RETURNS TO EDUCATION AND CHANGES IN WAGE STRUCTURE: IS THERE AN UNSKILLED BIAS TECHNOLOGICAL CHANGE IN ITALY?

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Preliminary version

Abstract

In this paper we analyse the role of education on the dynamics of wage structure in Italy. Using SHIW data over the period 1993-2004, we derive two main results in a quintile regression framework. First, returns to education decline over time almost uniformly across the wage distribution. Second, using a quintile decomposition method *à la* Machado-Mata we point out that the composition effect associated with the increased share of educated workers is positive, while the price effect of education is negative in the whole wage distribution. Assuming a standard demand and supply paradigm, this leads us to the conclusion that a sort of "unskilled" bias technological change could have been prevailing in the Italian labour market during last decade.

JEL codes: J24, J31,

Keywords: Return to Education, Human Capital, Technological Change, Quantile regression, Wage Decomposition, Italy.

1. Introduction

The analysis of changes in the distribution of wages has been an active research area in labour economics over the last two decades. The main reason for this increasing interest is that wage inequality and schooling premium increased steeply in United States since the early 1980s (Bound and Johnson, 1992; Katz and Murphy 1992). To a less extent the increases of returns to education and wage inequality are also documented for many other OECD countries (Gottschalk and Smeeding, 1997).

To explain these changes in wage structures standard economic theory asserts that the observed patterns in schooling premium and earnings inequality were generated by the shifts in the relative labour demand favouring high skilled workers at the expense of low skilled workers, due to the diffusion of new IC technologies in productive processes (Krueger, 1998). The evidence supporting this hypothesis is based on the fact that, despite the steady increases over time of the relative supply of high skilled workers, the conventional Mincerian wage equations show a rise in the returns to schooling. Then, to make coherent the increase in the skills of the working population with increasing returns to education and wage inequality, some authors have suggested that labour demand must have shifted to more than compensate the shifts in relative supply.

Undoubtedly, the supply-demand-technology paradigm represents the accepted theoretical framework for understanding the evolution of the schooling premium and wage structures in industrialized countries.[1] This theoretical consensus, however, stems from the fact that the supply and demand analysis focuses on the average wage dynamics rather than on the changes across the entire wage distribution, ignoring that more educated individuals typically experience more unequal wage distribution than less educated ones. In fact, when educational attainments have grater impact upon the wages of individuals at the top of the wage distribution than upon wages of individuals at the bottom of that distribution, the supply and demand framework must consider another channel through which education affect the wage structures, the composition effect (Lemieux, 2005).

By increasing the number of educated workers, a pressure is exerted toward a decrease of their wages. However, if more educated individuals experience greater wage spreads, increased educational levels may also contribute to an increase in wage inequality. In other words, to understand

[1] The skill bias technological change explanation has been questioned by some revisionist studies. It is the case of Di Nardo, Fortin and Lemieux (1996) and Lee (2000), where the observed changes in U. S. wage structures during the 1980s are primarily attributed to the decline in the real value of the minimum wage experienced in the same period.

the relationship between the patterns of returns to education and changes of the wage structures it needs to go further the conventional approach based on the estimates of mincerian wage equations by least square methods, at least in two dimensions. Firstly, it is necessary to analyze the impact of education on the entire wage distribution, not only for the average tendency of the data. Secondly, it requires dividing the changes of the wage distribution into the effects due to changes in the stock of human capital in the labour force and the effects of changes in returns to education.

In this perspective, the first goal of our paper is to estimate the dynamics of returns to education in Italy to verify whether the patterns of the schooling premium across the wage distribution show distinctive features with respect to other countries. Another related goal is to analyze the relationship between changes of wage structure and the returns to education, once taken into account the composition effect associated with the increased supply of more educated workers. The last goal is to provide and indirect test of the relevance of the skill bias technological change in Italy, by relating our empirical strategy to a standard supply and demand framework.

To pursue these goals we use a quantile regression approach and related decomposition techniques, which represents a powerful statistical tool both to investigate the changes of the whole income distribution and to decompose these variations into price and quantity effect of the attributes of the conditional wage distribution (Buchinsky, 1994; Melly, 2005; Machado and Mata, 2005; Autor, Katz and Kearney, 2005).[2] In particular, this methodology has been recently applied in a number of studies aiming at identifying the key factors behind the observed dynamics of wage structures in the US and in Europe (Machado Mata, 2005; Fitzenberger and Kurz, 2003).

Two main results are then achieved. First, even though the cross sectional analysis shows that education returns are higher at highest quantiles of the conditional distribution (in line with previous research), the schooling premium has decreased almost uniformly across the wage distribution from 1993 to 2004. Second, the composition effect of education has exerted a positive influence on the dynamics of wage structure while the price effect would have reduced wages at all quantiles of the distribution. As a consequence a sort of *unskilled biased technological changes* seems to have been at work in Italy, in the sense that the relative demand of high-skilled

[2] The quantile decomposition method extends the traditional Oaxaca decomposition to the entire wage distribution. In our application, this method is based on the estimation of the marginal density function of wages in a given year implied by counterfactual distribution of educational attainments of the working population.

workers have increased less than its relative supply, reducing the educational premia.

The paper is organized as follows. In section 2 we review some empirical literature on returns to education and wage inequality. In section 3 the characteristics of the sample are analyzed and descriptive statistics presented. In section 4 we apply a standard quantile regression analysis to estimate the returns to education in a cross sectional and dynamic perspective. In section 5 a decomposition exercise is presented in order to illustrate the negative effects exerted by schooling premium across the wage distribution as opposed to the positive effects associated with the increased supply of more educated workers. Section 6 concludes.

2. Empirical literature

The conventional explanations proposed to describe observed trends in US earning inequality are based on different conjectures (the role of no neutral technological progress, reforms of wage setting institutions, variation of educational composition of workforce, increased international trade with low income countries). Most of these theories and empirical findings emphasize the central role played by human capital accumulation and returns to education in affecting the dynamics of wage structures (see Acemoglu, 2002).

In particular, several contributions argue that the increasing wage differential between college and high school workers experienced in the 1980s in the United States might be due to the skill bias technological changes (SBTC, henceforth). Katz and Murphy (1992) and Bound and Johnson (1992), for instance, suggest that the relative demand for more educated workers increased steadily during 1970s and 1980s, while the growth in the relative supply did slowdown in the 1980s relative to the previous decade. Accordingly, the growth in the relative demand due to skilled biased technological change overcomes the growth in the relative supply, entailing the relative wages of college education workers to increase.[3] On the contrary, more recent papers suggest that the increase in earning inequality for both men and women during the same period has been primarily determined by labour market institutions, namely the decline in the real value of the minimum wage which has negatively affected

[3] The supply demand technology paradigm remains the main theoretical framework also when the analysis take into account the whole wage distribution, not only the mean wage differential by educational group. Juhn, Murphy and Pierce (1993) use a quantile accounting approach to confirm that much of the increased in wage inequality for US men in 1980s is due to increased returns to skills and unobservable components.

individuals employed in the lower part of wage distribution, i.e. mainly young and less educated workers (Di Nardo, Fortin and Lemieux, 1996: Lee, 1998).

These analyses, on the other hand, cannot be easily extended to other European countries, where different degrees of adoption of new technologies and labour market institutions have produced a different wage dynamics with respect to Anglo-Saxon countries (Gottshalk, 1997). For example, using data from different sources Pereira e Martins (2004) analyze the impact of education upon wage inequality in fifteen European countries during the period from 1980 to 1995, finding that education-related dispersion in earnings increases with education in most of these countries. In particular, they estimate quantile regressions of wage mincerian equations studying the differences in returns to education across the wage distribution and across time. Four different patterns emerge: i) a positive increasing contribution of education upon within wage inequality in Portugal; ii) a positive and stable effect of education on inequality in Austria, Finland, France, Spain, Sweden, Ireland, etc.; iii) a neutral role in Denmark and Italy; and iv) a negative impact in Germany and Greece.

Country specific studies generally confirm such cross country picture, with some exceptions. Fitzenberger and Kurz (2003), for example, find that education has a grater effect upon wages of individuals at the top of the wage distribution than upon wages at the bottom of that distribution in Germany. Using pooled data for the period 1984-1994, they find out that a college premium –with respect to high school- equal to 32% at the 10th percentile and to 41% at the 90th, even though there are not significant changes in these estimates over the period. In other words, in Germany more educated individuals experience more unequal wage distributions and this seems to have been increased during the 1980s. Instead, Machado and Mata (2005) introduce a quantile decomposition method that enables the identification of the sources of the increased wage inequality observed in Portugal between the late 1980th and the early 1990s. By applying this methodology to the Portuguese data for the period 1986-1995 they find that the observed increase in educational levels strongly contributed to the higher wage inequality in Portugal.

With regard to Italy, changes of earning structure display a U shaped trend during last decades: the reduction in earning inequality detected between the late 1970s and the mid 1980s have been followed by a rapid increase in the late 1980s and early 1990s. A raise that seems to have slowed down in the second half of 1990s (Brandolini, Cipollone and Sestito, 2001). To what extent these changes can be attributed to the educational attainments of the working population is not clear, as there is no exhaustive evidence about the relationship between the returns to schooling and changes of the wage distributions. Giustinelli (2004), for instance, applies a quantile regression framework to study the returns to schooling over the period 1993-2000 using SHIW data collected by the Bank of Italy. The main result is that schooling premium shows an U shaped pattern across the wage distribution in each sample year, while there is no a clear dynamic tendency of these premia over the period considered. Other papers have focused on returns to education in Italy, but their emphasis has been on average returns by applying least square or IV techniques, rather than on the entire wage distribution (Brunello and Miniaci, 1999).

The analysis of returns to education can be also investigated in a demand-supply-technology paradigm. In this perspective, Casavola, Sestito and Gavosto (1996) created a panel of firms representing the private sector for the period 1986-90 matching two different data set: the INPS firm level data set and the company's balance sheet data, the CADS. The resulting panel enables the authors to assess both wages and employment dynamics, and to relate it to technological change, measured by a proxy of firms' intangible assets. Their results seem to confirm the peculiarity of the Italian case with respect to the SBTC phenomenon. On one side, the up-skilling trend is at work, with white collar employment share increasing over the period. On the other, a traditional measure of wage inequality, the overall variance of earning, is mainly explained by a within phenomenon and only residually by a between effect (white collar and blue collar groups). The evidence of a limited magnitude of the wage premium connected to the use of new technology is explained by authors with the contemporary increases in the supply of skilled labour and the centralized wage setting system.

Another contribution to this strand of literature is Bratti and Matteucci (2004), which use a panel of firm level data for the period 1995-2000 to test for the presence of SBTC in Italian manufacturing. Bratti and Matteucci (2004) estimate employment share equations and find a positive impact of R&D activities and technological investments on the skill ratio, measured as the ratio between white collars and blue collars within firms, which mainly operates though the reduction of unskilled workers.

It is worth noting, however, that demand side investigations reveal methodological and empirical caveats which may weaken the empirical test of SBTC. Firstly, the arbitrarily chosen measure of technological change, generally formalized using a dummy variable. Secondly, these studies refer to the difference of average wages in term of aggregate measure of skills. In other words, whatever definition is adopted, the impact of technology is typically studied with reference to average tendency of wage distribution, not considering the whole wage distribution.

Our attempt to deal with these problems consists of limiting the analysis to the supply side of the labour market in such a way to exploit information about both the educational attainments of the workforce and individual wages without imposing any definition of the technological change.

3. Data description and descriptive statistics

In our analysis we use several waves of the *Survey of the Household Income and Wealth* of the Bank of Italy (SHIW from 1993 to 2004). Samples are composed by employees aged 16-64 who satisfy the following restrictions: a) they do not attend school; b) they work in private and public sectors c) they are neither employed in agricultural sector nor self-employed. We refer to the real monthly net wage, obtained by dividing annual income from employment, net of taxes and social security contributions, by the number of months worked in the year in each job and deflating by the consumer price index. We control for differences in working time by taking into account the worked hours of part time workers. More specifically, we correct the monthly wage using a part-time share, computed comparing the number of worked hours by part-timers with respect to average full-time workers. The sample structure does not vary significantly during the time span involved. [4]

Table 1 reports the descriptive statistics of the main variables for each sample years. Focusing on the pattern of educational dummies we observe that the percentage of individuals with upper secondary education or university degree has been increasing over time, though not monotonically, while the share of individuals with only elementary education has been decreasing. The share of employees younger than 30 declined reflecting the fact the fact that people enter the labour force later in 2004 than they used to in 1993 because of increased education. On the contrary, the increasing proportion of persons older than 50 is probably linked to the reform of the Italian pension system in the mid 1990s while the workers in the middle age group increase due demographic evolution of the workforce. The level of experience in the sample follows the changes of age structure, with a falling incidence of employees with less than 15 years of experience and an increasing share of those with more than 16 years. From 1993 to 2004 the share of female workers rose steadily from 36 to 41 per cent, a trend linked to the higher labour force participation of women in the last decade.

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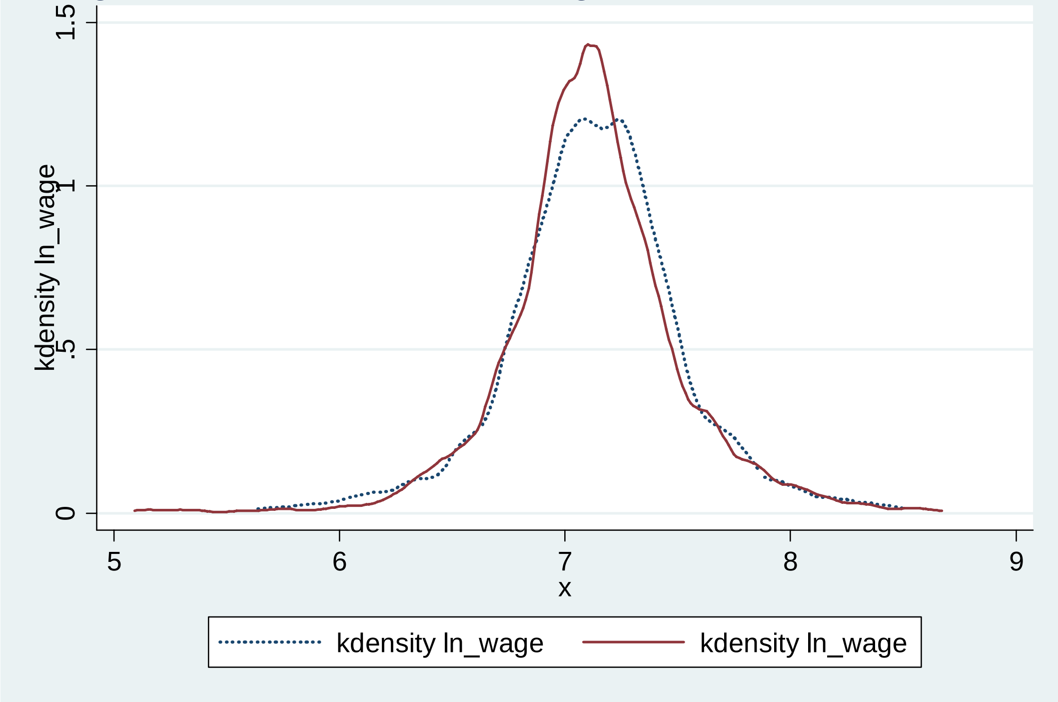
[4] Given the higher share of high educated workers among economically dependent workers (parasubordinati), we decided to include them in the analysis where identifiable (2004).

With regard to the wage changes, Table 1 shows that from 1993 to 2004 the average log monthly wage declined from 7.137 to 7.125, which slightly shifted the whole distribution to the left (see Figure 1). Comparing Kernel estimates of the wage densities in 1993 and 2004 in figure 1, we verify that the decline of net wages is concentrated at the median and at the third quartile while wages remain substantially unchanged at the top decile and at the bottom of the distribution.

Table 1: Sample descriptives

	1993	1995	1998	2000	2002	2004
Wage (log)	7.137	7.094	7.109	7.120	7.115	7.125
Female	0.365	0.370	0.395	0.405	0.397	0.409
Education						
Elementary or lower	0.146	0.127	0.096	0.087	0.078	0.073
Lower secondary	0.389	0.337	0.321	0.323	0.338	0.341
Upper secondary	0.365	0.428	0.456	0.459	0.464	0.469
Univ. Degree or higher	0.100	0.108	0.127	0.131	0.121	0.117
age classes						
15-24	0.116	0.105	0.090	0.082	0.080	0.062
25-30	0.158	0.172	0.160	0.149	0.134	0.140
31-35	0.151	0.155	0.153	0.155	0.153	0.151
36-40	0.164	0.151	0.153	0.171	0.166	0.173
41-45	0.153	0.150	0.167	0.166	0.171	0.173
46-50	0.121	0.129	0.137	0.126	0.142	0.131
51-55	0.090	0.087	0.088	0.101	0.103	0.106
56-64	0.047	0.050	0.052	0.051	0.052	0.064
Experience						
0-5	0.154	0.141	0.141	0.137	0.141	0.129
6-10	0.131	0.140	0.127	0.116	0.111	0.118
11-15	0.145	0.136	0.142	0.140	0.121	0.130
16-20	0.148	0.144	0.150	0.150	0.159	0.160
21-25	0.144	0.146	0.142	0.153	0.166	0.154
26-30	0.112	0.119	0.133	0.129	0.129	0.128
31-35	0.086	0.095	0.092	0.094	0.102	0.096
>36	0.081	0.081	0.074	0.081	0.071	0.085
Qualification						
Blu collar	0.463	0.478	0.451	0.460	0.462	0.465
White collar	0.364	0.327	0.374	0.365	0.385	0.403
Teachers	0.100	0.103	0.094	0.077	0.076	0.065
Senior white collar	0.054	0.072	0.058	0.070	0.055	0.049
Managers	0.019	0.020	0.023	0.028	0.021	0.018
Observations	6014	5963	5338	5879	5582	5647

Figure 1:Kernel densities of wages in 1993 -dotted- and 2004



It is worth noting that the overall picture which emerges from descriptive statistics is coherent with findings from other data sources. As for international comparisons, for instance, Italy displays lower educational attainments other European countries. According to OECD (2004), in Italy the share of individuals who had achieved in 2002 a tertiary education degree is 10%, while the same ratio for France amounts to 24%, in Germany to 23%, in UK to 27%, and to 38% in the US. These impressive gaps might suggest that since skilled workers are scarse in Italy, their wage premium should be higher. This is not the case, at all. OECD (2005) states that tertiary education premia in Italy are lower than in other OECD countries. More specifically, with respect to secondary education (equal to 100), the premium for having a tertiary education degree for individuals aged between 30 and 44 is 137 in Italy, 150 in France, 163 in UK and 185 in the US (OECD, 2005). This evidence suggests that education issues are worth to be investigated in Italy, since they display different patterns with respect to other industrialized countries.

4. The Italian case: a falling dynamics of return to education.

To estimate the returns to education in a quantile regression framework we adopt a linear model of the type introduced by Mincer (1974):

(1) $$\ln w_i = \alpha_\theta + \delta_\theta \cdot educ_i + x^T \beta_\theta + \varepsilon_i$$

where i=1,…N is the number of observations each year, θ is the quantile being analysed, lnw_i is the natural logarithm of monthly wages, *educ* is a measure of educational attainment, x^T is the vector of all other covariates and ε_i is an idiosyncratic error term. Using equation (1) we compute five quantile regression, namely $\theta = .1,.25,.5,.75,.9$, with the same set of independent variables each regression.[5] More specifically, as covariates we use gender, education, experience (8 dummies), age (8 dummies), qualification (5 dummies), area (9 dummies), industry (9 dummies), being a head of household, number of household members, number of the individuals who earns money in the household, partime/fulltime, being married, population of the related province.

In a first specification education is introduced in dummies as well as all other covariates (e.g. age groups, work experience groups, part time etc…) while in a second specification education is expressed in a linear 'continuous' specification.[6]

As the focus of the analysis is the evolution of the returns to education over time across the distribution, we rule out any concern about the distribution of unobserved ability, supposed to be time invariant. Furthermore, the wage equation (1) includes neither square term of education nor interaction terms between education and other covariates, so that the derivative of the conditional quantile with respect to *educ* is given by:

(2) $$\frac{\partial Q_\theta[\ln(w_i) \mid educ_i, X_i)}{\partial educ_i} = \delta(\theta)$$

In (2) the estimated coefficient $\delta(\theta)$ measures, at each quantile, the wage variation required for remaining at the θth quantile of the conditional distribution after any educational attainment, when the heteroscedasticity hypothesis for the error terms holds. In this framework, the education coefficients vary across quantiles. On the contrary, in case of

[5] In particular, we perform simultaneous quantile regressions obtaining an estimate of the variance-covariance matrix via bootstrapping. The standard errors are based on the heteroscedastic bootstrap methods where the sample size is equal to the number of observations each year.

[6] Education in the continuous specification is computed attributing 5 years for elementary school attainment, 8 years for lower secondary school, 13 years for upper secondary school and 17 for higher educated workers. Moreover, work experience is calculated as the difference between the age of the worker and the years from the beginning of the labour career of this worker.

homoscedasticity, equation (1) is a pure location model and the slope coefficients do not vary across the distribution.

In order to verify the heteroscedastic hypothesis, we successfully test that the estimates of the coefficient vectors from the different quantile regressions are statistically different from each other (Buchinsky, 1995, Koenker and Basset, 1982).

Table 2 reports the returns to education at five quantiles, $\theta = .10,.25,.50,.75,.90$, for the model (1) using the whole sample period. Considering the returns to years of schooling (continuous specification), the estimated coefficients tend to be constant or, even, to decrease for those individuals staying below the median. Then they increase rather steadily along the right part of the distribution in almost all years considered, with exception of the 2004 sample, where the returns to schooling are slightly increasing over the wage distribution. A similar picture emerges when we use educational dummies in the wage equation, i.e. when we run a quantile regression of the log net monthly wages on the binary variables "primary school", "lower secondary", "upper secondary" and "university degree" and controlling, as before, for all other covariates.[7]

The pattern of these estimates confirms a positive non monotonic relationship between the returns to education and the quantiles of the wage distribution, with little variability across the sample years. Thus, the cross sectional analysis seems to replicate standard prediction of previous literature. Whatever measure is adopted, the schooling premium is generally increasing across the wage distribution even though some convex patterns emerge at lowest quantiles and for same of the sampled years.

In a dynamic perspective, instead, one can see from table 2 that returns to education declined in all the selected quantiles from 1993 to 2004.[8] The decline of the schooling premium is almost uniformly distributed along the wage distribution even though its magnitude depends on the adopted definition. For instance, when years of schooling are concerned, the falling of the estimated coefficients is more evident in the upper tail of the distribution while the returns to a university degree is more pronounced for individuals below the median earners. Similarly, the OLS estimates decrease over time

[7] The estimated coefficients on the educational dummies should be interpreted as differentials with respect to the omitted category, i.e. having a primary school degree. For example, in the 75th quantile an employee with university degree earns 30% more than an employee belonging to the reference group in 1993. This differential was reduced to 27% in the 2004 sample.

[8] Note that this trend is not monotonic from 1993 to 2004. More specifically, returns to education decrease after 1993, increase around 2000-2002 and then decline again in 2004.

supporting the evidence that also average returns to schooling have reduced along the period.

Table 2: Quantile Estimates of returns to education*

	Dep var log monthly wage	1993	1995	1998	2000	2002	2004
q10	Lower secondary	0.063	0.099	0.102	0.140	0.086	0.031*
	Upper Secondary	0.144	0.175	0.179	0.213	0.156	0.071
	University	0.235	0.264	0.277	0.279	0.258	0.197
	(continous)	0.018	0.020	0.017	0.019	0.017	0.013
q25	Lower secondary	0.082	0.093	0.100	0.090	0.050	0.041
	Upper Secondary	0.165	0.175	0.157	0.147	0.109	0.090
	University	0.255	0.234	0.233	0.238	0.242	0.206
	(continous)	0.019	0.018	0.015	0.017	0.015	0.014
q50	Lower secondary	0.070	0.091	0.112	0.075	0.057	0.043
	Upper Secondary	0.159	0.158	0.164	0.134	0.107	0.104
	University	0.261	0.229	0.238	0.221	0.248	0.238
	(continous)	0.019	0.017	0.017	0.016	0.021	0.016
q75	Lower secondary	0.078	0.089	0.102	0.061	0.059	0.034*
	Upper Secondary	0.185	0.171	0.177	0.123	0.132	0.112
	University	0.300	0.273	0.273	0.252	0.293	0.268
	(continous)	0.024	0.018	0.021	0.016	0.020	0.018
q90	Lower secondary	0.084	0.077	0.085	0.017*	0.079*	0.034
	Upper Secondary	0.208	0.186	0.179	0.065	0.159	0.109
	University	0.331	0.329	0.286	0.237	0.351	0.305
	(continous)	0.029	0.023	0.022	0.019	0.020	0.021
OLS	Lower secondary	0.087	0.100	0.098	0.085	0.057	0.040*
	Upper Secondary	0.193	0.184	0.176	0.151	0.118	0.096
	University	0.309	0.272	0.275	0.267	0.271	0.244
	(continous)	0.024	. .0195995	0.019	0.018	0.017	0.016

* Not significant at 5%

The negative pattern of the estimated coefficients has also a relevant effect on the dynamics of the wage structures as well as inequality trends. On the other hand, as the dependent variable is in log, the difference in the estimated coefficients at two different quantiles provides a measure of the impact of that covariate upon the logarithm of the ratio between wages at these quantiles. Table 2 shows that more educated individuals earn more than less educated ones (i.e. coefficients are positive) and that the schooling premium generally increases as we move up through the distribution. This fact implies that the wage distribution for more educated workers is more dispersed than that for less educated ones. However the conclusion that a larger proportion of high skilled workers in the labour force leads to increased inequality cannot be derived in our analysis, as the positive sign of the estimated coefficients is mitigated over time. To do it, we need to introduce a quantile decomposition method.

5. A counterfactual decomposition using quantile regression

In this section we want to disentangle the contribution of labour force characteristics and labour market prices in the dynamics of Italian wage structure. This literature goes back to the seminal contribution of Oaxaca (1973) and Blinder (1973), and it has been enormously developed in the last three decades. The most recent approach to this phenomenon is to consider a quantile regression setting, in which all the wage distribution dynamics is concerned. This approach has been recently developed by Machado & Mata (2005), Melly (2005) and Autor et al (2005), which use the same general idea but slightly different techniques in the implementation.

The main idea of this approach is to extend the decomposition effect on mean wages (Oaxaca, 1973) to the entire wage distribution. More precisely, in this setting it is possible to compute, for each quantile, the marginal distribution of wages related to some counterfactual distribution for all (or some) covariates.

This approach is essentially made by two main parts, which we will briefly describe in the following. In the first part, we compute quantile regression for all the wage distribution, thus deriving quantile coefficient β (the return to each characteristic at every quantile of the distribution), applying the standard quantile regression approach:

(3) $$Q_\theta(w/z) = z'\beta(\theta)$$

where θ stands for quantiles and Z for the set of covariates. As standard in this literature (Koenker and Basset, 1978), $\beta(\underline{\underline{\theta}})$ can be estimated minimising in β the following expression:

(4) $$n-1\left(\sum_{i=1}^{n}\rho_\theta(w-z'\beta)\right)$$

where $\begin{cases}\rho\theta(u)=\theta u \text{ if } u>0\\ \rho\theta(u)=(\theta-1)u \text{ if } u<0\end{cases}$

In this setting we can compute the conditional quantile process ($Q_\theta(z/x)$, for all θ) that provides a complete characterization of the conditional distribution of wages given the set of covariates Z. As stressed by Machado & Mata (2004) and Autor et al (2005), if U is a uniform random variable on [0,1], then $F^{-1}(U)$ has distribution F. This means that if θ_1, θ_2, θ_j, are drawn from a uniform [0,1], then the associated j estimates of the conditional quantiles of wages at Z, $\hat{w} = [z'\beta(\theta)]_{i=1}^{j}$, represent a random sample from the estimated conditional distribution of wages given Z.

The second part of this procedure is the most innovative one, because it allows us to derive the unconditional (or marginal) distribution of wages, and in this way also to derive the counterfactual distributions of wages. The idea is quite simple. Under the partial equilibrium assumption that aggregate quantities of covariates do not affect labour market prices,[9] we can draw a random sample of the rows of data Z and for each row of Z we can draw a random θ from the uniform (0,1), in this way deriving a random sample of the marginal density implied by the model $\hat{w} = [z'\beta(\theta)]_{i=1}^{j}$. Repeating this procedure it is possible to draw a large number of estimations of the marginal distribution,[10] which is crucial in order to reconstruct the counterfactual densities we are interested in. For instance, in this framework it is possible to generate a counterfactual density computing the distribution of wages in 2004 using as covariates the ones of 1993.

As in Machado & Mata (2005), we define as *f(w(t)* the marginal density of w, and as *f*(w(t))* an estimator of the density of density estimated by the model. Our relevant counterfactual is defined by *f*[w(2004); z(1993)]*, i.e. the density for 2004 that we would be derived by the model if all covariates (or some of them) were set at their 1993 levels.

As already stressed, this methodology allows us to disentangle the effect of covariates and the one of coefficients in the overall variation of the distribution of wages over time. According to Machado & Mata (2005), we define as *f(w(2004))* and *f(w(1993))* the observed distribution of wages in 2004 and 1993. Moreover, considering the estimated wage distribution in 2004 and 1993 *(f*)*, adding and subtracting *f*(w(2004);Z(1993))* that is the simulated distribution of wages in 2004 if the covariates are set at the 1993 levels-, we can decompose the overall changes of a generic summary statistics (α(.)) -related to the observed distributions- in the following components:

$$\alpha(f(w(2004)) - \alpha(f(w(1993))) = \alpha(f^*(w(2004); Z(1993)) - \alpha(f^*(w(1993)) +$$
$$+ (f^*(w(2004)) - \alpha(f^*(w(2004); Z(1993))) + residual$$

where the first term in the right left hand represents the contribution of coefficients, the second term is related to covariates contribution and the

[9] Note that this partial equilibrium hypothesis is common to this literature.
[10] Note that this is equivalent to integrate numerically the estimated conditional quantile function over the distribution of x and θ. For further details see Melly (2005).

third term represents the residual, which is related to the differences between the observed and simulated distributions.

The same strategy can be implemented considering the counterfactual distribution for only one covariate of interest, such as education in our case. More specifically, we simulate the distribution of wages in 2004 imposing the distribution of Z be the one of 1993 for educational dummies while for the other covariates it remains at the 2004 levels.

As in the previous section we use SHIW Bank of Italy data, in 1993 and 2004. We focus on subordinate workers in all sectors, which have worked more than 3 months in the reference year. We consider the monthly wages (in log) as dependent variable, and as covariates we use the same set of covariates of the estimate of returns of education of the previous sections.

In the first step of our procedure we implement 200 weighted quantile estimations, from 0 to 1 (0.005, 01, 015, …., 0.99, 0.995), deriving the conditional distribution of wages given Z. In the second step we derive the unconditional wage distribution. According to Autor et al (2005), we multiply the full matrix of Z by the (transposed) matrix containing the quantile regression coefficients. As already stressed, this method produces a large number of estimations that can be thought as drawn from the unconditional wage distribution.[11]

5.1. Decomposition results

The procedure described above is applied to decompose the changes of the wage structure between 1993 and 2004 into changes attributable to covariates (individual workers' attribute), to coefficients (remuneration of these attributes) and to residual changes, that is, changes unaccounted for by the estimation method. Results are summarized in table 3. The first row presents the estimates of the overall changes occurred during the period by comparing the actual marginal density in 2004 and in 1993, $f(w(2004)) - f(w(1993))$, at the selected quantiles of the wage distribution $\tau = .1,.25,.5,.75,.9$.

[11] Note also that, as in Autor et al (2005) we produce a much larger set of simulated values of the unconditional wage distribution (200 times larger).

	diff_p10	diff_p25	diff_p50	diff_p75	diff_p90
Total observed variation	-0.0014	0.0051	-0.0274	-0.0220	0.0177
Coefficients contribution	-0.0228	-0.0232	-0.0373	-0.0414	-0.0187
Covariates contribution	0.0255	0.0190	0.0142	0.0129	0.0138
Residual contribution	-0.0041	0.0093	-0.0043	0.0065	0.0226

Table 3. Quantile decomposition in the contributions related to coefficients, covariates and residuals

It is straightforward to note that wages reveal an irregular pattern throughout the whole distribution. We find a positive wage growth at the 25th and 90th quantiles while at the first decile and in the range between the median and the 75th quantile the wage structure has shifted to the left. The next three rows decompose the total changes at each chosen quantile into changes due to coefficient - $\left[f^*(w(2004);Z(1993))-f^*(w(1993))\right]$- changes due to the covariates - $\left[f^*(w(2004);Z(1993))-f^*(w(2004))\right]$- and residual changes (estimated as the difference between the estimates of the total changes provided by using the empirical wage density and by using the estimated wage density). Covariates and coefficients contribute to the actual evolution of the location estimates with opposite sign and different magnitude in all estimated quantiles. The negative effect of the coefficients dominates the positive effect of covariates in the 25th-75th interquantile range. The model works rather well as the residual account for a relatively small portion of the total change, even though at the first decile the unexplained changes is negative and contribute substantially to the observed decline of wages in the left tail of the distribution.

To illustrate the role played by education in this context, we replicate the same decomposition by comparing the 2004 estimated *vs* counterfactual marginal densities when education was distributed as in 1993, i.e. the wage distribution that would have been prevailed in 2004 if only the educational dummies had been distributed as in 1993.

	diff_p10	diff_p25	diff_p50	diff_p75	diff_p90
Total observed variation	-0.0014	0.0051	-0.0274	-0.0220	0.0177
Coefficients contribution	-0.0016	-0.0088	-0.0312	-0.0420	-0.0334
Education contribution	0.0044	0.0047	0.0081	0.0134	0.0285
Residual contribution	-0.0041	0.0093	-0.0043	0.0065	0.0226

Table 4. Quantile decomposition in the contributions related to coefficients, covariates (education) and residuals

Table 4 shows that estimated returns to education have a negative impact upon wage growth across the distribution.[12] This evidence is coherent with previous results (Table 2) where we found that schooling premium has been declining almost uniformly for our selected quantiles between 1993 and 2004. On the contrary, the composition effect of education has exerted a positive impact on all the estimated quantiles, with greater effect on the right tail of the distribution.[13]

Focusing on the 50th and 75th quantile, the observed shift to the left is about -0.0274 and -0.0220 respectively. Had the share of more educated workers remained as it was in 1993, we estimate that the 50th would have increased by 0.081 and the 75th by 0.0134. However, the falling of the returns to education at correspondent estimated quantiles compensate such a positive composition effect, generating eventually lower wages. In other words, without changes in market price of education, the raising schooling attainments would have increased the wage for each quantile.

To interpret the meaning of our results we refer to a standard demand and supply framework where workers can be split into two types, low and high skilled or, equivalently, high school and college graduates. In such a context it is straightforward to show that an increased proportion of skilled workers leads to a reduction in wage inequality because of a conventional price effect: becoming relatively more abundant, skilled workers experience on average a decrease of their relative wage. The composition effect can also contribute to compress the wage structure, as a grater proportion of individuals is skilled, i.e. in the highest wage group. These combined effects lead to the standard prediction that shifts to the right of the relative supply of skilled workers (more educated workers) should result in lower wage inequality, if the central tendency of the data is concerned. Obviously, it is also possible that the relative demand of skilled workers shifts to the right to more than compensate the increase in relative supply of educated workers.[14]

In our analysis the returns to education are more spread for high skilled workers, so one could expect that an increase of schooling levels leads to an increased overall wage dispersion (90-10, 90-50, 50-10), by reducing the weight of the low spread group in the workforce. In the first column of table

[12] It is worth noting that for the negative sing of the total observed variation at the first decile is driven by the residual contribution.

[13] Note that In this case the decline of returns to education play no role since the changes of education composition in the workforce are weighted by the constant wage schedule of 2004.

[14] The skill bias technological change theories, on the other hand, stress that this latter phenomenon could have been effectively at work in Anglo Saxon countries, where returns to education and wage inequality have increased dramatically during last decades.

5, however, we observe that standard indexes of wage inequality increase in the upper tail of wage distribution, while in the lower tail there is a wage compression over the period. This phenomenon is due to the fact that wages of low skilled group declined less than wages of individuals around the median income level.

To illustrate the dynamic relationship between the education attainments of the working population and wage inequality, Table 5 reports the results of the quantile decomposition analysis. In our data, we find that the observed increases of the share of educated workers would have led to a shift to the right of the wage schedule if returns to education had remained constant (composition effect). Furthermore, the evolution of the price of skilled labour declines remarkably during the period 1993-2004, mostly concentrated in the right tail of the distribution (coefficients effect). Then, the extent to which the positive composition effect offsets the negative price effect depends on their relative magnitude across the wage distribution. More specifically, the composition and coefficient contributions help us to explain why the 50-10 indicator declines along the period while both the 90-50 and 90-10 increase.

	50-10	90-10	90-50
Total observed variation	-0.0261	0.0191	0.0451
Coefficients contribution	-0.0296	-0.0318	-0.0021
Education contribution	0.0038	0.0241	0.0204
Residual contribution	-0.0002	0.0267	0.0269

Table 5. Decomposition of inequality measures between 1993 and 2004

To sum up, the picture we get from these decomposition exercises could be explained by a sort of "unskilled" technological change. The individuals currently employed in the labour market are more educated than those in 1993 but receive lower wages than workers with comparable education in 1993. This means that the choice of schooling could have been crowded out by the low technological content of the productive process, where high skilled workers are employed.

6. Conclusion

In this paper we analyse the role of education on the dynamics of wage structure in Italy. The first result is that the returns to schooling declined almost uniformly across the wage distribution during the last decade. Given the pattern of the estimated coefficients with quantiles in each sample year, this falling exerts a pressure toward an increased inequality in the upper tail of the wage distribution and an earnings compression in the lower tail.

The second result regards the role of demand and supply of high educated workers behind these changes. The quantile decomposition method shows that the composition effect associated with the share of educated workers in the labour market is always positive while the price effects of education is negative across the wage distribution. Assuming a standard demand and supply paradigm, this leads to the conclusion that a sort of unskilled bias technological change could have prevailed in Italy.

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