.

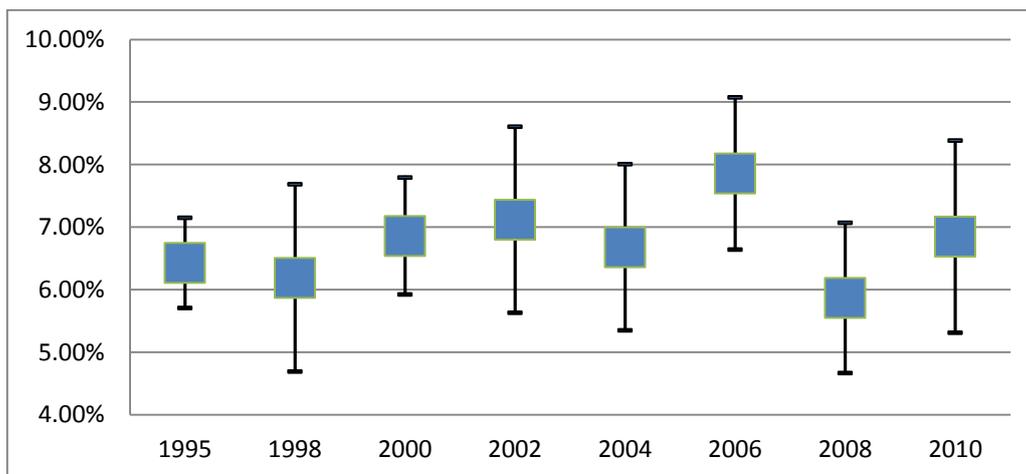
We confirm for this sample the finding that the estimated returns to education are significantly larger with IV than with OLS, as stressed by large part of the international literature. The downward OLS bias implied by IV estimates could arise from the attenuation effect of a measurement error in the schooling variables, but also a distortion from omission of the variable “ability” could lead to a similar result. This means that the more “able” (in terms of capacity to earn higher wages) individuals have lower preference for schooling, and those preferences could be justified by the higher opportunity costs faced by the “able” individuals. However, there is also another possible explanation of the higher IV estimates, in case of heterogeneity in the economic benefit of schooling, as well as heterogeneity in costs or tastes for schooling. Assume the existence of an exogenous event that reduces the marginal costs of schooling only for a subsample of the population. Therefore, it is possible to define an instrumental variable assuming value 1 on this subsample (treatment group) and value 0 on the rest of the population (the control group). The reason of the bias is clarified considering that an instrument that reduces the cost of schooling is more effective on people with the higher marginal cost of education. Then, if the cost component plays a minor role in an individual school choice, then the individual would be virtually unaffected by an exogenous

event that influences costs¹¹. This means no random selection of the treatment group, implying the violation of the necessary assumption for IV and leading to an inconsistent estimation. The bias is positive if the average marginal return in the treatment group is higher than the average marginal return in the overall population, otherwise the bias is negative. The same idea is formalized in the Local Average Treatment Effect literature¹²: the IV estimate is the average return to schooling for people that acquire more education only because of this particular exogenous event and that would have not acquired additional education in the absence of this particular event.

6.1.1 The Returns to Schooling

The evidence is that returns have not changed much over the period considered. The estimates of the returns to schooling are between 5.9% and 7.9%, recording the highest level for 2006. Looking at the previous estimates made for Italy, as shown in table 5, we can notice that our estimate are in line with the literature. Moreover, it is not present a clear patterns of the return to schooling, either increasing or decreasing.

Table 8 - Estimates of the Return to Education, 1995-2010 (with confidence intervals at 95%)



¹¹ See Card (1998).

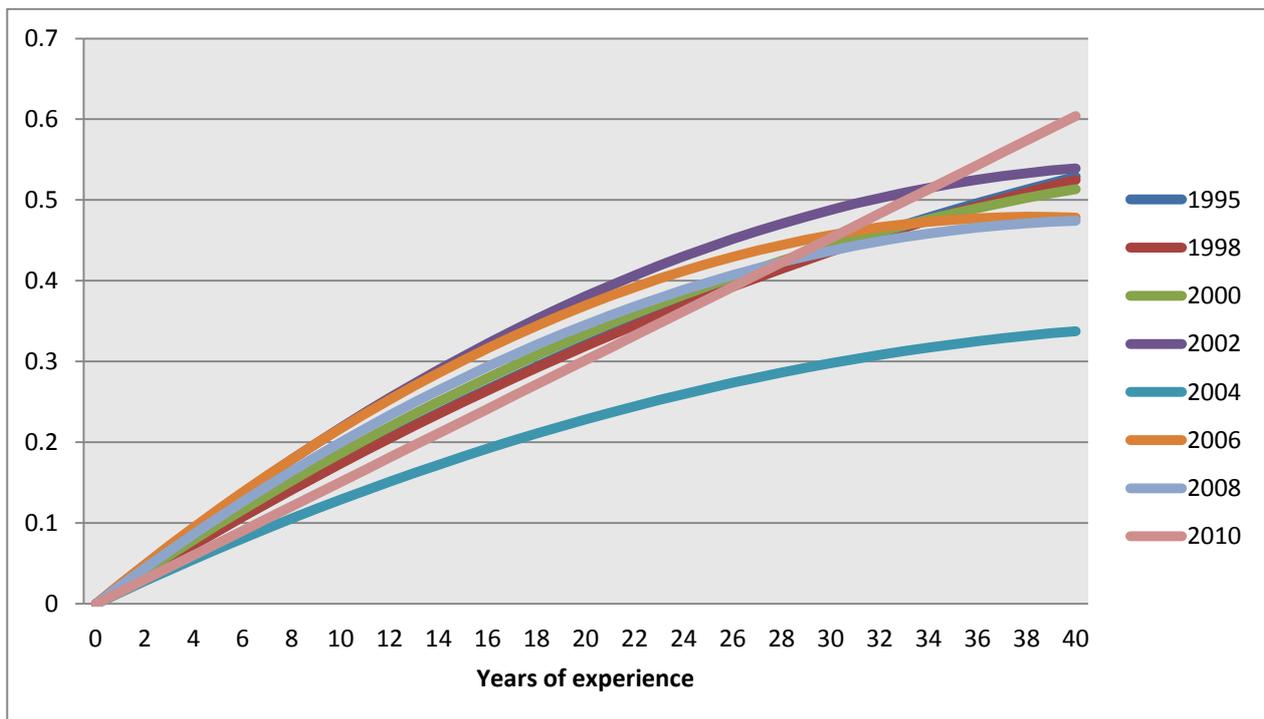
¹² See Imbens and Angrist (1994), Angrist, Imbens and Rubin (1996).

6.1.2 Experience

Looking at the dynamics of experience (Table 9), we observe different pattern for each year of the sample: from 1995 to 2008 the experience profile is a concave function, more or less steeper, while in 2010 it is approximately a linear function.

Then, we can affirm that the experience profile is not linear function (except for 2010) and that the estimates are quite stable over the time period considered.

Table 9 - Estimates of the Experience Profile, 1995-2010



6.1.3 Control Variables

If we consider the DUMMY_MALE variable, we observe a strong evidence of a gender pay gap, in favor of men for all the period considered, with an increasing trend, passing from 13.2% in 1995 to 15.4% in 2010.

Looking at the geographical variables (DUMMY_NORTH and DUMMY_SOUTH), we observe that when the estimates are significant, the DUMMY_NORTH is positive while the other one is negative. This means that it is more convenient to work in the north regions in comparison to the centre regions, instead if an individual works in the south region he will earn less than in the center regions. Then, working in the same sector of the father or the mother

(DUMMY_SECT_PARENTS) seems to not bring particular benefits, except for year 1998 and 2008 where this dummy is significant and positive.

Finally, considering different sector of employment, working in the agricultural sector is less convenient than working in the industrial sector. On the contrary, looking at the public sector, when the dummy is significant then it is positive, meaning that working in the public sector is more convenient than working in the industrial sector.

6.2 Estimation of the Returns for Different Type of School

The empirical specification in eq. (6) is based on the assumption that the return to education is constant and independent of the level of attained education. We allow the marginal return to schooling to vary with the level of completed education by replacing years of schooling with three educational dummies, one for each level of completed schooling above compulsory school, that is vocational school, secondary and tertiary education.

This is the multiple factor model, an alternative way to estimate returns to schooling, where different educational levels have separate effects on earnings.

As suggested by the 'credentialism' hypothesis, in the presence of heterogeneity what really matters is the type of school rather than the overall number of years spent in formal education. We investigate these issues by considering the highest degree attained by individual using educational dummies rather than years of schooling in our earnings regressions. In particular, we look at education achievements by broad levels: compulsory school (no schooling, primary school and junior high school), vocational, upper secondary and tertiary education, and also we address the issue of "credentialism" by distinguishing among types of school (for instance scientific, humanistic, technical) within upper secondary and tertiary education.

Also in the case of the estimate the returns of education from different type of school, we deal with the problem of endogeneity by using instrumental variables.

We apply the two step methodology proposed by Vella and Gregory (1996). The empirical strategy consists of estimating the two following equations:

$$\ln w_i = X_i' \beta + \sum_{h=1,3} \alpha_h E_{ih} + u_i \quad (9)$$

$$S_i^* = Z_i' \gamma + v_i \quad (10)$$

where w_i is the real hourly wage, E are educational dummies that correspond to the highest degree achieved by the individual, X and Z are vectors of observed attributes, u and v are normally distributed error terms with zero means and finite variances, S_i^* is the latent level of education. We define S as the observed level of education, that takes the following discrete values:

$$S_i = 1 \text{ if } S_i^* < \mu_0; S_i = 2 \text{ if } \mu_0 \leq S_i^* \leq \mu_1; S_i = 3 \text{ if } S_i^* \geq \mu_1 \quad (11)$$

and associate S to the educational dummies by setting $E_{ih} = 1$ if $S_i = h$ and $E_{ih} = 0$ otherwise.

We use a two step procedure to estimate the coefficients. In the first step we estimate an ordered probit model for educational attainment as a function of the instrument used in the previous IV estimation. In the second step, we include the score¹³ associated to the ordered probit in the earnings equation and then we apply ordinary least squares. This method is closely related to instrumental variables estimation.

Our specification of the ordered probit includes the same covariates of the instrumental equation used before.

The interpretation of the estimated coefficients is in terms of additional return that the educational level grants to the individual with respect to the reference group that is compulsory school. Our results are reported in table 10. For instance, in 2010, an employee with a high school degree earns, on average, 36.8% more than an employee with the same covariate belonging to the reference group. This differential increase to 74.6% for graduated individuals.

¹³ See Idson and Feaster (1990) for details on the computation of the score.

The estimated coefficients of the score have always a negative sign when they are significant, implying that the covariance between unobservable variables that affect earnings and educational choice is negative. This means that an individual attains a lower educational level than predicted, because abler individuals have a higher marginal cost of schooling in terms of foregone earnings, due to more attractive wage offer. Hence, these individuals tend to acquire less education than predicted education and earn higher wages.

Table 10 – Second stage OLS estimates. Dependent Variable: log of hourly earnings less tax. Omitted categories are: Center (DUMMY_CENTER); Industrial sector (DUMMY_INDUSTRIAL).

VARIABLES	1995	1998	2000	2002	2004	2006	2008	2010
VOCATIONAL	0.210*** (0.0349)	0.0631 (0.0558)	0.214*** (0.0333)	0.218*** (0.0368)	0.138*** (0.0403)	0.158*** (0.0313)	0.0670* (0.0392)	0.150*** (0.0570)
UPPER_SECONDARY	0.372*** (0.0304)	0.253*** (0.0505)	0.379*** (0.0363)	0.354*** (0.0439)	0.223*** (0.0556)	0.351*** (0.0404)	0.278*** (0.0398)	0.368*** (0.0578)
TERTIARY	0.752*** (0.0508)	0.513*** (0.0838)	0.768*** (0.0570)	0.739*** (0.0827)	0.637*** (0.0880)	0.740*** (0.0682)	0.606*** (0.0695)	0.746*** (0.105)
EXPERIENCE	0.0213*** (0.00328)	0.0191*** (0.00669)	0.0237*** (0.00348)	0.0281*** (0.00509)	0.0155*** (0.00433)	0.0264*** (0.00355)	0.0242*** (0.00435)	0.0160*** (0.00437)
EXPERIENCE^2	-0.0003*** (7.85e-05)	-0.0002 (0.00015)	-0.0003*** (7.96e-05)	-0.0004*** (0.000122)	-0.0002* (0.000111)	-0.0004*** (8.39e-05)	-0.0003*** (0.000111)	-6.27e-05 (0.000101)
DUMMY_MALE	0.135*** (0.0256)	0.124*** (0.0344)	0.100*** (0.0183)	0.0986*** (0.0244)	0.0683*** (0.0265)	0.109*** (0.0201)	0.156*** (0.0215)	0.160*** (0.0268)
DUMMY_MARRIED	0.00754 (0.0254)	0.0535 (0.0447)	0.0525** (0.0244)	0.00591 (0.0370)	0.0434 (0.0310)	-0.00679 (0.0222)	-0.0446 (0.0276)	0.0209 (0.0276)
NCOMP	0.0165** (0.00734)	0.0111 (0.0144)	0.00168 (0.00745)	0.00227 (0.0101)	-0.00471 (0.00910)	0.0322*** (0.00840)	0.0249*** (0.00860)	-0.000861 (0.0108)
DUMMY_HOUSEHOLD	-0.00255 (0.0257)	-0.00837 (0.0352)	0.00911 (0.0179)	0.0269 (0.0240)	0.0267 (0.0239)	0.0376** (0.0187)	0.0126 (0.0237)	0 (0)
DUMMY_TOWN	0.00673 (0.0211)	0.0374 (0.0411)	0.00621 (0.0209)	-0.0793** (0.0349)	-0.00872 (0.0422)	0.0443* (0.0239)	0.0191 (0.0304)	-0.0296 (0.0373)
DUMMY_NORTH	0.0366** (0.0168)	0.0775*** (0.0282)	0.0467*** (0.0162)	0.0494** (0.0232)	0.0599** (0.0282)	-0.00513 (0.0182)	0.00316 (0.0227)	0.0606** (0.0283)
DUMMY_SOUTH	-0.0345* (0.0187)	0.0428 (0.0314)	-0.0284 (0.0214)	-0.0114 (0.0273)	-0.00933 (0.0330)	-0.0761*** (0.0219)	-0.0489** (0.0249)	0.0167 (0.0289)
DUMMY_AGRICULTURAL	-0.118 (0.0717)	-0.143 (0.0921)	-0.192*** (0.0581)	-0.0991* (0.0577)	-0.129*** (0.0406)	-0.151** (0.0746)	-0.0997** (0.0502)	-0.00494 (0.0694)
DUMMY_PUBLIC	0.114*** (0.0227)	0.0991*** (0.0330)	0.0224 (0.0229)	0.0214 (0.0312)	0.0935*** (0.0346)	0.0465* (0.0282)	0.105*** (0.0273)	0.0545 (0.0390)
DUMMY_OTHER_SECTOR	0.0103 (0.0179)	0.0165 (0.0387)	-0.000192 (0.0198)	-0.00674 (0.0232)	0.00655 (0.0260)	-0.0132 (0.0194)	0.00673 (0.0235)	0.00186 (0.0263)
DUMMY_SECT_PARENTS	0.00569 (0.0180)	0.0543** (0.0255)	-0.0110 (0.0146)	-0.000539 (0.0185)	0.00188 (0.0188)	-0.0120 (0.0160)	0.0292 (0.0189)	0.00830 (0.0215)
DUMMY_PART_TIME	0.0355 (0.0346)	0.0618 (0.0633)	0.0610* (0.0330)	-0.0749* (0.0430)	-0.0360 (0.0391)	0.000124 (0.0398)	0.0177 (0.0355)	0.0393 (0.0368)
SCORE	-0.0543*** (0.0187)	0.00663 (0.0317)	-0.0953*** (0.0215)	-0.0772*** (0.0275)	-0.0362 (0.0319)	-0.0856*** (0.0238)	-0.0436* (0.0255)	-0.0960*** (0.0369)
Constant	1.519*** (0.0462)	1.540*** (0.0985)	1.543*** (0.0459)	1.558*** (0.0612)	1.746*** (0.0568)	1.551*** (0.0597)	1.577*** (0.0545)	1.544*** (0.0705)
Observations	4,352	1,468	3,783	3,321	3,405	3,437	2,836	2,145
R-squared	0.412	0.317	0.338	0.287	0.245	0.327	0.345	0.295

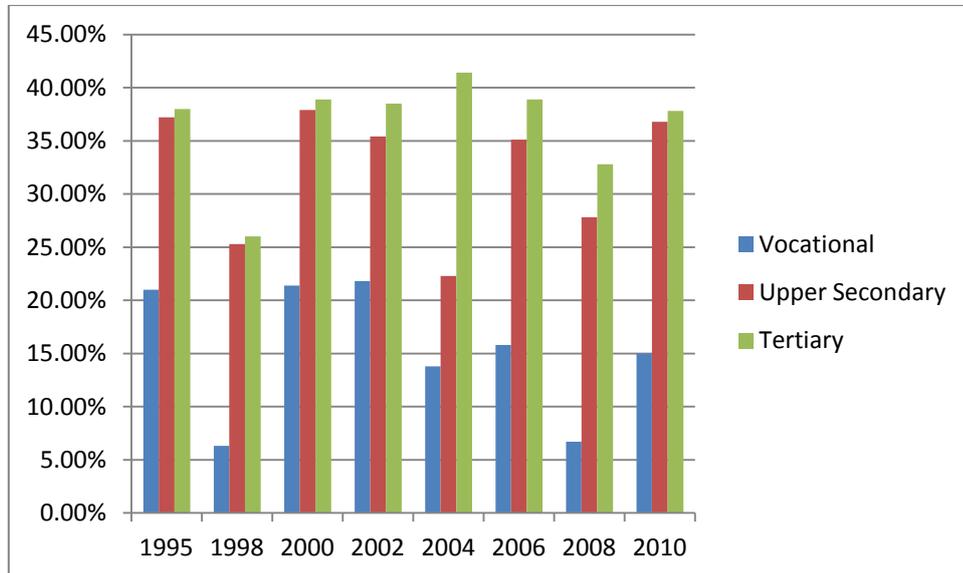
Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Looking at the different level of education, vocational school seems to have a not clear pattern, passing from 21% in 1995 to 15% in 2010.

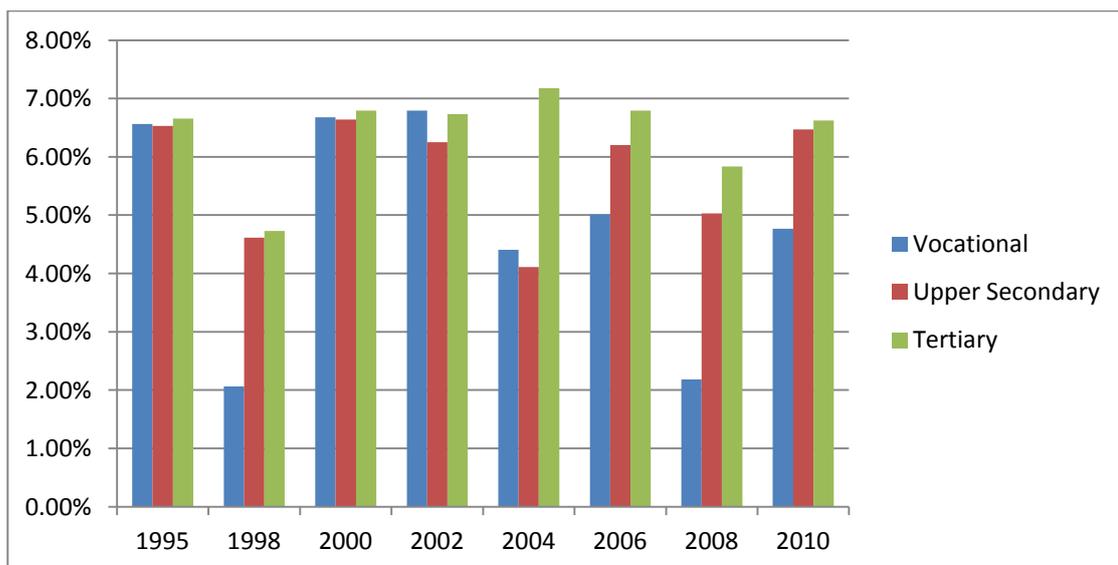
The rate of return of secondary school is not constant over the period considered, but it shows a slightly decreasing trend from 1995 to 2010. The same trend is observed for the rate of return of tertiary education (university).

Table 11 – Rate of Return of Different Type of School 1995-2010



However, even if the college premium does not have a particular trend, going to college allows to have between 30% and 40% of high wages (excluding year 1998).

**Table 12 – Annual Rate of Return of Different Type of School 1995-2010
(reference category: compulsory school)**



Moreover, we assume that these returns can be spread evenly among the years of school required to complete a degree (see Table 12). It turns out that the increase in

earnings due to an additional year of vocational school, upper secondary school and college is respectively 5%, 7.4% and 7.6% for 2010. Hence, there is evidence that returns to education are not constant but increase with the level of attained education.

Finally, considering experience and the other control variables that are included in the estimation, we do not observe significant changes from the IV estimates.

7 Concluding Remarks

We have studied the economic returns to education in Italy using cross-sectional data from the 1995 to 2010 waves of the Bank of Italy survey on the income and wealth of Italian household. We apply instrumental variables estimation to solve the problem of endogeneity. The evidence is that returns to schooling have not changed much over the period considered, 1995-2010, and are between 5.9% and 7.9%, recording the highest level for 2006. Looking to the different sector of employment, a relative convenience to work in the public sector emerges. In addition, there is an evidence of a gender pay gap, in favor of men for all the period considered.

When the type of school attended is taken into consideration, we also find that the returns to education increase with higher levels of educational attainment. In this case, to solve the problem of endogeneity, an ordered probit is applied to the choice of educational attainment and then we add the score of the probit estimation, to the original equation and apply OLS. In particular, for 2010, the estimated coefficient of the educational dummy is respectively 15% for vocational school, 36.8% for upper secondary, and 74.6% college education. Able individuals, who received better wage offers, have lower education than predicted, because of the relative incentive to anticipate labor market entry (as signaled by the negative coefficient of the score).

In this analysis we take into consideration only employees excluding self-employed because of low reliability of their declared earnings. Restricting the analysis only to employees probably leads to an underestimation of the returns to education in Italy.

However, the possible presence of outliers in earnings of certain categories of self-employed (typically professionals and managers) could lead to an upward bias. The use of quantile regression could be the solution to this problem and is left to future research.

References

- Acemoglu, D. and J. D. Angrist (2001). How Large are Human-Capital Externalities? Evidence from Compulsory-Schooling Laws. In B. Bernanke and K. Rogoff, NBER Macroeconomics Annual (9-74). Cambridge: National Bureau of Economic Research.
- Angrist, J. D., G. W. Imbens, D. B. Rubin (1996). Identification of Causal Effects Using Instrumental Variables, *Journal of the American Statistical Association*, V. 91, 444- 455.
- Angrist, J. D. and Newey, W. (1991). Over-Identification Test in Earnings Function with Fixed Effects, *Journal of Business and Economic Statistics*, July, 317-323.
- Angrist, J. D. and A. B. Krueger, (1991). Does Compulsory Schooling Affect Schooling And Earnings?, *Quarterly Journal of Economics*, November, 979-1014.
- Angrist, J. D. and A. B. Krueger, (1992). Estimating the Payoff to Schooling Using the Vietnam Era Draft Lottery, NBER Working Paper No. 4067.
- Antonelli, G. (1985). *Risorse Umane e Redditi da lavoro*. Franco Angeli, Milan.
- Ashenfelter, O. and A. B. Krueger (1994). Estimates of the Economic Return to Schooling from a New Sample of Twins”, *American Economic Review*, December, 84(5), 1157-73.
- Ashenfelter, O. and D. J. Zimmerman (1993). Estimates of the Return to Schooling from Sibling Data: Fathers, Sons, and Brothers”, NBER Working Paper No. 4491.
- Ashenfelter, O., Harmon, C and H. Oosterbeek (1999). A Review of the Estimates of the Schooling/Earnings Relationship, with Tests for Publication Bias, *Labour of Economis*, 6 (3), 453-470.
- Becker, G. S. (1962). Investment in Human Capital: A theoretical Analysis, *The Journal of Political Economy*, 70 (5), 9-49.
- Becker, G. S. (1991). *Treatise on the Family*, Cambridge: Harvard University Press. (first ed. 1981)
- Becker, G. S. (1993). *Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education*, Chicago: University of Chicago Press (first ed. 1975).

- Ben-Porath, Y. (1967). The Production of Human Capital and the Life Cycle of Earnings, *Journal of Political Economy*, 75(4), part 1, 352-65.
- Bound, J., Jaeger, D. and R. Baker (1995). Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variables is weak, *Journal of the American Statistical Association*, 443-450.
- Bowman, A.W. and A. Azzalini (1997). *Applied Smoothing Techniques for Data Analysis: the Kernel Approach with S-Plus Illustrations*. Oxford University Press, Oxford.
- Brandolini A., Cannari L. (1994). “Methodological appendix: the Bank of Italy's Survey of Household income and wealth”, in Ando A., Guiso L., Visco I. (a cura di), *Savings and the accumulation of wealth. Essays on Italian households and government saving behaviour*, Cambridge University Press.
- Brunello, G., Comi, S. and C. Lucifera (1999). The Returns to Education in Italy: A Review of the Applied Literature, in R. Asplund and P.T. Pereira, *Returns to Human Capital in Europe. A Literature Review*, ETLA, Helsinki.
- Brunello, G., Comi, S. and C. Lucifera (2000). The Returns to Education in Italy: A new look at evidence, IZA DP No. 130.
- Brunello, G. and R. Miniaci (1999). The Economic Returns to Schooling for Italian men. An Evaluation Based on Instrumental Variables, *Labour Economics* 6, 509–519.
- Cannari, L., and G. D'Alessio (1995). *Il Rendimento Dell'Istruzione: Alcuni Problemi Di Stima*. Temi di Discussione n. 253, Bank of Italy, Rome.
- Cannari, L., Pellegrini, G. and P. Sestito (1989). *Età, Istruzione e Retribuzioni, Contributi all'analisi economica*, Bank of Italy, Rome.
- Card, D. (1994). Earnings, Schooling and Ability Revisited. In S. Polacheck (ed.), *Research in Labor Economics*, Vol. 14, Greenwich: JAI Press. (NBER, Working Paper No. 4832)
- Card, D. (1999). The Causal Effect of Education on Earnings. In Ashenfelter, O. and D. Card, *Handbook of Labor Economics*, Rotterdam: Elsevier.
- Card, D. (2001). Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems, *Econometrica*, 69 (5), 1127-60.
- Chiswick, B. (2003). Jacob Mincer, Experience and the Distribution of Earnings, *Review of Economics of the Household* 1, 343-361.

- Ciccone, A. (2004). Human Capital as a Factors of Growth and Employment at the Regional Level. The Case of Italy. Report for the European Commission, DG for Employment and Social Affairs.
- Ciccone, A., Cingano, F. and P. Cipollone, (2006). The private and social return to schooling in Italy, Temi di Discussione n. 569, Bank of Italy, Rome.
- Cingano, F., and P. Cipollone (2009). I rendimenti dell'istruzione, Questioni di Economia e Finanza (Occasional Papers) n.53, Bank of Italy, Rome.
- Colussi, A. (1997). Il Tasso Di Rendimento dell'Istruzione In Italia: un'Analisi Cross-Section, *Politica Economica* 13 (2), 273-294.
- De La Fuente, A. and A. Ciccone (2002). Human Capital in a Global and Knowledge-Based Economy, European Commission: DG Employment and Social Affairs.
- Flabbi, L. (1997). Investire In Istruzione: Meglio per lui o per lei?, mimeo, Bocconi University, Milan.
- Flabbi, L. (1999). Returns to Schooling in Italy: OLS, OV and Gender Differences. Working paper of Bocconi University, Serie di econometria ed economia applicata.
- Garen, J. (1984). The returns to schooling: a selectivity bias approach with a continuous choice variable. *Econometrica*, 52, 1199-1218.
- Griliches, Z. (1977). Estimating the Returns to Schooling: Some Econometric Problems, *Econometrica*, 45, 1, 1-22.
- Harmon, C.P. and I. Walker (1995). Estimates of the Economic Return to Schooling for the UK, *American Economic review*, 1278-86.
- Harmon, C.P., Oosterbeek, H and I. Walker (2003). The Returns to Education: Microeconometrics, *Journal of Economic Surveys*, 17(2), 115-155.
- Heckman, J. J. (1979). Sample Selection Bias as A Specification Error, *Econometrica*, 47(1), 153-161.
- Heckman, J. J. and M.R. Killingsworth (1986). Female Labor Supply: a Survey, in Ashenfelter O. and R. Layard (ed.) *Handbook of Labor Economics*, Amsterdam: North Holland.
- Heckman, J. J., Lochner, L. and P. Todd (2003). Fifty Years of Mincer Earnings Regressions, NBER, Working Paper no. 9732.

- Heckman, J. J., Lochner, L. and P. Todd (2006). Earnings Functions, Rates of Return and Treatment Effects: The Mincer Equation and Beyond, In E. Hanushek and F. Welch, *Handbook of the Economics of Education*, 307-458, Rotterdam: Elsevier.
- Heckman, J. J., Lochner, L. and P. Todd (2008). Earnings Functions and Rates of Return. *Journal of Human Capital*, 2 (1), 1-31.
- Ichino, A. and R. Winter-Ebmer, (1999). Lower and Upper Bounds of Returns to Schooling: An Exercise in IV Estimation with Different Instruments, *European Economic Review*, 43, 889-901.
- Idson, T. L. and D. J. Feaster (1991). A Selectivity Model of Employer-Size Wage Differentials, *Journal of Labor Economics*, Vol. 8 (1), 99-122.
- Imbens, G., Angrist, J.D., 1994. Identification and estimation of local average treatment effects, *Econometrica* 62, 467-475.
- Lam, D. and R.F. Schoeni (1993). Effects of Family Background on Earnings and Returns to Schooling: Evidence from Brazil, *Journal of Political Economy*, Vol. 101 (4), 710-740.
- Lucifora, C. and B. Reilly (1990). Wage Discrimination and Female Occupational Intensity, *Labour*, n.4, 147-168.
- Meghir, C. and S. G. Rivkin (2010). *Econometric Methods for Research in Education*, NBER, Working Paper no. 16003.
- Mendolicchio, C. (2006). A Disaggregate Analysis of Private Returns to Education in Italy. Discussion Paper 54, Département des Sciences Économiques de l'Université catholique de Louvain.
- Mincer, J. (1974). *Schooling, Experience and Earnings*. New York: Columbia University Press.
- OECD (2011) *Education at a Glance*, Paris.
- Peracchi, F. (2004). "Educational wage premia and the distribution of earnings: an international perspectives", in E.Hanushek and F.Welch (eds.), *Handbook of the Economics of Education*, North-Holland, Amsterdam.
- Psacharopoulos, G. (1994). Returns to Investment in Education: A Global Update, *World Development*, v.22, n.9, 1325-1343.
- Schultz, T. W. (1961). Investment in "Human Capital", *The American Economic Review*, 51 (1).

- Sianesi, B. and J. V. Reenen (2003). The Returns to Education: Macroeconomics, *Journal of Economic Surveys*, Vol. 17 (2), 157-200.
- Spence, M. (1973). Job Market Signaling. *Quarterly Journal of Economics*, 87 (3), 355-373.
- Vella, F. and R. G. Gregory (1996), Selection Bias and Human Capital Investment: Estimating the Rates of Return to Education for Young Males, *Labour Economics: An International Journal*, 197-219.
- Vieira, J.A.C. (1999). Returns to Education in Portugal, *Labour Economics*, Vol. 6 (4), 535-541.
- Willis, R. (1986). Wage Determinants: A Survey and Reinterpretation of Human Capital Earnings Functions. In O. Ashenfelter and R. Layard (eds), *Handbook of Labor Economics*, Amsterdam and New York: North Holland.
- Wooldridge, J.M. (2002). *Econometric Analysis of Cross Section and Panel Data*. MIT press.

Appendix

Table 13 – Mean of the Log of hourly earnings less tax (1995 -2010)

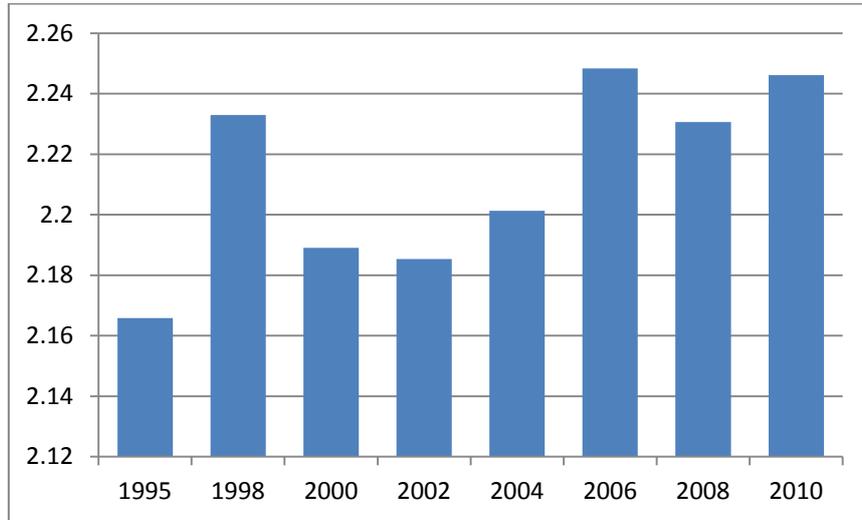


Table 14 – Mean of the number of year of Schooling (1995 -2010)

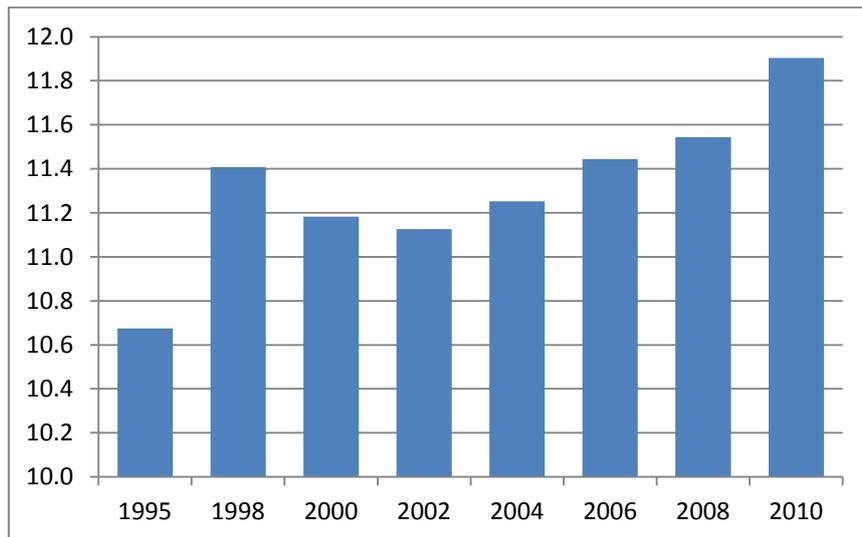


Table 15 – Mean of the number of year of Experience (1995 -2010)

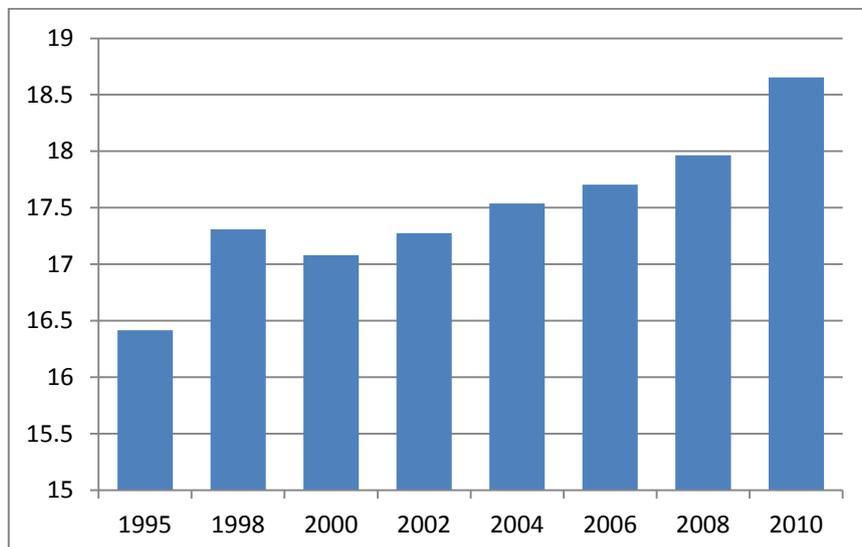


Table 16 shows OLS estimates, obtained by including in the original specification controls for the composition of her/his family, the geographical area of residence and the sector in which the individual is currently working.

The evidence is that returns to education are fairly stable from 1998 to 2010, but if we compare the year 1995 with 2010, returns to education have decreased from 5.14% to 4.16%.

Moreover, Table 16 shows that returns are higher for male over the entire sample period, confirming the gender pay gap.

Table 16 - OLS estimates. Dependent Variable: log of hourly earnings less tax. Omitted categories are: Center (DUMMY_CENTER); Industrial sector (DUMMY_INDUSTRIAL).

VARIABLES	1995	1998	2000	2002	2004	2006	2008	2010
SCHOOL	0.0514*** (0.00173)	0.0447*** (0.00315)	0.0425*** (0.00188)	0.0454*** (0.00229)	0.0409*** (0.00224)	0.0450*** (0.00196)	0.0442*** (0.00229)	0.0416*** (0.00214)
EXPERIENCE	0.0272*** (0.00277)	0.0275*** (0.00458)	0.0254*** (0.00246)	0.0271*** (0.00285)	0.0210*** (0.00300)	0.0250*** (0.00268)	0.0275*** (0.00274)	0.0194*** (0.00249)
EXPERIENCE^2	-0.000352*** (6.82e-05)	-0.000351*** (0.000114)	-0.000363*** (6.05e-05)	-0.000362*** (7.46e-05)	-0.000308*** (8.14e-05)	-0.000386*** (6.75e-05)	-0.000405*** (7.15e-05)	-0.000207*** (6.20e-05)
DUMMY_MALE	0.0855*** (0.0155)	0.0422 (0.0282)	0.0769*** (0.0137)	0.106*** (0.0163)	0.0790*** (0.0174)	0.0904*** (0.0159)	0.112*** (0.0144)	0.116*** (0.0143)
DUMMY_MARRIED	0.0739*** (0.0165)	0.0666** (0.0331)	0.105*** (0.0148)	0.0616*** (0.0190)	0.0702*** (0.0180)	0.0536*** (0.0161)	0.0310** (0.0157)	0.0685*** (0.0153)
NCOMP	-0.00338 (0.00535)	0.00475 (0.0105)	-0.0104* (0.00551)	-0.00938 (0.00653)	-0.0122* (0.00665)	0.0140** (0.00655)	0.00779 (0.00573)	-0.00191 (0.00609)
DUMMY_HOUSEHOLD	0.0436*** (0.0167)	0.0463 (0.0285)	0.0326** (0.0134)	0.0382** (0.0159)	0.0385** (0.0165)	0.0651*** (0.0147)	0.0502*** (0.0135)	0.0169 (0.0128)
DUMMY_TOWN	0.0333* (0.0175)	0.0209 (0.0340)	0.0458*** (0.0178)	-0.0370 (0.0278)	0.0233 (0.0313)	0.0587*** (0.0215)	0.0281 (0.0243)	-0.0120 (0.0240)
DUMMY_NORTH	0.0404*** (0.0140)	0.0778*** (0.0241)	0.0481*** (0.0136)	0.0399** (0.0169)	0.0473** (0.0198)	-0.00849 (0.0160)	-0.0296* (0.0164)	0.0441*** (0.0170)
DUMMY_SOUTH	-0.0379** (0.0172)	0.0570** (0.0288)	-0.0292 (0.0189)	0.00365 (0.0232)	-0.0232 (0.0241)	-0.0821*** (0.0188)	-0.0783*** (0.0186)	-3.73e-05 (0.0189)
DUMMY_AGRICULTURAL	-0.117* (0.0679)	-0.0967 (0.0705)	-0.132*** (0.0439)	-0.0424 (0.0568)	-0.0935*** (0.0329)	-0.168*** (0.0480)	-0.00792 (0.0419)	-0.0596 (0.0388)
DUMMY_PUBLIC	0.174*** (0.0168)	0.109*** (0.0268)	0.108*** (0.0150)	0.110*** (0.0182)	0.141*** (0.0197)	0.126*** (0.0188)	0.143*** (0.0190)	0.148*** (0.0176)
DUMMY_OTHER_SECTOR	0.0109 (0.0149)	-0.00141 (0.0301)	0.0294* (0.0152)	0.0102 (0.0177)	0.00797 (0.0189)	0.000988 (0.0161)	-0.00310 (0.0160)	0.0161 (0.0146)
DUMMY_SECT_PARENTS	0.00296 (0.0151)	0.0797*** (0.0228)	0.0175 (0.0121)	0.0138 (0.0157)	0.00658 (0.0146)	-0.00163 (0.0135)	0.0340*** (0.0131)	0.0114 (0.0133)
DUMMY_PART_TIME	0.0734** (0.0324)	0.0345 (0.0525)	0.0375 (0.0274)	-0.0842** (0.0365)	-0.0479 (0.0311)	-0.00797 (0.0301)	0.0293 (0.0268)	-0.00400 (0.0216)
Constant	1.116*** (0.0408)	1.136*** (0.0708)	1.255*** (0.0355)	1.224*** (0.0420)	1.381*** (0.0460)	1.285*** (0.0438)	1.250*** (0.0437)	1.304*** (0.0459)
Observations	6,066	2,016	5,724	5,461	5,425	5,378	5,409	5,161
R-squared	0.450	0.366	0.353	0.306	0.261	0.326	0.353	0.327

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17 shows OLS estimates of the empirical specification, including interaction of the variable schooling with experience and with gender.

Table 17 - OLS estimates with interactions. Dependent Variable: log of hourly earnings less tax. Omitted categories are: Center (DUMMY_CENTER); Industrial sector (DUMMY_INDUSTRIAL).

VARIABLES	1995	1998	2000	2002	2004	2006	2008	2010
SCHOOL	0.0471*** (0.00663)	0.0445*** (0.0108)	0.0291*** (0.00625)	0.0388*** (0.00831)	0.0420*** (0.00657)	0.0267*** (0.00555)	0.0242*** (0.00553)	0.0330*** (0.00539)
EXPERIENCE	0.0216*** (0.00810)	0.0455*** (0.0138)	0.00859 (0.00760)	0.0158* (0.00923)	0.0199*** (0.00772)	0.00516 (0.00846)	-0.000305 (0.00879)	0.00707 (0.00714)
EXPERIENCE^2	-0.000294 (0.000196)	-0.000970*** (0.000344)	-6.90e-05 (0.000183)	-0.000172 (0.000229)	-0.000413** (0.000199)	-0.000174 (0.000219)	0.000133 (0.000228)	-0.000119 (0.000177)
SCHOOL*EXPER	0.000492 (0.000704)	-0.00170 (0.00112)	0.00137** (0.000639)	0.000929 (0.000824)	-6.37e-07 (0.000702)	0.00155** (0.000678)	0.00230*** (0.000699)	0.000962 (0.000590)
SCHOOL*EXPER^2	-4.17e-06 (1.78e-05)	5.86e-05* (3.04e-05)	-2.26e-05 (1.60e-05)	-1.48e-05 (2.13e-05)	1.22e-05 (1.85e-05)	-1.33e-05 (1.81e-05)	-4.40e-05** (1.82e-05)	-5.12e-06 (1.51e-05)
DUMMY_MALE	0.129*** (0.0432)	-0.0537 (0.0821)	0.0986** (0.0436)	0.173*** (0.0567)	0.200*** (0.0505)	0.146*** (0.0440)	0.137*** (0.0484)	0.236*** (0.0474)
SCHOOL*MALE	-0.00403 (0.00360)	0.00848 (0.00645)	-0.00207 (0.00366)	-0.00590 (0.00482)	-0.0106** (0.00426)	-0.00498 (0.00362)	-0.00206 (0.00418)	-0.00994** (0.00395)
DUMMY_MARRIED	0.0732*** (0.0166)	0.0700** (0.0323)	0.105*** (0.0148)	0.0611*** (0.0190)	0.0703*** (0.0182)	0.0572*** (0.0161)	0.0284* (0.0156)	0.0659*** (0.0153)
NCOMP	-0.00398 (0.00537)	0.00307 (0.0105)	-0.0113** (0.00546)	-0.01000 (0.00646)	-0.0130* (0.00664)	0.0133** (0.00653)	0.00832 (0.00571)	-0.00198 (0.00606)
DUMMY_HOUSEHOLD	0.0441*** (0.0168)	0.0438 (0.0281)	0.0334** (0.0134)	0.0393** (0.0160)	0.0391** (0.0165)	0.0624*** (0.0146)	0.0491*** (0.0135)	0.0172 (0.0127)
DUMMY_TOWN	0.0317* (0.0175)	0.0142 (0.0342)	0.0465*** (0.0178)	-0.0389 (0.0278)	0.0216 (0.0312)	0.0585*** (0.0214)	0.0266 (0.0241)	-0.0177 (0.0239)
DUMMY_NORTH	0.0399*** (0.0140)	0.0745*** (0.0238)	0.0468*** (0.0136)	0.0402** (0.0169)	0.0481** (0.0198)	-0.0101 (0.0159)	-0.0320* (0.0164)	0.0437*** (0.0168)
DUMMY_SOUTH	-0.0416** (0.0172)	0.0563* (0.0287)	-0.0322* (0.0189)	0.00139 (0.0232)	-0.0274 (0.0237)	-0.0864*** (0.0188)	-0.0825*** (0.0185)	-0.00393 (0.0186)
DUMMY_AGRICULTURAL	-0.116* (0.0686)	-0.108 (0.0679)	-0.129*** (0.0441)	-0.0435 (0.0567)	-0.0942*** (0.0331)	-0.173*** (0.0482)	-0.00882 (0.0421)	-0.0569 (0.0384)
DUMMY_PUBLIC	0.173*** (0.0169)	0.111*** (0.0268)	0.104*** (0.0150)	0.106*** (0.0181)	0.138*** (0.0197)	0.120*** (0.0187)	0.140*** (0.0191)	0.141*** (0.0174)
DUMMY_OTHER_SECTOR	0.00895 (0.0151)	-0.00333 (0.0301)	0.0280* (0.0150)	0.0107 (0.0179)	0.0108 (0.0190)	1.25e-05 (0.0161)	-0.00294 (0.0158)	0.0146 (0.0145)
DUMMY_SECT_PARENTS	0.00368 (0.0151)	0.0778*** (0.0225)	0.0178 (0.0121)	0.0145 (0.0157)	0.00647 (0.0146)	0.00102 (0.0135)	0.0353*** (0.0132)	0.0122 (0.0131)
DUMMY_PART_TIME	0.0763** (0.0325)	0.0278 (0.0518)	0.0397 (0.0271)	-0.0803** (0.0367)	-0.0440 (0.0312)	-0.00795 (0.0300)	0.0287 (0.0268)	-0.00227 (0.0215)
Constant	1.168*** (0.0821)	1.153*** (0.144)	1.424*** (0.0766)	1.307*** (0.0980)	1.375*** (0.0819)	1.518*** (0.0812)	1.496*** (0.0766)	1.416*** (0.0773)
Observations	6,066	2,016	5,724	5,461	5,425	5,378	5,409	5,161
R-squared	0.451	0.371	0.356	0.308	0.264	0.334	0.358	0.333

Table 18 shows the estimates of the first stage regression of the instrumental variables estimation.

Table 18 – First stage of IV estimates. Dependent Variable: schooling. Omitted categories are: Center (DUMMY_CENTER); Industrial sector (DUMMY_INDUSTRIAL).

VARIABLES	1995	1998	2000	2002	2004	2006	2008	2010
SCHOOL_F	0.296*** (0.0213)	0.292*** (0.0393)	0.298*** (0.0248)	0.267*** (0.0253)	0.237*** (0.0240)	0.261*** (0.0247)	0.261*** (0.0289)	0.281*** (0.0431)
SCHOOL_M	0.216*** (0.0254)	0.207*** (0.0513)	0.150*** (0.0284)	0.172*** (0.0290)	0.189*** (0.0261)	0.135*** (0.0285)	0.183*** (0.0332)	0.145*** (0.0433)
EXPERIENCE	0.0363 (0.0268)	-0.0375 (0.0492)	-0.0129 (0.0304)	-0.00837 (0.0350)	-0.0495 (0.0302)	-0.0452 (0.0297)	-0.0311 (0.0311)	-0.0588 (0.0449)
EXPERIENCE^2	-0.00226*** (0.000662)	0.000503 (0.00118)	-0.000842 (0.000739)	-0.000697 (0.000844)	0.000760 (0.000727)	-0.000107 (0.000696)	-0.000191 (0.000719)	0.000484 (0.00101)
DUMMY_MALE	0.269 (0.195)	0.408 (0.340)	-0.332* (0.172)	-0.414** (0.190)	-0.395** (0.174)	-0.311 (0.193)	-0.332 (0.202)	-0.592*** (0.219)
DUMMY_MARRIED	0.510** (0.246)	-0.428 (0.419)	-0.0309 (0.243)	0.293 (0.250)	0.617*** (0.221)	0.417** (0.209)	0.792*** (0.251)	-0.0912 (0.250)
NCOMP	-0.169*** (0.0643)	-0.196* (0.114)	-0.0198 (0.0754)	0.0849 (0.0777)	-0.0318 (0.0754)	-0.0222 (0.0732)	-0.170** (0.0784)	0.226** (0.0980)
DUMMY_HOUSEHOLD	-0.168 (0.199)	-0.629* (0.344)	0.194 (0.165)	-0.0168 (0.181)	0.109 (0.171)	0.178 (0.180)	0.0705 (0.218)	0 (0)
DUMMY_TOWN	0.223 (0.189)	-0.179 (0.354)	0.903*** (0.209)	0.529** (0.247)	0.110 (0.216)	0.398* (0.225)	0.347 (0.273)	0.435 (0.292)
DUMMY_NORTH	-0.158 (0.159)	0.0633 (0.268)	0.237 (0.168)	0.379** (0.181)	0.0236 (0.172)	-0.233 (0.179)	0.173 (0.214)	-0.252 (0.247)
DUMMY_SOUTH	-0.197 (0.177)	0.0838 (0.293)	0.0493 (0.190)	0.310 (0.225)	-0.315 (0.222)	-0.621*** (0.212)	-0.241 (0.240)	-0.281 (0.304)
DUMMY_AGRICULTURAL	-1.372*** (0.466)	-2.770*** (0.562)	-1.450*** (0.371)	-1.442*** (0.332)	-1.328*** (0.335)	-0.756** (0.312)	-1.059*** (0.397)	-1.098* (0.636)
DUMMY_PUBLIC	2.465*** (0.177)	2.268*** (0.285)	2.546*** (0.175)	2.452*** (0.205)	2.520*** (0.192)	2.490*** (0.175)	2.424*** (0.201)	2.235*** (0.294)
DUMMY_OTHER_SECTOR	0.00794 (0.159)	0.473 (0.300)	0.806*** (0.172)	0.502*** (0.176)	0.865*** (0.180)	0.715*** (0.176)	0.646*** (0.192)	0.643*** (0.229)
DUMMY_SECT_PARENTS	0.154 (0.151)	0.273 (0.218)	0.290** (0.135)	-0.161 (0.151)	0.182 (0.139)	0.393*** (0.144)	0.192 (0.163)	-0.0290 (0.204)
DUMMY_PART_TIME	-0.629*** (0.228)	-0.659* (0.377)	-0.681*** (0.226)	-0.553** (0.261)	-0.819*** (0.248)	-0.856*** (0.237)	-0.601** (0.292)	-0.822** (0.411)
Constant	7.434*** (0.385)	8.903*** (0.732)	7.910*** (0.398)	7.579*** (0.467)	7.968*** (0.412)	8.905*** (0.423)	8.515*** (0.461)	9.259*** (0.599)
Observations	4,352	1,468	3,783	3,321	3,405	3,437	2,836	2,145
R-squared	0.408	0.408	0.391	0.373	0.365	0.365	0.364	0.322
Sargan test $\chi^2(1)$	1.691	1.891	0.239	0.05	0.515	0.197	0.026	0.457
p-Value	0.1935	0.1691	0.6248	0.8239	0.473	0.657	0.8716	0.5038
F-test on excl. instrum.	461.28	147.101	288.83	201.88	225.05	195.76	188.55	107.67
p-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 19 reports the results of both OLS estimates that use educational dummies rather than years of schooling. The estimated coefficient of educational dummies should be interpreted in terms of the additional return that the combination of educational level plus school type grants to the individual with respect to the reference category (compulsory school¹⁴).

¹⁴ We include no schooling, primary school and junior high school.

Table 19 - OLS estimates. Dependent Variable: log of hourly earnings less tax. Omitted categories are: compulsory school (no schooling, primary school and junior high school); diploma professionale (DIP_PROF); laurea scientifica (L_SCIEN); Center (DUMMY_CENTER); Industrial sector (DUMMY_INDUSTRIAL).

VARIABLES	1995	1998	2000	2002	2004	2006	2008	2010
VOCATIONAL	0.162*** (0.0258)	0.0949** (0.0388)	0.0786*** (0.0191)	0.0962*** (0.0234)	0.0777*** (0.0221)	0.0981*** (0.0220)	0.0278 (0.0204)	0.0452** (0.0228)
UPPER_SECONDARY	0.230*** (0.0261)	0.151*** (0.0342)	0.153*** (0.0269)	0.162*** (0.0299)	0.0856** (0.0371)	0.104*** (0.0241)	0.154*** (0.0266)	0.148*** (0.0253)
DIPL_TECN	0.0504* (0.0276)	0.0581 (0.0357)	0.0627** (0.0269)	0.0430 (0.0305)	0.0548 (0.0396)	0.114*** (0.0257)	0.0277 (0.0278)	0.0328 (0.0266)
DIPL_LIC	0.0896*** (0.0347)	0.0794 (0.0586)	0.0772** (0.0376)	0.0797** (0.0387)	0.136*** (0.0463)	0.0882*** (0.0321)	0.0588 (0.0362)	0.0236 (0.0340)
DIPL_MAG	0.145*** (0.0336)	0.240*** (0.0740)	0.103*** (0.0360)	0.127** (0.0515)	0.134*** (0.0475)	0.227*** (0.0358)	0.152*** (0.0362)	0.0986*** (0.0345)
DIP_OTHER	-0.0391 (0.0608)	0.188** (0.0778)	0.119** (0.0493)	-0.0293 (0.0666)	0.0834 (0.0594)	0.0351 (0.0607)	0.0532 (0.0488)	0.178* (0.0968)
TERTIARY	0.621*** (0.0341)	0.568*** (0.0482)	0.506*** (0.0322)	0.582*** (0.0426)	0.561*** (0.0415)	0.497*** (0.0370)	0.498*** (0.0386)	0.522*** (0.0331)
L_LETT	0.0281 (0.0481)	-0.0776 (0.0671)	0.0146 (0.0493)	-0.121** (0.0558)	-0.00562 (0.0615)	0.0203 (0.0500)	0.0310 (0.0660)	-0.0515 (0.0436)
L_UMAN	-0.0577 (0.0545)	-0.0562 (0.0676)	-0.0325 (0.0461)	-0.0120 (0.0676)	-0.140*** (0.0528)	-0.0474 (0.0486)	-0.0575 (0.0451)	-0.0808* (0.0480)
L_OTHER	-0.0526 (0.0695)	-0.138 (0.0966)	-0.128* (0.0662)	-0.242** (0.115)	-0.0682 (0.0636)	-0.0366 (0.0604)	-0.0490 (0.0864)	-0.204*** (0.0561)
EXPERIENCE	0.0284*** (0.00274)	0.0285*** (0.00461)	0.0274*** (0.00246)	0.0286*** (0.00281)	0.0228*** (0.00296)	0.0259*** (0.00265)	0.0289*** (0.00278)	0.0204*** (0.00253)
EXPERIENCE^2	-0.0004*** (6.73e-05)	-0.0004*** (0.000115)	-0.0004*** (6.06e-05)	-0.0004*** (7.35e-05)	-0.00037*** (7.97e-05)	-0.0004*** (6.70e-05)	-0.00045*** (7.27e-05)	-0.0002*** (6.32e-05)
DUMMY_MALE	0.102*** (0.0161)	0.0660** (0.0274)	0.0852*** (0.0142)	0.109*** (0.0162)	0.0872*** (0.0176)	0.102*** (0.0157)	0.127*** (0.0144)	0.122*** (0.0144)
DUMMY_MARRIED	0.0664*** (0.0161)	0.0625* (0.0328)	0.0962*** (0.0149)	0.0532*** (0.0192)	0.0610*** (0.0175)	0.0485*** (0.0163)	0.0238 (0.0153)	0.0607*** (0.0151)
NCOMP	-0.00215 (0.00530)	0.00744 (0.0103)	-0.00791 (0.00542)	-0.00793 (0.00642)	-0.0108 (0.00663)	0.0170** (0.00646)	0.00881 (0.00567)	-0.000711 (0.00592)
DUMMY_HOUSEHOLD	0.0423** (0.0166)	0.0517* (0.0286)	0.0319** (0.0133)	0.0400** (0.0159)	0.0396** (0.0162)	0.0688*** (0.0147)	0.0506*** (0.0133)	0.0169 (0.0126)
DUMMY_TOWN	0.0362** (0.0178)	0.0167 (0.0333)	0.0357** (0.0177)	-0.0415 (0.0270)	0.0199 (0.0302)	0.0588*** (0.0216)	0.0198 (0.0240)	-0.0135 (0.0235)
DUMMY_NORTH	0.0380*** (0.0141)	0.0837*** (0.0246)	0.0497*** (0.0135)	0.0424** (0.0171)	0.0403** (0.0191)	-0.00494 (0.0161)	-0.0238 (0.0164)	0.0482*** (0.0172)
DUMMY_SOUTH	-0.0495*** (0.0173)	0.0435 (0.0288)	-0.0432** (0.0186)	-0.00330 (0.0231)	-0.0404* (0.0232)	-0.0952*** (0.0185)	-0.0924*** (0.0184)	-0.00475 (0.0188)
DUMMY_AGRICULTURAL	-0.172** (0.0674)	-0.162** (0.0651)	-0.174*** (0.0426)	-0.0812 (0.0574)	-0.129*** (0.0318)	-0.175*** (0.0469)	-0.0275 (0.0427)	-0.0829** (0.0385)
DUMMY_PUBLIC	0.162*** (0.0169)	0.0973*** (0.0255)	0.105*** (0.0150)	0.105*** (0.0186)	0.128*** (0.0197)	0.121*** (0.0189)	0.134*** (0.0188)	0.134*** (0.0172)
DUMMY_OTHER_SECTOR	0.00640 (0.0149)	0.00866 (0.0303)	0.0360** (0.0151)	0.0146 (0.0180)	0.0158 (0.0186)	0.00982 (0.0163)	0.00909 (0.0156)	0.0168 (0.0144)
DUMMY_SECT_PARENTS	0.0120 (0.0149)	0.0741*** (0.0220)	0.0179 (0.0119)	0.0135 (0.0155)	0.0101 (0.0142)	-0.00224 (0.0133)	0.0331** (0.0130)	0.0128 (0.0131)
DUMMY_PART_TIME	0.0680** (0.0323)	0.0397 (0.0533)	0.0336 (0.0267)	-0.0823** (0.0360)	-0.0513* (0.0311)	-0.00954 (0.0300)	0.0300 (0.0270)	-0.00800 (0.0214)
Constant	1.488*** (0.0350)	1.459*** (0.0605)	1.570*** (0.0303)	1.575*** (0.0359)	1.707*** (0.0376)	1.628*** (0.0368)	1.596*** (0.0335)	1.637*** (0.0359)
Observations	6,066	2,016	5,724	5,461	5,425	5,378	5,409	5,161
R-squared	0.454	0.379	0.359	0.313	0.281	0.332	0.364	0.338

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

For year 2010, we find that, conditional on experience and other characteristics, individuals who have completed upper secondary school earn 14.8% more than individuals with only compulsory education. The earnings of individuals with upper secondary who have completed college are 52.2%.

We confirm that the estimated returns to education are not constant but increase with the level of education attained. Then, it confirms the positive monotonic relationship that links returns to education to the highest level of education attained. Table 20 reports the results of the ordered probit model for educational attainment as a function of the instrument used in the IV estimation. This is the first step necessary to estimate the score associated to the ordered probit that we add in the earnings equation in order to apply ordinary least squares as second step.

Table 20 – Ordered probit estimates. Dependent Variable: education. Omitted categories are: Center (DUMMY_CENTER); Industrial sector (DUMMY_INDUSTRIAL).

VARIABLES	1995	1998	2000	2002	2004	2006	2008	2010
PRIMARY_F	-0.836*** (0.0653)		-0.716*** (0.0762)	-0.586*** (0.0774)				-0.564*** (0.0912)
PRIMARY_M	-0.495*** (0.0729)					-0.293*** (0.0775)		
EXPERIENCE	0.00682 (0.0102)	-0.0206 (0.0189)	-0.0173 (0.0111)	-0.0142 (0.0133)	-0.0385*** (0.0121)	-0.0194 (0.0125)	-0.0130 (0.0127)	-0.0178 (0.0157)
EXPERIENCE^2	-0.000571** (0.000254)	0.000451 (0.000449)	0.000125 (0.000272)	8.52e-05 (0.000319)	0.000781*** (0.000283)	3.78e-05 (0.000301)	3.49e-05 (0.000294)	0.000118 (0.000364)
DUMMY_MALE	0.0436 (0.0738)	0.112 (0.140)	-0.185*** (0.0648)	-0.149** (0.0717)	-0.174** (0.0687)	-0.115 (0.0810)	-0.137* (0.0766)	-0.240*** (0.0805)
DUMMY_MARRIED	0.194** (0.0983)	-0.188 (0.159)	0.0617 (0.0881)	0.112 (0.0984)	0.292*** (0.0896)	0.130 (0.0869)	0.342*** (0.0979)	-0.0254 (0.0946)
NCOMP	-0.0637** (0.0247)	-0.117*** (0.0443)	-0.00799 (0.0263)	0.0140 (0.0304)	-0.0326 (0.0302)	-0.0215 (0.0308)	-0.0469 (0.0312)	0.0634* (0.0364)
DUMMY_HOUSEHOLD	-0.0893 (0.0749)	-0.321** (0.140)	0.0665 (0.0624)	-0.0681 (0.0698)	0.0224 (0.0681)	0.0294 (0.0792)	0.0408 (0.0856)	
DUMMY_TOWN	0.113 (0.0703)	0.0409 (0.126)	0.295*** (0.0783)	0.193** (0.0957)	0.0735 (0.0901)	0.220** (0.0885)	0.149 (0.102)	0.190* (0.106)
DUMMY_NORTH	-0.0315 (0.0614)	-0.0376 (0.100)	0.142** (0.0643)	0.148** (0.0729)	0.0359 (0.0714)	-0.130* (0.0724)	0.0135 (0.0830)	-0.103 (0.0889)
DUMMY_SOUTH	-0.0787 (0.0675)	0.0320 (0.106)	0.0551 (0.0704)	0.0977 (0.0876)	-0.134 (0.0868)	-0.291*** (0.0877)	-0.196** (0.0941)	-0.192* (0.106)
DUMMY_AGRICULTURAL	-0.426** (0.191)	-1.421*** (0.282)	-0.397*** (0.147)	-0.564*** (0.199)	-0.770*** (0.183)	-0.528*** (0.167)	-0.463** (0.186)	-0.334 (0.251)
DUMMY_PUBLIC	0.929*** (0.0682)	0.749*** (0.113)	0.947*** (0.0646)	0.976*** (0.0760)	0.987*** (0.0760)	0.991*** (0.0736)	0.922*** (0.0790)	0.892*** (0.104)
DUMMY_OTHER_SECT	0.0287 (0.0651)	0.0761 (0.116)	0.300*** (0.0670)	0.256*** (0.0719)	0.342*** (0.0735)	0.309*** (0.0709)	0.285*** (0.0775)	0.298*** (0.0869)
DUMMY_SECT_PARENTS	0.0724 (0.0616)	0.127 (0.0843)	0.135*** (0.0505)	-0.00387 (0.0592)	0.117** (0.0560)	0.221*** (0.0585)	0.110* (0.0629)	0.0442 (0.0734)
DUMMY_PART_TIME	-0.264** (0.104)	-0.338** (0.156)	-0.218** (0.0939)	-0.164 (0.108)	-0.233** (0.0969)	-0.288*** (0.0959)	-0.193* (0.110)	-0.327** (0.141)
SECONDARY_F		0.950*** (0.109)			0.628*** (0.0700)	0.676*** (0.0735)	0.726*** (0.0807)	
SECONDARY_M		0.376*** (0.120)	0.422*** (0.0833)	0.553*** (0.0838)	0.436*** (0.0784)		0.453*** (0.0849)	0.280*** (0.0989)
cut1								
Constant	-1.009*** (0.153)	-0.484* (0.256)	-0.416*** (0.157)	-0.247 (0.184)	0.148 (0.165)	-0.399** (0.174)	0.194 (0.181)	-0.799*** (0.220)
cut2								
Constant	-0.771*** (0.153)	-0.226 (0.254)	-0.105 (0.157)	0.0291 (0.184)	0.421** (0.165)	-0.0802 (0.176)	0.515*** (0.183)	-0.424* (0.220)
cut3								
Constant	0.649*** (0.153)	1.160*** (0.258)	1.233*** (0.158)	1.407*** (0.188)	1.881*** (0.173)	1.379*** (0.181)	1.927*** (0.194)	0.855*** (0.221)
Observations	4,352	1,468	3,783	3,321	3,405	3,437	2,836	2,145

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1