Chapter 1

An estimate of Wage Function in Italy

Abstract. Education can be seen as an investment with returns incorporates in the future wages. The general model points out that higher individual education implies higher individual wages. Many studies have tested this relationship, in different countries. Using data come from the 1995 to 2012 waves of the Bank of Italy's Survey of Household Income and Wealth, we estimate the determinants of the wage function, focusing on the role of schooling and experience.

The findings highlight the evidence of returns to schooling that have changed over the period considered and are between 5.4% and 7.9%, recording the highest level for 2006 and the lowest in 2012. Therefore, the advantage to invest in education are decreasing in Italy. Moreover, a relative convenience to work in the public sector emerges. Finally, there is evidence of a gender pay gap, in favor of men for all the period considered.

1.1 Introduction

Education is one of the most important components of individual human capital (Becker, 1993) thus a significant determinant of wages. The estimation of the economic return to education has 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 in the works of led economist such as Gary Becker, Jacob Mincer and Theodore Schultz. According the human capital theory, education is seen as an investment of current resources to get future returns.

The estimation of economic return of schooling is a relevant parameter of interest in economics studies and in public policy design. Indeed, a huge body of literature focus in the estimation of returns to education.

This interest is due by the link between schooling and productivity growth (Lucas, 1988). Moreover, Economists studying inequality and poverty seek to learn how schooling increases the incomes of the poor.

Therefore, the evaluation of policies that promote education is a central research question. The increase in wages due to additional schooling, what is usually called the return to schooling, is a main component of the benefits of the proposed policies. In fact, to the policy maker perspective, it is crucial to understand if the higher wages observed for better educated people are determined only by their higher education level or if they reflect inherent ability differences that correlate with educational attainment. Therefore, treating schooling as a way to increase market productivity it is important to understand if any increase in public spending for education is meaningful for people.

The benchmark model for the development of empirical estimation of the returns to education is the relationship derived by Mincer (1974) between log hourly wages and schooling. The original Mincer equation assumes linear effect on wages of each year of education regardless of the attainment level. Since the pioneer work of Mincer (1974) who has written the methodological foundation to estimate wage equations, a huge body of works were dedicated to finding the causal return to education. The causal return to education is the extra amount of wage that a randomly selected worker receives from an additional year of education. As explained before, knowing the causal return is important for policy makers, because it directly informs about the utility of educational programs in terms of monetary payoffs for its beneficiaries and for the economic system at all.

However, the empirical estimation of the causal returns is not an easy task i.e. the simple regressions between wage and schooling does not report causal returns to education (and produce biased estimates) as the schooling variable is likely to be endogenous due to omitted variable, namely ability.

One well-established route to circumvent the endogeneity problem is to use instrument variable (IV) methods. These methods, while theoretically appealing, are not easy to implement in practice as they rely on the availability of valid and significant instruments.

The research question of this chapter is to investigate how years of education, experience and other variable affect wages in Italy. In addition, we want understand if the impact of these variables on wages vary over time.

Since education can be seen as a private decision to invest in human capital, we calculate the internal rate of return to this private investment. Moreover, we take into account differential effects of different educational level: vocational, upper-secondary and tertiary education. The data come from the Survey of Household Income and Wealth (SHIW) carried out by the Bank of Italy, covering the period from 1995 to 2012 where information about education, wage and demographics characteristics are collected at individual and household level.

Our results shows that returns to education have changed over the considered period, varying between 5.4% and 7.9%. Considering 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 kind of school attended is taken into consideration, the returns to education increase with higher levels of educational attainment.
The reminder of the paper is organized as follows. Section 2 presents the theoretical background of the wages equation to be estimated. Section 3 describes the dataset used in the empirical estimation and the characteristics of the sample. Section 4 reports the estimates of the effect of schooling, experience and other variables on wages. Finally, section 5 summarizes and concludes.

1.2 Theoretical Framework for the Empirical Analysis

The theoretical framework underlying most empirical studies on the determinants of wages, and the related estimate of the return to schooling, is the model of accumulation of human capital developed by Schultz (1961), Becker (1962) and Mincer (1958, 1974). In particular, Mincer (1974) focuses on the life-cycle dynamics of earnings and on the relationship between (observed) earnings, earnings capacity (proportional to the individual stock of human capital) and investment in earnings capacity (human capital); such investments can regard both formal schooling and on-the-job training (learning by doing). Earnings will be a function of earnings capacity net of the costs of investment in earnings capacity. In particular, let E_t be the earnings capacity at time *t*. Earnings capacity can be increased by investment in human capital. To maintain as simple as possible the analysis, investments are expressed as a fraction of earnings capacity:

$$C_t = k_t E_t, \tag{1.1}$$

where k_t is the fraction of earnings capacity invested at time *t*. Let ρ_t be the return on investments made at time *t*. Then:

$$E_{t+1} = E_t + C_t\rho_t - \delta_t E_t = E_t(1 + k_t\rho_t) - \delta_t E_t, \tag{1.2}$$

where δ_t is the depreciation on obsolescence of earnings capacity (see Rosen, 1974). Recursive substitution yields:

$$E_t = \prod_{j=0}^{t-1}\left(1 + \rho_j k_j - \delta_t\right)E_0, \tag{1.3}$$

where E_0 is the earnings capacity, independent of schooling and experience.

Formal schooling is defined as the numbers of years spent in full-time investment ($k_t = 1$). Assume that the rate of return on formal schooling of length s is constant for all years of schooling and equal to ρ_s and that formal schooling takes place at the beginning of life, i.e. $\rho_t = \rho_s \,\forall\, t = 0, \dots, s$. Therefore, assume that the rate of return to post-school investment is constant over time and equals ρ_{ps}, i.e. $\rho_t = \rho_{ps} \,\forall\, t \geq s$. Then, we can write:

$$\ln E_t = \ln E_0 + s\ln(1 + \rho_s) + \sum_{j=s}^{t-1}\ln\left(1 + \rho_{ps}k_j - \delta_t\right), \tag{1.4}$$

which yields the approximate relationship (for small ρ_s and ρ_{ps})[1]:

$$\ln E_t \approx \ln E_0 + \rho_s s + \rho_{ps}\sum_{j=s}^{t-1} k_j - \sum_{j=s}^{t-1}\delta_j. \tag{1.5}$$

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

$$k_{s+x} = \kappa\left(1 - \frac{x}{T}\right), \tag{1.6}$$

where $\kappa > 0$ is a scale parameter, $x = t - s \geq 0$ is the amount of work experience as of age t. The length of working life, T, is assumed to be

[1] See pag.19 of Mincer (1974).

independent of years of schooling[2]. Given Equation (1.6), the relationship between earnings capacity, schooling and experience is given by:

$$\ln E_{x+s} \approx \ln E_0 - \kappa\rho_{ps} + \rho_s s + \rho_{ps}\kappa x\left(1+\frac{1}{2T}\right) - \frac{\rho_{ps}\kappa}{2T}x^2 - x\delta, \tag{1.7}$$

under the assumption that $\delta_j = \delta \ \ \forall\, j.$ Observed earnings are to equal earnings capacity less investment costs, i.e. $w(s,x) = (1-k_{s+x})E_{x+s}$. Therefore:

$$\ln w(s,x) \approx \ln E_{x+s} - \kappa\left(1-\tfrac{x}{T}\right) =$$

$$= \ln E_0 - \kappa\rho_{ps} - \kappa + \rho_s s + \left[\kappa\left(\rho_{ps} + \tfrac{\rho_{ps}}{2T} + \tfrac{1}{T}\right) - \delta\right]x - \tfrac{\rho_{ps}\kappa}{2T}x^2 =$$

$$= \alpha_0 + \rho_s s + \beta_0 x + \beta_1 x^2, \tag{1.8}$$

where $\alpha_0 = \ln E_0 - \kappa(1+\rho_{ps}),\ \ \beta_0 = \kappa\left[\rho_{ps}\left(1+\tfrac{1}{2T}\right) + \tfrac{1}{T}\right] - \delta,\ \ \beta_1 = -\tfrac{\rho_{ps}\kappa}{2T}.$

Starting from this standard form of the Mincer wages model, it is possible to derive an econometrics model in order to estimate the parameters. Therefore, the log wages are regressed 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_s , ρ_{ps} and δ are the same across workers and do not depend on the schooling level. However, Mincer formulates a more general model that allows for the possibility that E_0, κ, ρ_s , ρ_{ps} and δ differ across workers, which produces a random coefficient model:

$$\ln w(s_i, x_i) = \alpha_{0i} + \rho_{si}s_i + \beta_{0i}x_i + \beta_{1i}x_i^2. \tag{1.9}$$

Denoting $\alpha_0 = E(\alpha_{0i}), \rho_s = E(\rho_{si}), \beta_0 = E(\beta_{0i}), \beta_1 = E(\beta_{1i})$, we can rewrite Equation (1.9) as:

[2] This means that educated workers retire after not educated workers.

$$\ln w(s_i, x_i) = \rho_s s_i + \beta_0 x_i + \beta_1 x_i^2 + [\alpha_{0i} + (\rho_{si} - \rho_s) s_i + (\beta_{0i} - \beta_0) x_i + (\beta_{1i} - \beta_1) x_i^2], \quad (1.10)$$

where the terms in brackets are part of the error. Mincer assumes that $\alpha_{0i}, (\rho_{si} - \rho_s), (\beta_{0i} - \beta_0), (\beta_{1i} - \beta_1)$ are independent of (s_i, x_i) which reduces Equation (1.10) to Equation (1.8) in terms of estimations with individual data, i.e:

$$\ln w(s_i, x_i) = \alpha_{0i} + \rho_s s_i + \beta_0 x_i + \beta_1 x_i^2 + \varepsilon_i. \quad (1.11)$$

That is the Mincerian wage equation where ε_i is a mean zero residual with $E(\varepsilon_i | s_i, x_i) = 0$

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 ρ_{ps} are identical across persons and do not depend on the schooling level s, we have that $\frac{\partial \ln w(s_i, x_i)}{\partial s_i \partial x_i} = 0$ and $\frac{\partial \ln w(s_i, x_i)}{\partial s_i \partial t} = \frac{\rho_{ps} \kappa}{T} > 0$. These two conditions imply:

(i) log-wages experience profiles are parallel across schooling levels;

(ii) log-wages age profile diverge with age across schooling levels.

Equation (1.10) highlights how error term ε_i captures unobservable individual effects, as unobserved ability; this also influences schooling decision s, and thus induces a correlation between schooling and the error term in the wages function. With endogeneity, the estimation of the return to schooling by ordinary least squares is biased. In literature, the problem has been addressed in different ways. 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 (Mendolicchio, 2006). Another solution is to apply within-twins differences in wages and education, assuming that unobserved effects are additive and common within twins so they can be differentiated out by regressing the wage difference within twins against their education differences (Bonjour et al., 2003). An additional approach deals with the simultaneous relationship between schooling and wages by specifying a two-equation system, which is identified by exploiting instrumental variables that affect s but not w (Blundell, Dearden and Sianesi, 2001), where family background is used as instruments for schooling. The last approach is the most applied in the literature and will be our strategy to deal with endogeneity.

1.3 Data and Sources

The analysis is based on data drawn from the Bank of Italy's Survey of Household Income and Wealth (SHIW), which reports several socio-economic characteristics of Italian households. The SHIW is a biannual survey on Italian families with a sample of approximately 8,000 household per year. From 1995 to 2012 observations from nine subsequent surveys are available. In particular, the SHIW contains information both on households (family composition) and on individuals. Moreover, it provides detailed information on several characteristics of workers within each household, such as their net yearly wages, average weekly hours of work and number of months of employment per year, educational attainment (the highest completed school degree), job experience, gender, marital status, sector of employment, household composition, parents background, regions of residence, and town size.

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 sector and such that information about wages are available. In the analysis, we exclude self-employed because of the low reliability of their declared earnings. As discussed by Brandolini and Cannari (1994), SHIW seems to underestimate the self-employed earnings of about 50 percentage points.

1.3.1 Variables Used in the Analysis

As shown by Equation (1.11), wages, schooling attainment, and working experience of each individual are the key variables in the estimate of Mincer equation.

Mincer equation refers to the (log of) hourly price of labor as the correct measure of worker's wages (LOGY_H), and, indeed, this is the measure used by most empirical studies[3] (Brunello and Miniaci, 1999; Blundell, Dearden and Sianesi, 2005; Ciccone, Cingano and Cipollone, 2006). SHIW contains yearly net wages 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 estimate the hourly net wage, which is calculated by yearly net wages divided by months worked multiplied by hours worked each month.

Schooling attainment (SCHOOL) 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 individuals. Following a common approach in literature (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 maximum level of educational attainment[4]. 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 consider 16, 18 and 21 years for the university diploma,

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[3] Hourly wage can be affected by measurement errors because we calculate them as total earnings divided by hours of work.

[4] Standard and 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.

the college degree, and the postgraduate degree (e.g. Ph.D.) respectively. In the analysis of Section 1.4.2, we will also treat education as a categorical variable divided into 4 categories: no education or primary school or junior high school (COMP_SCHOOL), 3-year vocational school (VOCATIONAL), upper secondary school (UPPER SECONDARY), tertiary education (TERTIARY; including university diploma, college and post-graduate education). It is important to remark that in Italy 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.

In this work, we use as proxy for experience (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.

We introduce several control variables in the analysis to account for individual characteristics and for differences in the labor market. 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, 0 otherwise. 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 wages (constancy of the hourly wage) cannot hold across workers with different time status (part time versus full time).

In addition, controls are introduced for family composition, as a proxy for the influence of housework, particularly important in the female labor supply

(Heckman and Killingsworth, 1986). We control for the number of components of the family (NCOMP) and for the fact that the individual is the head of his/her household (DUMMY_HOUSEHOLD).

Controls for sector (DUMMY_AGRICULTURAL for the agricultural sector, DUMMY_INDUSTRIAL for the industrial sector, DUMMY_PUBLIC for the public sector and DUMMY_OTHER_SECTOR for other sector different from the previous ones) should capture potential factor from the demand side of labor market (e.g. imperfectly competitive labor markets). In the same light, we add some 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 Italian macro-regions: North, Center and South (DUMMY_NORTH, DUMMY_CENTER and DUMMY_SOUTH)[5].

Table 1.1 reports some descriptive statistics of the main variables used in the empirical analysis for all the waves (wages are expressed in euro 2012).

Table 1.1 - Means and standard deviations of the variables used in the empirical analysis for the entire sample (1995, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012)

Variable	Mean	S. d.	Description
LOGY_H	2,265	0,438	Logarithm of the hourly real wages less tax
SCHOOL	11,373	3,800	Schooling attainment, that is the number of years spent at school
COMP_SCHOOL	0,383	0,486	Compulsory school: no schooling, primary school and junior high school
VOCATIONAL	0,090	0,288	3-years Vocational degree
UPPER_SECONDARY	0,379	0,485	Upper secondary degree
TERTIARY	0,146	0,354	Tertiary degree
EXPERIENCE	17,683	10,673	Number of years for which it has been paid social security contributions, as a proxy for years of training on the job
DUMMY_MALE	0,578	0,494	Gender dummy
DUMMY_MARRIED	0,647	0,478	Dummy variable for marital status

[5] Card and Krueger (1992) showed how students who grew up in states with better quality schools acquire more education. Moreover, the place of residence is linked to the possibility to find a job and be well-paid.

NCOMP	3,329	1,185	Number of components of the family
DUMMY_HOUSEHOLD	0,475	0,499	Household dummy, that is equal to 1 if the individual is the household of the family
DUMMY_PART_TIME	0,094	0,292	Dummy variable for part time work
DUMMY_AGRICULTURAL	0,034	0,180	Dummy variable for agricultural sector
DUMMY_INDUSTRIAL	0,312	0,463	Dummy variable for industrial sector
DUMMY_PUBLIC	0,320	0,466	Dummy variable for public administration sector
DUMMY_OTHER_SECTOR	0,335	0,472	Dummy variable for other sector
DUMMY_TOWN	0,083	0,275	Dummy variable for the town of residence that has more than 500.000 inhabitants
DUMMY_NORTH	0,501	0,500	Dummy variable for North regions
DUMMY_CENTER	0,214	0,410	Dummy variable for Center regions
DUMMY_SOUTH	0,286	0,452	Dummy variable for South regions
DUMMY_SETT_GEN	0,374	0,484	Dummy variable equal to 1 if the individual works in the same sector of the father and/or of the mother
SCHOOL_F	6,094	4,094	Schooling attainment of the father's worker
SCHOOL_M	5,346	3,711	Schooling attainment of the mother's worker

1.4 Estimates

In a first model, we consider schooling as measured by the years of schooling. In a second step of analysis, we consider separately different level of educational attainment.

1.4.1 Mincerian Model with years of education

For each available wave, we estimate the Mincerian wage equation reported in Equation (1.11). However, as discussed in a very large literature reviewed by Card (1995), OLS estimation of the returns to education via Mincerian wage Equation are not consistent either because of i) the measurement errors in the schooling variable, and ii) the endogeneity bias of schooling.

In particular, the measurement of years of schooling in our data is exposed to error because it is possible to observe only the last completed degree. However, individuals with the same completed degree could have spent a significantly different number of years in education. Moreover, the endogeneity bias arise either from unobserved differences in the individual ability or from a general unobserved heterogeneity. Indeed, if individual with higher education have greater ability than others, the estimated return to education is biased upwards since part of the productivity differential is due to their ability or to other skills acquired outside the school (ability bias). Thus, the ability bias interacts with heterogeneous subjective discount rates that result in under-estimating the true effect of schooling on wages when workers with lower education are 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 Equation (1.11) by using instrumental variables (IVs). The identification of a valid instrument is not an easy task and it 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 the log of) wages conditional on schooling (Wooldridge, 2012).

There is a long tradition in using family background variables, typically the level 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. Some previous articles on returns to education in Italy derived instrumental variables in the SHIW data, exploiting information provided by the school reforms of the 1960s (Brunello and Miniaci, 1999). However, this type of instrumental variables becomes much less convincing when the focus of the analysis is the time dynamics of return to education. Since the effects of school reforms change according to the population sub-group involved in the reforms, the group of people affected by the instruments changes over time, affecting in turn dynamic comparison of the estimates.

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 respondents. More educated parents are likely to value education more and to fill better jobs. Furthermore, early educational investment decisions are usually taken not by the individual him/herself, but rather by other agents such as the parents. The assumption is that not only the level and also the kind of education owned by the parents affects the children's one, both through direct decisions, when children are young, and indirect decisions, by encouraging a certain career over another. Checchi, Ichino, Rustichini (1999) show that students choose the level and kind of education not only in relation to their previous curricula but also according to the level and type of education of their parents.

In our estimation strategy, the instruments 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, 2012). An important requirement is also that selected instrument should be correlated with the endogenous variable and to test for this, as suggested by Bound et al. (1995)[6], in the first-stage regression of the endogenous variable we compute the F-statistic on the excluded instruments. The F-test on excluded variables shows that our set of instruments is valid, meaning that instruments play a significant role in the reduced form for education and it explains a substantial share of variation in education. Hence, the condition for a valid instrument is satisfied.

[6] If the instruments are weakly correlated with the endogenous variable, this 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.

Table 1.2 - IV estimates[7]. Dependent Variable: log of hourly wages less tax. Omitted categories are: Center (DUMMY_CENTER); Industrial sector (DUMMY_INDUSTRIAL).

VARIABLES	1995	1998	2000	2002	2004	2006	2008	2010	2012
SCHOOL	0.0643***	0.0619***	0.0687***	0.0712***	0.0668***	0.0786***	0.0587***	0.0685***	0.0542***
	(0.00368)	(0.00764)	(0.00475)	(0.00760)	(0.00678)	(0.00621)	(0.00613)	(0.00784)	(0.00813)
EXPERIENCE	0.0189***	0.0188***	0.0209***	0.0246***	0.0144***	0.0250***	0.0226***	0.0151***	0.0169***
	(0.00331)	(0.00671)	(0.00354)	(0.00530)	(0.00450)	(0.00375)	(0.00447)	(0.00439)	(0.00435)
EXPERIENCE^2	-0.000142*	-0.000142	-0.000199**	-0.000278**	-0.000149	-0.000326***	-0.000270**	-4.20e-05	-7.98e-05
	(7.92e-05)	(0.000155)	(8.13e-05)	(0.000128)	(0.000115)	(9.04e-05)	(0.000112)	(0.000100)	(0.000100)
DUMMY_MALE	0.132***	0.114***	0.0967***	0.0984***	0.0812***	0.109***	0.156***	0.154***	0.101***
	(0.0250)	(0.0354)	(0.0186)	(0.0253)	(0.0261)	(0.0210)	(0.0215)	(0.0266)	(0.0232)
DUMMY_MARRIED	0.00438	0.0501	0.0562**	0.00849	0.0369	-0.00942	-0.0498*	0.0292	0.00841
	(0.0249)	(0.0448)	(0.0251)	(0.0382)	(0.0317)	(0.0235)	(0.0279)	(0.0283)	(0.0326)
NCOMP	0.0177**	0.0150	-0.00134	0.00120	-0.00221	0.0315***	0.0277***	-0.00232	0.0210*
	(0.00728)	(0.0146)	(0.00777)	(0.0101)	(0.00898)	(0.00896)	(0.00893)	(0.0110)	(0.0117)
DUMMY_HOUSEHOLD	-0.00637	-0.00124	0.00590	0.0225	0.0188	0.0306	0.00893		
	(0.0254)	(0.0369)	(0.0184)	(0.0247)	(0.0245)	(0.0200)	(0.0237)		
DUMMY_TOWN	0.00582	0.0310	0.0126	-0.0814**	-0.0184	0.0423*	0.0164	-0.0339	-0.00380
	(0.0210)	(0.0405)	(0.0215)	(0.0360)	(0.0447)	(0.0242)	(0.0305)	(0.0395)	(0.0407)
DUMMY_NORTH	0.0378**	0.0671**	0.0459***	0.0455*	0.0667**	-0.00831	-0.00197	0.0514*	0.0404
	(0.0167)	(0.0286)	(0.0171)	(0.0238)	(0.0297)	(0.0193)	(0.0230)	(0.0288)	(0.0273)
DUMMY_SOUTH	-0.0239	0.0635**	-0.00599	0.00619	0.0224	-0.0493**	-0.0344	0.0201	-0.00710
	(0.0185)	(0.0319)	(0.0224)	(0.0280)	(0.0353)	(0.0230)	(0.0254)	(0.0316)	(0.0340)
DUMMY_AGRICULTURAL	-0.0394	0.0209	-0.116*	-0.0404	-0.0661	-0.127*	-0.0606	0.0278	-0.102*
	(0.0703)	(0.104)	(0.0629)	(0.0578)	(0.0435)	(0.0742)	(0.0481)	(0.0692)	(0.0574)
DUMMY_PUBLIC	0.109***	0.0435	0.0199	0.00801	0.0525*	0.0100	0.0947***	0.0677*	0.0689*
	(0.0218)	(0.0343)	(0.0216)	(0.0314)	(0.0311)	(0.0290)	(0.0288)	(0.0356)	(0.0400)
DUMMY_OTHER_SECTOR	0.0156	-0.00728	-0.00811	-0.0140	-0.0144	-0.0299	-0.00180	0.00405	-0.0520**
	(0.0179)	(0.0397)	(0.0196)	(0.0232)	(0.0263)	(0.0204)	(0.0235)	(0.0265)	(0.0252)
DUMMY_SECT_PARENTS	-0.00735	0.0423*	-0.0131	-0.00227	-0.0113	-0.0150	0.0307*	0.00793	-0.0157
	(0.0182)	(0.0250)	(0.0151)	(0.0186)	(0.0188)	(0.0172)	(0.0186)	(0.0224)	(0.0236)
DUMMY_PART_TIME	0.0387	0.0781	0.0826**	-0.0605	-0.0123	0.0191	0.0131	0.0444	-0.0191
	(0.0360)	(0.0651)	(0.0322)	(0.0444)	(0.0385)	(0.0415)	(0.0366)	(0.0333)	(0.0348)
Constant	1.130***	1.085***	1.112***	1.088***	1.240***	0.980***	1.172***	1.082***	1.209***
	(0.0596)	(0.132)	(0.0692)	(0.0939)	(0.0854)	(0.0879)	(0.0877)	(0.112)	(0.110)
Observations	4,352	1,468	3,783	3,321	3,405	3,437	2,836	2,145	2,112
R-squared	0.403	0.308	0.294	0.261	0.206	0.267	0.331	0.250	0.302

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

Table 1.2 presents the IV estimates for the period 1995-2012[8]. 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 always rejects the null hypothesis of no correlation between education and additional instruments.

[7] 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 and year 2012 only for the households.

[8] We also estimate return to education by applying OLS (the results are showed in the Appendix). Consistent with the existing literature, we find large positive returns to education after instrumenting for education; the two-stage least squares estimates are much larger than their OLS counterparts. OLS approach, failing to address endogeneity and measurement errors problems consistently underestimates the returns to education. IV estimates are generally 20–40% above their OLS counterpart (Trostel et al., 2002).

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.

1.4.1.1 The Return on Schooling

The main features of empirical research on returns to education in Italy are shown in Table 1.3. The estimated rate of return to an additional year of schooling 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 wages 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 wages function using the ENI special survey on earning and they find that the marginal return to schooling is slightly higher for women than for men but again around 4 per cent.

Table 1.3 – A summary of the estimated rates of return to schooling of an additional year of schooling in Italy.

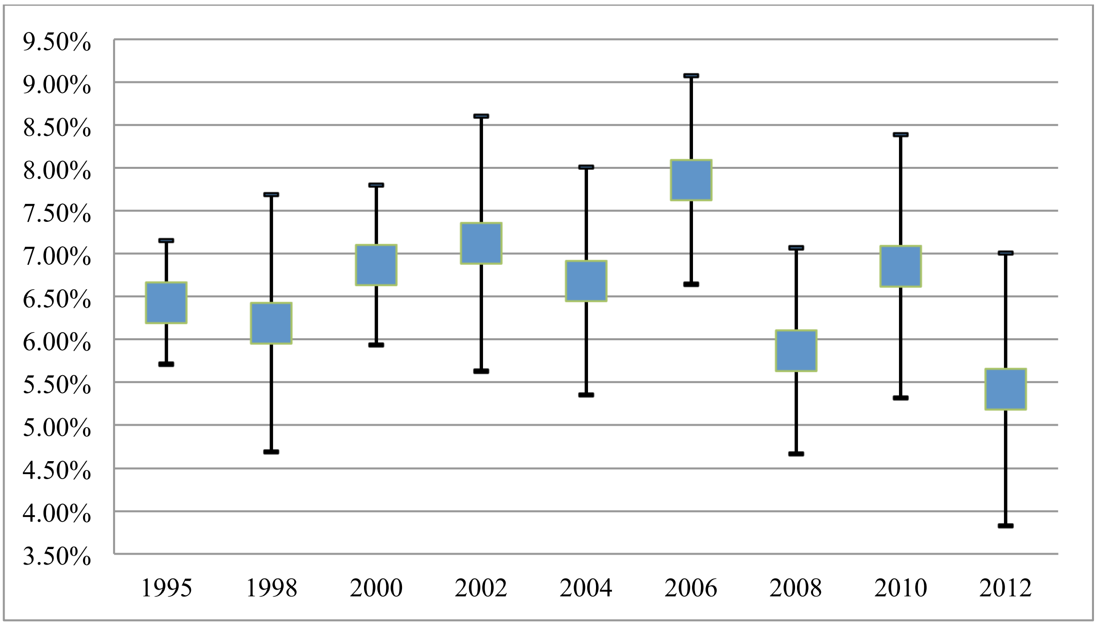
Author	Method of estimation	Years	Estimated rates of return Schooling%
Antonelli (1985)	OLS	1977	4.6
Cannari, Pellegrini, and Sestito (1989)	OLS	1986	4.0
Lucifora and Reilly (1990)	OLS	1985	4.0 (women) 3.6 (men)
Cannari and D'Alessio (1995)	IV	1993	7.0
Colussi (1997)	IV	1993	7.6
Flabbi (1997)	IV	1991	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 (1997) 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 wages. 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 our results from the estimations of the Mincerian wage equation, the evidence is that returns have changed over the period considered. The estimations of the returns to schooling are between 5.4% and 7.9%, recording the highest level in 2006 and the lowest in 2012, and on average the rate of return to schooling is equal to 6.6%. Looking at the previous estimates made for Italy, as shown in Figure 1.1, we can notice that our estimate are in line with the literature. Moreover, from 1995 to 2012, it is not present a clear patterns of the return to schooling, either increasing or decreasing.

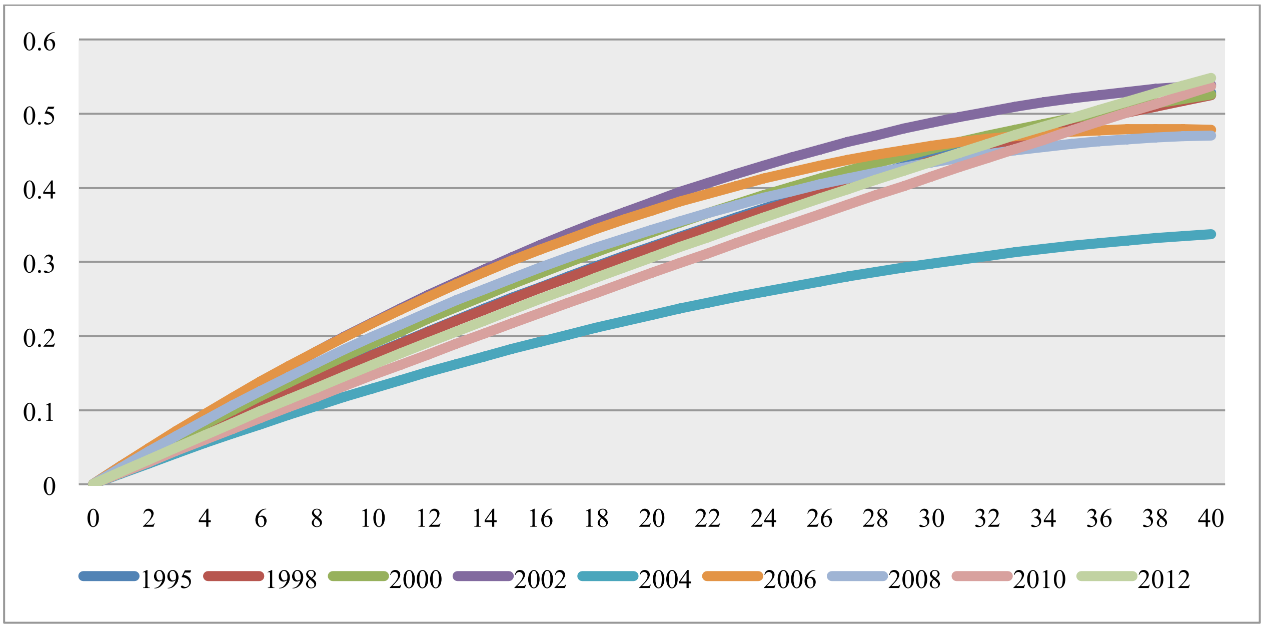
Figure 1.1 - Estimates of the Return to Education, 1995-2012 (with confidence intervals at 95%)



1.4.1.2 The Return on Experience

The dynamics of experience is drawn in Figure 1.2. 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. Therefore, we can affirm that the experience profile is not linear function (except for 2010 and 2012) and that the estimates are quite stable over the time period considered.

Figure 1.2 - Estimates of the Experience Profile, 1995-2012



1.4.1.3 The Impact of Other 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 and to 10.1 in 2012.

Considering the geographical residence of the workers and the sector of employment, differences in estimates mainly reflect territorial and sectorial performance of Italy.

The DUMMY_NORTH is positive while the DUMMY_SOUTH in negative. This means that it is more convenient to work in the north regions in comparison to the central regions, instead if an individual works in the south region he will earns less than in the center regions. Therefore, 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, working in the public sector is more convenient than working in the industrial sector.

1.4.2 Mincerian Wage Model with Different Types of School

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 divided 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 2012, average education attainments of the upper secondary education in Italy is substantially low as shown in Table 1.4. On average across OECD countries, the percentage of 25-34 year-olds with at least upper secondary education is 18 per cent higher than that among 55-64 year-olds (about 82 per cent against 64 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 1.4 - Percentage of adults who have attained at least upper secondary education, by age group (2012)

	25-34 years old	55-64 years old
OECD average	82	64
Italy	72	42

Source: OECD (2014)

In Italy, just 72 per cent of the age-group 25-34 (versus an OECD average of 82 per cent) has attained at least upper secondary education; however, such a percentage is much higher than the 42 per cent of the 55-64 age-group.

For what concerns tertiary education in OECD countries we observe the same upward trend of education attainment for younger cohorts of population as reported in Table 1.5 (from 24 per cent to 39 per cent): younger adults have higher tertiary education than older adults by an average of 15 percentage points.

Table 1.5 - Percentage of adults who have attained tertiary education, by age group (2012)

	25-34 years old	55-64 years old
OECD average	39	24
Italy	22	11

Source: OECD (2014)

In Italy in 2012 the percentage of population in the 25-34 years-olds cohort with a university degree is equal to 22 per cent, much lower than the OECD average of 39 per cent. Although Italy shows a very significant increase over time of the percentage of the population attaining tertiary education (22 per cent of the 25-34 age group must be compared with 11 per cent of the 55-64 age group), we notice that such difference is well below that observed for OECD countries (from 24 per cent to 39 per cent).

Considering 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 1.6 and 1.7). 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 higher for women.

Table 1.6 – Percentage of adults who have attained at least upper secondary education, by age group and gender (2012)

	Women, by age group				
	25-64	25-34	35-44	45-54	55-64
OECD average	75	84	79	72	61
Italy	59	76	65	55	40

	Men, by age group				
	25-64	25-34	35-44	45-54	55-64
OECD average	76	81	78	74	68
Italy	56	68	59	51	45

Source: OECD (2014)

The gender gap in education in favor of women is recorded also in Italy: 8 per cent higher for the same group for upper secondary education, and 10 per cent higher for women aged 25-34 for tertiary education.

Table 1.7 - Percentage of adults who have attained tertiary education, by age group and gender (2012)

Women, by age group					
	25-64	25-34	35-44	45-54	55-64
OECD average	34	44	38	30	23
Italy	17	27	19	13	11

Men, by age group					
	25-64	25-34	35-44	45-54	55-64
OECD average	30	34	33	28	25
Italy	14	17	15	11	11

Source: OECD (2014)

In all OECD countries, adults with tertiary education earn more than adults with upper secondary or post-secondary non-tertiary education, who, in turn, earn more than adults without upper secondary education. Across OECD countries, compared with adults with upper secondary education who have income from employment, those without this qualification earn about 20% less, those with post-secondary non-tertiary education about 10% more, those with tertiary-vocationally oriented education about 30% more, and those with tertiary-academically oriented education or advanced research earn about 70% more.

Higher educational attainment is associated with higher wages during a person's working life. On average across OECD countries, wages increase with the level of educational attainment, but this increase is particularly large for older workers. People with higher levels of education are more likely to be employed, and remain employed, and have more opportunities to gain experience on the job. On average, the wages of tertiary-educated 55-64 year-olds is larger than that for 25-64 year-olds: by 36 per cent for OECD countries, by 43 per cent for Italy.

Regardless of the level of education, the gender gap in wages persists. Across OECD countries, a tertiary-educated woman earns about 73 per cent of what a

tertiary educated man earns (in Italy women who have obtained a tertiary degree earn 69 per cent or less of tertiary-educated men).
Finally, 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 2012, in Italy 79 per cent of the population with a tertiary education is employed against 71 per cent with an upper secondary education (84 per cent against 74 per cent in OECD countries).

1.4.2.1 The Return of Different Level of Schooling

The empirical specification in Equation (1.11) is based on the assumption that the return to education is constant and independent of the level of attained education. In this section, 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 wages.
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 wages 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.
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:

$$\ln w(s_i, x_i) = \alpha_{0i} + \sum_{h=1,3} \varphi_h E_{ih} + \beta_0 x_i + \beta_1 x_i^2 + \varepsilon_i \tag{1.12}$$

$$s_i^* = z_i \gamma + v_i \tag{1.13}$$

where w_i is the real hourly wage, E_{ih} are educational dummies that correspond to the highest degree achieved by the individual, x_i and z_i are observed attributes, ε_i and v_i are normally distributed error terms with zero means and finite variances, s_i^* is the latent level of education. We define s_i as the observed level of education, that takes the following discrete values:

$$s_i = \begin{cases} 1 & \text{if } s_i^* < \mu_0 \\ 2 & \text{if } \mu_0 \le s_i^* \le \mu_1 \\ 3 & \text{if } s_i^* \ge \mu_1 \end{cases} \tag{1.14}$$

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 steps 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 score[9] associated to the ordered Probit in the wages equation and we then apply ordinary least squares. 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 provides to the individual with respect to the reference group that is compulsory school. Our results are reported in Table 1.8. For instance, in 2012, an employee with a high school degree earns, on average,

[9] See Idson and Feaster (1990) for details on the computation of the score.

25.6% more than an employee with the same covariate belonging to the reference group. This differential increase to 56.5% for graduated individuals.

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

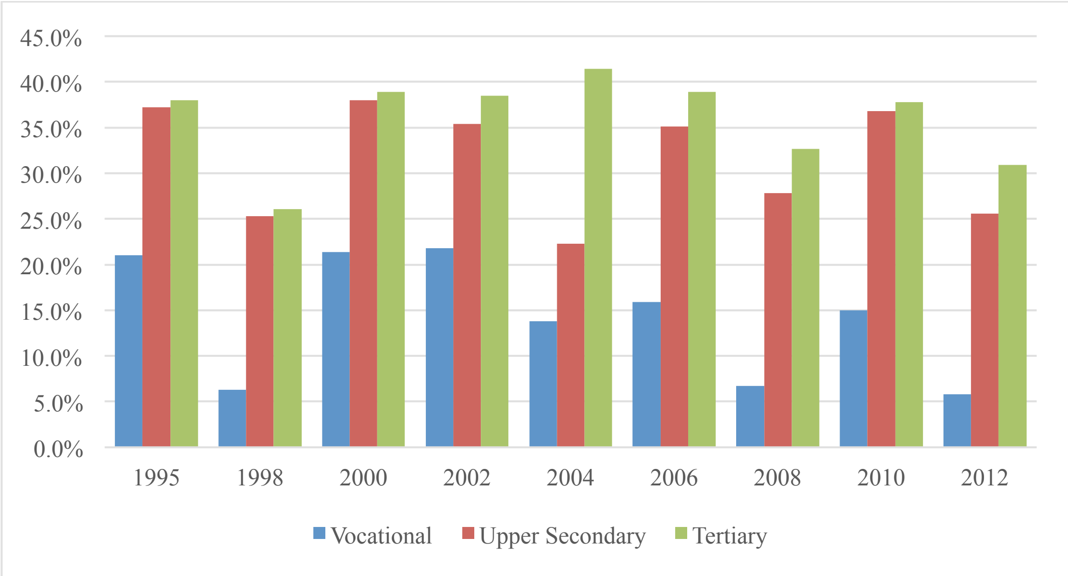
Table 1.8 – Second stage OLS estimates. Dependent Variable: log of hourly wages less tax. Omitted categories are: Center (DUMMY_CENTER); Industrial sector (DUMMY_INDUSTRIAL).

VARIABLES	1995	1998	2000	2002	2004	2006	2008	2010	2012
VOCATIONAL	0.210***	0.0632	0.214***	0.218***	0.138***	0.159***	0.0669*	0.150***	0.0581
	(0.0349)	(0.0558)	(0.0332)	(0.0368)	(0.0404)	(0.0313)	(0.0391)	(0.0570)	(0.0417)
UPPER_SECONDARY	0.372***	0.253***	0.380***	0.354***	0.223***	0.351***	0.278***	0.368***	0.256***
	(0.0304)	(0.0504)	(0.0362)	(0.0440)	(0.0556)	(0.0404)	(0.0398)	(0.0578)	(0.0532)
TERTIARY	0.752***	0.514***	0.769***	0.739***	0.637***	0.740***	0.605***	0.746***	0.565***
	(0.0508)	(0.0838)	(0.0567)	(0.0828)	(0.0880)	(0.0682)	(0.0695)	(0.105)	(0.0924)
EXPERIENCE	0.0213***	0.0191***	0.0239***	0.0281***	0.0155***	0.0264***	0.0242***	0.0160***	0.0183***
	(0.00328)	(0.00669)	(0.00348)	(0.00509)	(0.00433)	(0.00355)	(0.00436)	(0.00437)	(0.00442)
EXPERIENCE^2	-0.000239***	-0.000185	-0.000303***	-0.000394***	-0.000198*	-0.000386***	-0.000311***	-6.27e-05	-0.000107
	(7.85e-05)	(0.000155)	(7.95e-05)	(0.000122)	(0.000111)	(8.39e-05)	(0.000111)	(0.000101)	(0.000103)
DUMMY_MALE	0.135***	0.124***	0.102***	0.0987***	0.0684***	0.109***	0.155***	0.160***	0.105***
	(0.0256)	(0.0344)	(0.0181)	(0.0245)	(0.0265)	(0.0200)	(0.0215)	(0.0268)	(0.0226)
DUMMY_MARRIED	0.00754	0.0535	0.0531**	0.00621	0.0434	-0.00680	-0.0444	0.0209	0.00593
	(0.0254)	(0.0447)	(0.0244)	(0.0371)	(0.0310)	(0.0222)	(0.0276)	(0.0276)	(0.0325)
NCOMP	0.0165**	0.0112	0.00124	0.00223	-0.00471	0.0322***	0.0250***	-0.000861	0.0202*
	(0.00734)	(0.0144)	(0.00742)	(0.0101)	(0.00910)	(0.00840)	(0.00860)	(0.0108)	(0.0113)
DUMMY_HOUSEHOLD	-0.00255	-0.00839	0.00905	0.0269	0.0268	0.0376**	0.0125		
	(0.0257)	(0.0352)	(0.0179)	(0.0240)	(0.0239)	(0.0187)	(0.0237)		
DUMMY_TOWN	0.00673	0.0374	0.00600	-0.0792**	-0.00873	0.0444*	0.0189	-0.0296	-0.0102
	(0.0211)	(0.0411)	(0.0209)	(0.0349)	(0.0422)	(0.0239)	(0.0304)	(0.0373)	(0.0394)
DUMMY_NORTH	0.0366**	0.0775***	0.0463***	0.0494**	0.0599**	-0.00521	0.00325	0.0606**	0.0492*
	(0.0168)	(0.0282)	(0.0162)	(0.0232)	(0.0282)	(0.0182)	(0.0227)	(0.0283)	(0.0275)
DUMMY_SOUTH	-0.0345*	0.0428	-0.0284	-0.0114	-0.00934	-0.0761***	-0.0489**	0.0167	-0.0119
	(0.0187)	(0.0314)	(0.0214)	(0.0273)	(0.0330)	(0.0219)	(0.0249)	(0.0289)	(0.0332)
DUMMY_AGRICULTURAL	-0.118	-0.143	-0.190***	-0.0991*	-0.129***	-0.151**	-0.0997**	-0.00494	-0.115**
	(0.0717)	(0.0921)	(0.0578)	(0.0577)	(0.0406)	(0.0746)	(0.0502)	(0.0694)	(0.0564)
DUMMY_PUBLIC	0.114***	0.0991***	0.0230	0.0216	0.0935***	0.0464*	0.105***	0.0545	0.0664
	(0.0227)	(0.0330)	(0.0230)	(0.0313)	(0.0346)	(0.0282)	(0.0273)	(0.0390)	(0.0422)
DUMMY_OTHER_SECTOR	0.0103	0.0165	-0.000773	-0.00667	0.00656	-0.0134	0.00719	0.00186	-0.0487*
	(0.0179)	(0.0388)	(0.0197)	(0.0232)	(0.0260)	(0.0194)	(0.0235)	(0.0263)	(0.0254)
DUMMY_SECT_PARENTS	0.00569	0.0543**	-0.0108	-0.000419	0.00189	-0.0120	0.0293	0.00830	-0.0150
	(0.0180)	(0.0255)	(0.0146)	(0.0185)	(0.0188)	(0.0160)	(0.0189)	(0.0215)	(0.0240)
DUMMY_PART_TIME	0.0355	0.0622	0.0729**	-0.0739*	-0.0360	0.00195	0.0121	0.0393	-0.0212
	(0.0346)	(0.0637)	(0.0315)	(0.0433)	(0.0391)	(0.0398)	(0.0353)	(0.0368)	(0.0332)
SCORE	-0.0543***	0.00650	-0.0958***	-0.0770***	-0.0362	-0.0857***	-0.0437*	- 0.0960***	-0.0556*
	(0.0187)	(0.0317)	(0.0214)	(0.0275)	(0.0319)	(0.0238)	(0.0255)	(0.0369)	(0.0317)
Constant	1.576***	1.596***	1.596***	1.613***	1.803***	1.608***	1.634***	1.601***	1.636***
	(0.0462)	(0.0984)	(0.0456)	(0.0612)	(0.0568)	(0.0596)	(0.0545)	(0.0705)	(0.0655)
Observations	4,352	1,468	3,783	3,321	3,405	3,437	2,836	2,145	2,112
R-squared	0.412	0.317	0.339	0.286	0.245	0.327	0.345	0.295	0.327

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

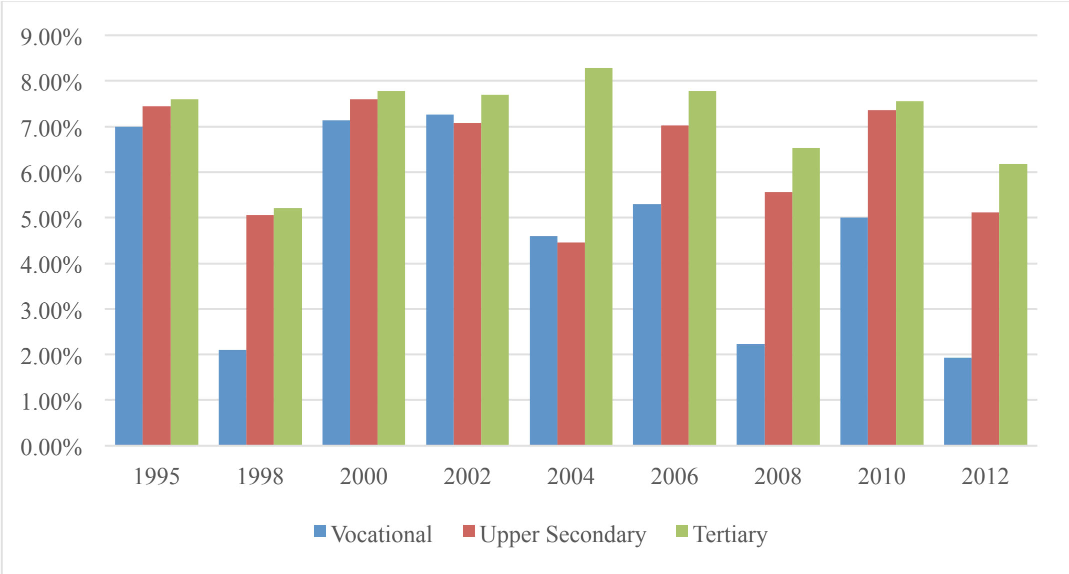
Considering different educational attainment, vocational school seems to have a not clear pattern, from 21% in 1995 to 15% in 2010. The rate of return of secondary school is not constant over the period considered, but it shows a slightly decreasing trend from 1995 to 2010. The same trend is observed for the rate of return of tertiary education (university).

Figure 1.3 – Rate of Return of Different Types of School 1995-2012



However, even if the college premium does not have a particular trend, attending college let to have between 30% and 40% of higher wages.

Figure 1.4 – Annual Rate of Return of Different Type of School 1995-2012 (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 Figure 1.4). It turns out that the increase in wages due to an additional year of vocational school, upper secondary school and college is respectively 5%, 7.4% and 7.6% in 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.

5 Concluding Remarks

We have studied the wage function in Italy, focusing on the role of return to education. Using cross-sectional data from the 1995 to 2012 waves of the Bank of Italy survey on the income and wealth of Italian household, we have applied instrumental variables estimation to solve the problem of endogeneity. The evidence is that returns to schooling have changed over the period considered, 1995-2012, and are between 5.4% and 7.9%, recording the highest level for 2006 and the lowest in 2012. Considering 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% for college education. More able subjects, 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 and the solution to this problem and is left to future research.

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Appendix to Chapter 1

A.1 Some descriptive statistics for our sample

Figure A.1 – Mean of the Log of hourly wages less tax (1995 -2012)

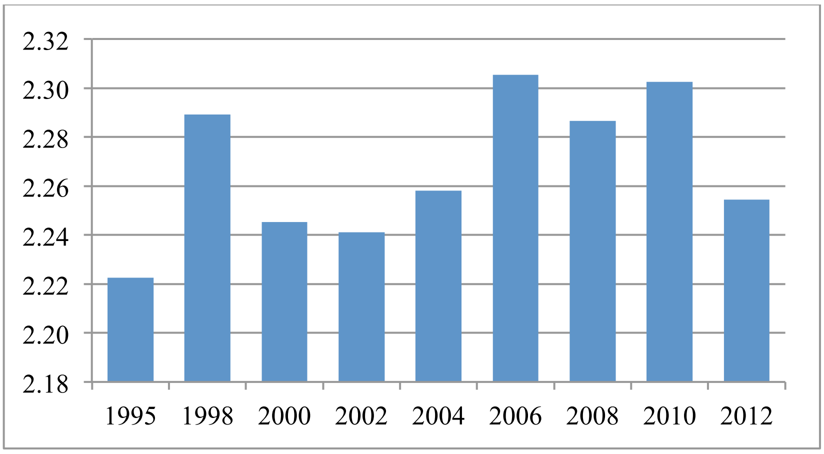


Figure A.2 – Mean of the number of year of Schooling (1995 -2012)

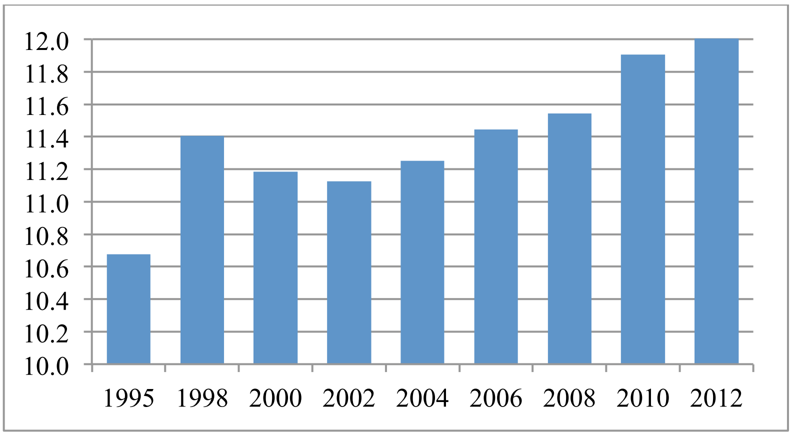
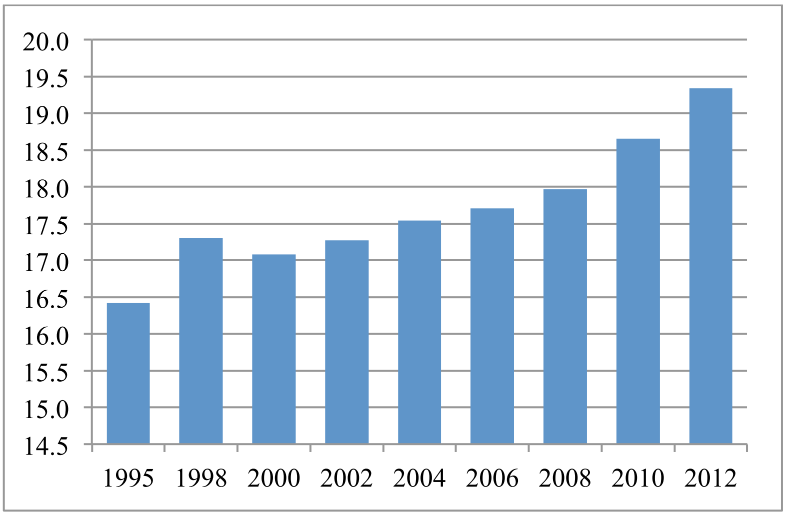


Figure A.3 – Mean of the number of year of Experience (1995 -2012)



A.2 OLS estimates

Table A.1 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.

Table A.1 - OLS estimates. Dependent Variable: log of hourly wages less tax. Omitted categories are: Center (DUMMY_CENTER); Industrial sector (DUMMY_INDUSTRIAL).

VARIABLES	1995	1998	2000	2002	2004	2006	2008	2010	2012
SCHOOL	0.0514***	0.0447***	0.0425***	0.0454***	0.0409***	0.0451***	0.0441***	0.0416***	0.0377***
	(0.00173)	(0.00315)	(0.00188)	(0.00229)	(0.00224)	(0.00196)	(0.00229)	(0.00214)	(0.00214)
EXPERIENCE	0.0272***	0.0275***	0.0255***	0.0271***	0.0210***	0.0250***	0.0274***	0.0194***	0.0221***
	(0.00277)	(0.00458)	(0.00246)	(0.00285)	(0.00300)	(0.00268)	(0.00275)	(0.00249)	(0.00285)
EXPERIENCE^2	-0.000352***	-0.000351***	-0.000365***	-0.000362***	-0.000308***	-0.000386***	-0.000405***	-0.000207***	-0.000226***
	(6.82e-05)	(0.000114)	(6.05e-05)	(7.46e-05)	(8.14e-05)	(6.75e-05)	(7.15e-05)	(6.20e-05)	(6.73e-05)
DUMMY_MALE	0.0855***	0.0422	0.0785***	0.106***	0.0790***	0.0905***	0.112***	0.117***	0.0654***
	(0.0155)	(0.0282)	(0.0137)	(0.0163)	(0.0174)	(0.0159)	(0.0143)	(0.0143)	(0.0165)
DUMMY_MARRIED	0.0739***	0.0666**	0.105***	0.0617***	0.0702***	0.0536***	0.0312**	0.0684***	0.0476***
	(0.0165)	(0.0331)	(0.0148)	(0.0191)	(0.0180)	(0.0161)	(0.0157)	(0.0153)	(0.0175)
NCOMP	-0.00338	0.00475	-0.0104*	-0.00937	-0.0122*	0.0140**	0.00783	-0.00193	0.0179**
	(0.00535)	(0.0105)	(0.00550)	(0.00653)	(0.00665)	(0.00654)	(0.00573)	(0.00609)	(0.00705)
DUMMY_HOUSEHOLD	0.0436***	0.0463	0.0325**	0.0381**	0.0385**	0.0651***	0.0503***	0.0168	0.0268*
	(0.0167)	(0.0285)	(0.0134)	(0.0159)	(0.0165)	(0.0147)	(0.0135)	(0.0128)	(0.0144)
DUMMY_TOWN	0.0333*	0.0209	0.0457**	-0.0369	0.0233	0.0587***	0.0280	-0.0120	0.0152
	(0.0175)	(0.0340)	(0.0178)	(0.0278)	(0.0313)	(0.0215)	(0.0243)	(0.0240)	(0.0296)
DUMMY_NORTH	0.0404***	0.0778***	0.0479***	0.0398**	0.0473**	-0.00852	-0.0296*	0.0441***	0.0249
	(0.0140)	(0.0241)	(0.0136)	(0.0169)	(0.0198)	(0.0160)	(0.0164)	(0.0170)	(0.0179)
DUMMY_SOUTH	-0.0379**	0.0570**	-0.0293	0.00369	-0.0233	-0.0821***	-0.0783***	-3.96e-05	-0.0216
	(0.0172)	(0.0288)	(0.0189)	(0.0232)	(0.0241)	(0.0188)	(0.0186)	(0.0189)	(0.0210)
DUMMY_AGRICULTURAL	-0.117*	-0.0967	-0.131***	-0.0424	-0.0935***	-0.168***	-0.00792	-0.0596	-0.0701
	(0.0679)	(0.0705)	(0.0437)	(0.0568)	(0.0329)	(0.0480)	(0.0419)	(0.0388)	(0.0518)
DUMMY_PUBLIC	0.174***	0.109***	0.108***	0.110***	0.141***	0.126***	0.143***	0.148***	0.128***
	(0.0168)	(0.0268)	(0.0150)	(0.0182)	(0.0197)	(0.0188)	(0.0190)	(0.0176)	(0.0212)
DUMMY_OTHER_SECTOR	0.0109	-0.00144	0.0288*	0.0103	0.00798	0.000915	-0.00276	0.0159	-0.0460***
	(0.0149)	(0.0301)	(0.0152)	(0.0177)	(0.0189)	(0.0161)	(0.0160)	(0.0146)	(0.0169)
DUMMY_SECT_PARENTS	0.00296	0.0797***	0.0176	0.0139	0.00659	-0.00164	0.0340***	0.0113	0.00327
	(0.0151)	(0.0228)	(0.0121)	(0.0157)	(0.0146)	(0.0135)	(0.0131)	(0.0133)	(0.0153)
DUMMY_PART_TIME	0.0734**	0.0348	0.0475*	-0.0834**	-0.0480	-0.00720	0.0260	-0.00241	-0.0312
	(0.0324)	(0.0527)	(0.0267)	(0.0367)	(0.0310)	(0.0301)	(0.0268)	(0.0215)	(0.0230)
Constant	1.173***	1.192***	1.309***	1.280***	1.437***	1.342***	1.307***	1.360***	1.340***
	(0.0408)	(0.0708)	(0.0354)	(0.0420)	(0.0460)	(0.0438)	(0.0437)	(0.0459)	(0.0462)
Observations	6,066	2,016	5,724	5,461	5,425	5,378	5,409	5,161	4,975
R-squared	0.450	0.366	0.353	0.306	0.261	0.326	0.353	0.327	0.314

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

Table A.2 shows OLS estimates of the empirical specification, including interaction of the variable schooling with experience and with gender.

Table A.2 - OLS estimates with interactions. Dependent Variable: log of hourly wages less tax. Omitted categories are: Center (DUMMY_CENTER); Industrial sector (DUMMY_INDUSTRIAL).

VARIABLES	1995	1998	2000	2002	2004	2006	2008	2010	2012
SCHOOL	0.0471***	0.0445***	0.0291***	0.0388***	0.0420***	0.0267***	0.0242***	0.0330***	0.0251***
	(0.00663)	(0.0108)	(0.00625)	(0.00831)	(0.00657)	(0.00555)	(0.00553)	(0.00539)	(0.00620)
EXPERIENCE	0.0216***	0.0455***	0.00857	0.0158*	0.0199***	0.00515	-0.000317	0.00709	0.0203**
	(0.00810)	(0.0138)	(0.00760)	(0.00923)	(0.00772)	(0.00846)	(0.00880)	(0.00714)	(0.00837)
EXPERIENCE^2	-0.000294	-0.000970***	-6.86e-05	-0.000172	-0.000413**	-0.000174	0.000133	-0.000119	-0.000474**
	(0.000196)	(0.000344)	(0.000183)	(0.000229)	(0.000199)	(0.000219)	(0.000228)	(0.000177)	(0.000193)
SCHOOL*EXPER	0.000492	-0.00170	0.00138**	0.000930	-5.80e-07	0.00155**	0.00230***	0.000961	3.08e-05
	(0.000704)	(0.00112)	(0.000640)	(0.000824)	(0.000702)	(0.000678)	(0.000700)	(0.000590)	(0.000696)
SCHOOL*EXPER^2	-4.17e-06	5.86e-05*	-2.29e-05	-1.48e-05	1.22e-05	-1.33e-05	-4.39e-05**	-5.10e-06	2.45e-05
	(1.78e-05)	(3.04e-05)	(1.60e-05)	(2.13e-05)	(1.85e-05)	(1.81e-05)	(1.82e-05)	(1.51e-05)	(1.64e-05)
DUMMY_MALE	0.129***	-0.0536	0.102**	0.173***	0.200***	0.146***	0.136***	0.236***	0.0299
	(0.0432)	(0.0821)	(0.0435)	(0.0568)	(0.0505)	(0.0439)	(0.0483)	(0.0474)	(0.0534)
SCHOOL*MALE	-0.00403	0.00848	-0.00222	-0.00589	-0.0106**	-0.00499	-0.00203	-0.00996**	0.00302
	(0.00360)	(0.00645)	(0.00365)	(0.00482)	(0.00426)	(0.00361)	(0.00418)	(0.00395)	(0.00416)
DUMMY_MARRIED	0.0732***	0.0700**	0.105***	0.0611***	0.0703***	0.0572***	0.0286*	0.0658***	0.0476***
	(0.0166)	(0.0323)	(0.0148)	(0.0190)	(0.0182)	(0.0161)	(0.0156)	(0.0153)	(0.0175)
NCOMP	-0.00398	0.00307	-0.0114**	-0.00998	-0.0130*	0.0133**	0.00836	-0.00200	0.0164**
	(0.00537)	(0.0105)	(0.00546)	(0.00646)	(0.00664)	(0.00653)	(0.00571)	(0.00606)	(0.00701)
DUMMY_HOUSEHOLD	0.0441***	0.0438	0.0332**	0.0392**	0.0391**	0.0624***	0.0491***	0.0172	0.0245*
	(0.0168)	(0.0281)	(0.0134)	(0.0160)	(0.0165)	(0.0146)	(0.0135)	(0.0127)	(0.0144)
DUMMY_TOWN	0.0317*	0.0142	0.0464***	-0.0388	0.0216	0.0585***	0.0265	-0.0177	0.0119
	(0.0175)	(0.0342)	(0.0178)	(0.0278)	(0.0312)	(0.0214)	(0.0241)	(0.0239)	(0.0296)
DUMMY_NORTH	0.0399***	0.0745***	0.0467***	0.0402**	0.0481**	-0.0101	-0.0320*	0.0436***	0.0245
	(0.0140)	(0.0238)	(0.0136)	(0.0169)	(0.0198)	(0.0159)	(0.0164)	(0.0168)	(0.0179)
DUMMY_SOUTH	-0.0416**	0.0563*	-0.0324*	0.00143	-0.0274	-0.0864***	-0.0825***	-0.00393	-0.0225
	(0.0172)	(0.0287)	(0.0189)	(0.0232)	(0.0237)	(0.0188)	(0.0185)	(0.0186)	(0.0210)
DUMMY_AGRICULTURAL	-0.116*	-0.108	-0.128***	-0.0434	-0.0942***	-0.173***	-0.00883	-0.0568	-0.0747
	(0.0686)	(0.0679)	(0.0440)	(0.0567)	(0.0331)	(0.0482)	(0.0421)	(0.0384)	(0.0503)
DUMMY_PUBLIC	0.173***	0.111***	0.104***	0.106***	0.138***	0.120***	0.140***	0.141***	0.121***
	(0.0169)	(0.0268)	(0.0150)	(0.0181)	(0.0197)	(0.0187)	(0.0191)	(0.0174)	(0.0213)
DUMMY_OTHER_SECTOR	0.00895	-0.00335	0.0275*	0.0107	0.0108	-3.01e-05	-0.00259	0.0144	-0.0480***
	(0.0151)	(0.0301)	(0.0150)	(0.0179)	(0.0190)	(0.0161)	(0.0158)	(0.0145)	(0.0170)
DUMMY_SECT_PARENTS	0.00368	0.0778***	0.0179	0.0146	0.00648	0.00102	0.0354***	0.0122	0.00324
	(0.0151)	(0.0225)	(0.0121)	(0.0157)	(0.0146)	(0.0135)	(0.0132)	(0.0131)	(0.0152)
DUMMY_PART_TIME	0.0763**	0.0280	0.0505*	-0.0794**	-0.0440	-0.00747	0.0251	-0.000550	-0.0349
	(0.0325)	(0.0519)	(0.0264)	(0.0369)	(0.0312)	(0.0300)	(0.0268)	(0.0215)	(0.0228)
Constant	1.225***	1.209***	1.478***	1.362***	1.432***	1.575***	1.553***	1.472***	1.513***
	(0.0821)	(0.144)	(0.0764)	(0.0980)	(0.0819)	(0.0812)	(0.0766)	(0.0773)	(0.0793)

Observations	6,066	2,016	5,724	5,461	5,425	5,378	5,409	5,161	4,975
R-squared	0.451	0.371	0.356	0.308	0.264	0.334	0.358	0.333	0.324

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

A.3 First stage regression of IV estimates

Table A.3 shows the estimates of the first stage regression of the instrumental variables estimation.

Table A.3 – 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	2012
SCHOOL_F	0.296***	0.292***	0.298***	0.267***	0.237***	0.261***	0.260***	0.281***	0.248***
	(0.0213)	(0.0393)	(0.0248)	(0.0253)	(0.0240)	(0.0247)	(0.0289)	(0.0431)	(0.0348)
SCHOOL_M	0.216***	0.207***	0.150***	0.172***	0.189***	0.135***	0.183***	0.145***	0.159***
	(0.0254)	(0.0513)	(0.0284)	(0.0290)	(0.0261)	(0.0285)	(0.0332)	(0.0433)	(0.0371)
EXPERIENCE	0.0363	-0.0374	-0.0130	-0.00816	-0.0495	-0.0453	-0.0308	-0.0588	-0.00311
	(0.0268)	(0.0492)	(0.0305)	(0.0350)	(0.0302)	(0.0297)	(0.0311)	(0.0449)	(0.0419)
EXPERIENCE^2	-0.00226***	0.000500	-0.000833	-0.000699	0.000762	-0.000104	-0.000199	0.000484	-0.000570
	(0.000662)	(0.00118)	(0.000740)	(0.000844)	(0.000727)	(0.000696)	(0.000718)	(0.00101)	(0.000910)
DUMMY_MALE	0.269	0.409	-0.317*	-0.411**	-0.395**	-0.310	-0.333	-0.592***	-0.412**
	(0.195)	(0.340)	(0.172)	(0.190)	(0.174)	(0.193)	(0.202)	(0.219)	(0.209)
DUMMY_MARRIED	0.510**	-0.428	-0.0373	0.294	0.618***	0.418**	0.792***	-0.0912	0.0893
	(0.246)	(0.419)	(0.243)	(0.251)	(0.221)	(0.209)	(0.251)	(0.250)	(0.250)
NCOMP	-0.169***	-0.196*	-0.0204	0.0844	-0.0318	-0.0220	-0.170**	0.226**	0.0448
	(0.0643)	(0.114)	(0.0755)	(0.0777)	(0.0754)	(0.0732)	(0.0784)	(0.0980)	(0.0935)
DUMMY_HOUSEHOLD	-0.168	-0.629*	0.188	-0.0163	0.109	0.177	0.0701		
	(0.199)	(0.344)	(0.165)	(0.181)	(0.171)	(0.180)	(0.218)		
DUMMY_TOWN	0.223	-0.179	0.908***	0.531**	0.110	0.398*	0.348	0.435	0.717**
	(0.189)	(0.354)	(0.209)	(0.247)	(0.216)	(0.225)	(0.273)	(0.292)	(0.323)
DUMMY_NORTH	-0.158	0.0635	0.238	0.378**	0.0239	-0.235	0.173	-0.252	-0.453*
	(0.159)	(0.268)	(0.168)	(0.181)	(0.172)	(0.179)	(0.214)	(0.247)	(0.248)
DUMMY_SOUTH	-0.197	0.0832	0.0470	0.310	-0.315	-0.622***	-0.240	-0.281	-0.340
	(0.177)	(0.293)	(0.190)	(0.225)	(0.222)	(0.212)	(0.240)	(0.304)	(0.291)
DUMMY_AGRICULTURAL	-1.372***	-2.769***	-1.473***	-1.443***	-1.327***	-0.756**	-1.060***	-1.098*	-0.958**
	(0.466)	(0.562)	(0.373)	(0.332)	(0.335)	(0.312)	(0.397)	(0.636)	(0.382)
DUMMY_PUBLIC	2.465***	2.268***	2.551***	2.454***	2.520***	2.491***	2.423***	2.235***	2.529***
	(0.177)	(0.285)	(0.175)	(0.205)	(0.192)	(0.175)	(0.201)	(0.294)	(0.274)
DUMMY_OTHER_SECTOR	0.00794	0.473	0.800***	0.501***	0.866***	0.715***	0.645***	0.643***	0.521**
	(0.159)	(0.300)	(0.172)	(0.176)	(0.180)	(0.176)	(0.192)	(0.229)	(0.229)
DUMMY_SECT_PARENTS	0.154	0.273	0.291**	-0.160	0.183	0.393***	0.193	-0.0290	0.255
	(0.151)	(0.218)	(0.135)	(0.151)	(0.139)	(0.144)	(0.163)	(0.204)	(0.187)
DUMMY_PART_TIME	-0.629***	-0.656*	-0.594**	-0.528**	-0.825***	-0.857***	-0.599**	-0.822**	-0.651**
	(0.228)	(0.378)	(0.232)	(0.262)	(0.248)	(0.237)	(0.295)	(0.411)	(0.265)
Constant	7.434***	8.901***	7.903***	7.570***	7.969***	8.906***	8.516***	9.259***	8.996***
	(0.385)	(0.732)	(0.399)	(0.467)	(0.412)	(0.423)	(0.461)	(0.599)	(0.548)
Observations	4,352	1,468	3,783	3,321	3,405	3,437	2,836	2,145	2,112
R-squared	0.408	0.408	0.390	0.373	0.365	0.365	0.364	0.322	0.338
Sargan test $\chi 2(1)$	1.691	1.891	0.239	0.05	0.515	0.197	0.026	0.457	0.868
p-Value	0.1935	0.1691	0.6248	0.8239	0.473	0.657	0.8716	0.5038	0.3516
F-test on excl. instrum.	461.28	147.101	288.83	201.88	225.05	195.76	188.55	107,67	106.27
p-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.0000

Robust standard errors in parenthesis

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

A.4 First step in the ordered Probit

Table A.4 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 wages equation in order to apply ordinary least squares as second step.

Table A.4 – 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	2012
PRIMARY_F	-0.836***	-0.950***	-0.716***	-0.586***	-0.628***	-0.677***	-0.725***	-0.564***	-0.523***
	(0.0653)	(0.109)	(0.0762)	(0.0774)	(0.0700)	(0.0735)	(0.0807)	(0.0912)	(0.0819)
PRIMARY_M	-0.495***	-0.375***	-0.421***	-0.553***	-0.436***	-0.293***	-0.453***	-0.280***	-0.468***
	(0.0729)	(0.120)	(0.0834)	(0.0838)	(0.0784)	(0.0775)	(0.0848)	(0.0989)	(0.0847)
EXPERIENCE	0.00682	-0.0205	-0.0171	-0.0141	-0.0386***	-0.0194	-0.0130	-0.0178	0.00268
	(0.0102)	(0.0189)	(0.0111)	(0.0133)	(0.0121)	(0.0125)	(0.0127)	(0.0157)	(0.0165)
EXPERIENCE^2	-0.000571**	0.000449	0.000122	8.38e-05	0.000782***	3.84e-05	3.19e-05	0.000118	-0.000270
	(0.000254)	(0.000449)	(0.000272)	(0.000319)	(0.000283)	(0.000301)	(0.000294)	(0.000364)	(0.000358)
DUMMY_MALE	0.0436	0.113	-0.177***	-0.147**	-0.175**	-0.115	-0.137*	-0.240***	-0.179**
	(0.0738)	(0.140)	(0.0648)	(0.0718)	(0.0687)	(0.0810)	(0.0766)	(0.0805)	(0.0806)
DUMMY_MARRIED	0.194**	-0.188	0.0600	0.112	0.292***	0.130	0.343***	-0.0254	0.0954
	(0.0983)	(0.159)	(0.0881)	(0.0985)	(0.0896)	(0.0869)	(0.0979)	(0.0946)	(0.0977)
NCOMP	-0.0637**	-0.117***	-0.00877	0.0137	-0.0325	-0.0213	-0.0470	0.0634*	0.00537
	(0.0247)	(0.0443)	(0.0263)	(0.0304)	(0.0302)	(0.0308)	(0.0312)	(0.0364)	(0.0354)
DUMMY_HOUSEHOLD	-0.0893	-0.320**	0.0640	-0.0679	0.0225	0.0290	0.0406		
	(0.0749)	(0.140)	(0.0624)	(0.0698)	(0.0681)	(0.0792)	(0.0856)		
DUMMY_TOWN	0.113	0.0415	0.297***	0.194**	0.0734	0.220**	0.149	0.190*	0.263**
	(0.0703)	(0.126)	(0.0784)	(0.0957)	(0.0901)	(0.0885)	(0.102)	(0.106)	(0.116)
DUMMY_NORTH	-0.0315	-0.0375	0.142**	0.148**	0.0360	-0.130*	0.0132	-0.103	-0.183**
	(0.0614)	(0.100)	(0.0643)	(0.0729)	(0.0715)	(0.0724)	(0.0830)	(0.0889)	(0.0888)
DUMMY_SOUTH	-0.0787	0.0318	0.0541	0.0981	-0.135	-0.292***	-0.196**	-0.192*	-0.170
	(0.0675)	(0.106)	(0.0705)	(0.0876)	(0.0868)	(0.0877)	(0.0941)	(0.106)	(0.105)
DUMMY_AGRICULTURAL	-0.426**	-1.420***	-0.407***	-0.564***	-0.770***	-0.528***	-0.463**	-0.334	-0.591**
	(0.191)	(0.282)	(0.151)	(0.199)	(0.183)	(0.167)	(0.186)	(0.251)	(0.234)
DUMMY_PUBLIC	0.929***	0.749***	0.950***	0.977***	0.987***	0.991***	0.922***	0.892***	0.967***
	(0.0682)	(0.113)	(0.0646)	(0.0760)	(0.0760)	(0.0736)	(0.0790)	(0.104)	(0.106)
DUMMY_OTHER_SECT	0.0287	0.0758	0.297***	0.255***	0.342***	0.309***	0.285***	0.298***	0.236***
	(0.0651)	(0.116)	(0.0670)	(0.0720)	(0.0735)	(0.0709)	(0.0775)	(0.0869)	(0.0902)
DUMMY_SECT_PARENTS	0.0724	0.127	0.136***	-0.00329	0.117**	0.222***	0.110*	0.0442	0.110
	(0.0616)	(0.0843)	(0.0505)	(0.0592)	(0.0560)	(0.0585)	(0.0629)	(0.0734)	(0.0713)
DUMMY_PART_TIME	-0.264**	-0.333**	-0.169*	-0.151	-0.235**	-0.292***	-0.194*	-0.327**	-0.229**
	(0.104)	(0.157)	(0.0918)	(0.108)	(0.0968)	(0.0960)	(0.111)	(0.141)	(0.101)
Constant cut1	-1.009***	-1.807***	-0.830***	-0.796***	-0.917***	-1.076***	-0.985***	-1.079***	-1.020***

	(0.153)	(0.260)	(0.152)	(0.174)	(0.163)	(0.172)	(0.175)	(0.201)	(0.219)
Constant cut2	-0.771***	-1.549***	-0.519***	-0.520***	-0.644***	-0.757***	-0.664***	-0.705***	-0.640***
	(0.153)	(0.258)	(0.152)	(0.173)	(0.162)	(0.174)	(0.177)	(0.201)	(0.219)
Constant cut3	0.649***	-0.163	0.818***	0.858***	0.816***	0.702***	0.748***	0.575***	0.677***
	(0.153)	(0.255)	(0.152)	(0.175)	(0.165)	(0.178)	(0.182)	(0.199)	(0.215)
Observations	4,352	1,468	3,783	3,321	3,405	3,437	2,836	2,145	2,112

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