# WAGE STRUCTURE, INEQUALITY AND SKILL-BIASED CHANGE: IS ITALY AN OUTLIER?

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Abstract

This paper investigates the relation between wage structure, inequality and skill-biased change in Italy between 1993 and 2004. Using a quantile decomposition analysis, we point out that changes in wage structure are mainly driven by the negative coefficients component, which represents also one of driving force of the trends of wage inequality. This evidence suggests that the changes in wage structure in Italy can hardly be explained referring to a skill-biased change explanation. Evidence that is further reinforced by a set of descriptive statistics showing that the increasing educational attainments of the workforce might have been crowded out by a stable trend in the demand for skills.

JEL codes: I20, J24, J31

Keywords: Educational wage premia, Human Capital, Skill Biased 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, especially after the steep increase of wage inequality and schooling premia in United States since the early 1980s (Bound and Johnson, 1992; Katz and Murphy 1992). To a less extent, increases of the educational wage premia[1] and wage inequality are also documented for many other OECD countries (Gottschalk and Smeeding, 1997).

Different economic theories provide explanations for the observed patterns in schooling premium and earnings inequality. Among these, the supply-demand-technology paradigm has become the most accepted theoretical framework.[2] Accordingly, the skill biased technological change linked to the diffusion of new IC technologies have shifted the relative labour demand toward high skilled workers at the expense of low skilled workers and, as a consequence, has generated an increase of the average wage of skilled workers with respect to the wage of unskilled ones (Krueger, 1998, Acemoglu, 2002).[3] The theoretical consensus on the skill-biased explanation, however, is largely due to the fact that the supply and demand analysis focuses on the average wage dynamics rather than on the changes across the entire wage distribution. In such a way it does not consider that more educated individuals typically experience more unequal wage distribution than less educated, i.e. the possibility that educational patterns affect the wage structure through a composition effect, not only through a price effect (Lemieux, 2002).

In other words, to understand the relationship between the dynamics of human capital accumulation and changes in the wage structures it needs to go further the conventional approach based on least square methods, at least in two dimensions. Firstly, it is necessary to analyze the impact of human capital variables on the entire wage distribution, not only for the average tendency of the data. Secondly, it

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[1] Peracchi (2004) distinguishes between returns to education, which is a measure of the causal effect of an extra level of schooling on the worker's earnings, and educational wage premia, which is a measure of statistical association between levels of schooling and wages. We make use of this terminology in the paper.

[2] The supply-demand-technology explanation is 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. Other explanations concerns the impact of international trade on domestic labour market (Burtless, 1995) and the relevance of the skill biased organizational change.

[3] 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, some authors suggested that labour demand must have shifted to more than compensate the shifts in relative supply (Acemoglu, 2002).

requires dividing the changes of the wage distribution into the effects due to changes in the stock of human capital, changes in educational wage premia, and changes in a residual-within component.

In this paper we investigate the relation between wage structure, inequality and skill-biased change for the Italian case, arguing that the quite flat trend observed of wage inequality in the last decade is actually the result of countervailing forces, which are related to covariates, coefficients and residuals.

In order to identify these forces we make use of the quantile decomposition methodology developed by Machado and Mata (2005), Melly (2005), Autor et al. (2005), which allows to derive counterfactual wage distributions, using alternative set of covariates, coefficients, and residuals. In such a way, the changes over time of the wage distribution are decomposed into price (coefficients), quantity (covariates), and residual (within) effects.

To perform the empirical analysis we use the *Survey of the Household Income and Wealth* (SHIW) of the Bank of Italy, from 1993 to 2004. This data source represents the main database used in the literature to investigate inequality issues in Italy. Samples are composed by employees aged 18-64, working either in the public or in the private sector, full time equivalent. Further, we make use of a mincerian equation, considering as covariates education, experience and gender.

Using the decomposition analysis, we point out that the main force that drives the changes in wage structure is the negative coefficients component, which grows along the wage distribution. This finding is also consistent with Naticchioni, Ricci, Rustichelli (2007), which point out that educational wage premia are decreasing in Italy in the period 1993-2004. Moreover, a negative coefficients component does not seem to be consistent with a standard skill-biased change explanation.

To find out an interpretation for the negative coefficients component, we carry out some descriptive statistics on the dynamics of labour demand, using LFS data that make use of more detailed information on industry and occupation classification.

We show that while educational attainments increased over time, the share of high-skilled occupations remained quite stable in the same period. This occupational mismatch might have crowded out the educational choices of individuals, since the quality of their occupations decrease over time. In other words, such a mismatch could have played a role in explaining why the increased relative demand for high educated workers has not translated in an increase of wage differentials, i.e. a positive coefficients (between) component across the wage distribution.

On the whole, the quantile decomposition results and the set of descriptive statistics show that the Italian case might be considered as an outlier with respect to the skill-biased technological change phenomenon, suggesting that the relative supply of skilled labour increases more than the demand for high-skilled occupations. In this setting, the occupational mismatch could be considered as a partial explanation for the decreasing educational wage premia.

The paper is organized as follow. In section 2 we review some empirical literature on educational wage premia and wage inequality. In section 3 the characteristics of the sample are analyzed and descriptive statistics presented. In section 4 we introduce the decomposition analysis, while in section 5 results are presented and discussed. Section 6 provides a set of descriptive statistics concerning the dynamics over time of labour demand, and section 7 concludes.

## 2. Empirical literature

The conventional explanations proposed to describe observed trends in US earning inequality are based on different conjectures, among which the role of no neutral technological progress, reforms of wage setting institutions, variation of educational composition of the workforce, increased international trade with low income countries, changes in the organizational structure of labour demand. Most of these theories and empirical findings emphasize the central role played by human capital accumulation and educational wage premia in affecting the dynamics of wage structures (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 skill biased 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 an increase of the relative wages of college education workers.[4]

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

These interpretations, on the other hand, cannot be easily extended to 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 and Smeeding, 1997). For example, using data

[4] 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.

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 educational wage premia 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 greater effect on wages of individuals at the top of the wage distribution than on wages at the bottom of that distribution in Germany. This means that in Germany more educated individuals experience more unequal wage distributions and this seems to have increased during the 1980s. As for te Portugal case, Machado and Mata (2005) introduce a quantile decomposition method that enables the identification of the sources of the increased wage inequality observed between the late 1980$^{th}$ 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.

In this theoretical and empirical framework the Italian labour market stands out as a peculiar case, worth to be investigated. As for international comparisons, for instance, Italy displays lower educational attainments than 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. Moreover, the catch-up process is slowing down, since the university enrolment rate decreased in 2004-2005 by 1.5% and in 2005-2006 by 4.5%. This last evidence is really surprising and disappointing: Italy displays among the lowest education attainments in comparison with OECD countries, and in the last two years these gaps are even getting wider.

These impressive international differences might suggest that since skilled workers are scarce in Italy, their wage premia might be higher with respect to other developed countries. 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).

As for the empirical literature for Italy, there are few papers concerning the evolution over time of earnings inequality. The paper that addresses this issue along a very long time period is Brandolini, Cipollone and Sestito (2002), which use the SHIW Bank of Italy data to investigate the dynamics of earnings inequality from 1977 to 1998. This paper points out that the distribution of net earnings narrowed from 1977 to the end of the 1980s, mainly due to a wage indexation mechanism (the so-called "Scala Mobile"), which granted a flat-sum wage increase correlated to the increase in the cost of living index. At the beginning of the nineties, the important economic crisis and the reform of the abolition of the wage indexation mechanism (in 1992) generated an increase in earnings inequality, which mainly took place between 1991 and 1993, as also explained by Manacorda (2004).

Then, from 1993 to 1998 Brandolini, Cipollone and Sestito (2002) argue that earnings inequality remained basically unchanged. In their analysis of earnings inequality they also investigate the patterns of different subgroups of the population, such as full-time employees, male and female, the North and the South, arguing that the related subgroup patterns are not so different from trend for the whole population.

More recent papers have extended the period of analysis to 2002, using SHIW data, such as Lilla (2005), who claims that in the period 1998-2003 earnings inequality slightly increased. [5]

To what extent the dynamics of wage inequality can be attributed to the educational and experience attainments of the working population is not investigated in the empirical literature for Italy, as there is no exhaustive analysis concerning the relationship between human capital variables and changes of the wage distributions.[6]

Other papers have investigated the issue of skilled bias technological change in the Italian labour market, in a demand-supply-technology paradigm. Using a panel of firms in the private sector for the period 1986-90, and matching two different data sets (the INPS firm level data set and the company's balance sheet data, the CADS), Casavola, Sestito and Gavosto (1996) assess both wages and employment dynamics, and the relations with 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

[5] Other papers have focused on educational wage premia in Italy. For instance, Brunello and Miniaci (1999) compute a casual effect by applying least square or IV techniques. Further, Giustinelli 2004) 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.

[6] Actually Lilla (2005) carries out a within-between analysis of wage inequality in Italy, taking into account human capital variables. Using a different methodology Lilla (2005) claims that both the within and the between components slightly increased until 2002.

(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, not considering the whole wage distribution.

To deal with this issue we restrict our analysis to the supply side of the labour market, in order 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 18-64, working either in the public or in the private sector, full time equivalent. 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 (base year 2004). 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 over time.

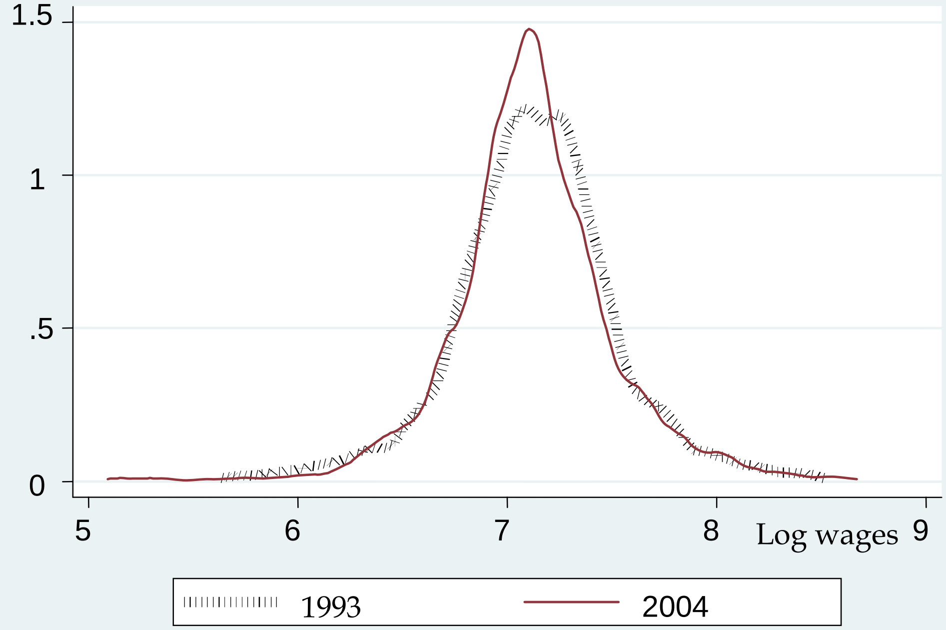
Table 1 reports the descriptive statistics of the main variables for each sample year. Focusing on the pattern of educational dummies we observe that the percentage of individuals with upper secondary education or university degree increased over time, though not monotonically, while the share of individuals with elementary and lower secondary education declined. 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.

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, with a slight shift of the whole distribution to the left (see Figure 1). Comparing Kernel estimates of the wage densities in 1993 and 2004 in figure 1, it is possible to note 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 |
| **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 |
| **Observations** | 6014 | 5963 | 5338 | 5879 | 5582 | 5647 |

Figure 1: Kernel densities of wages in 1993 and 2004




4. Quantile Regression Decomposition

In this section, we want to disentangle the contribution of labour force characteristics and labour market prices in the dynamics of the 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 contribution in this literature is to consider a quantile regression setting, which explores the dynamics of the whole wage distribution. This approach has been recently developed by Machado & Mata (2005), Melly (2005) and Autor et al (2005), papers that use the same general idea and slightly different techniques in the implementation.

The starting point of our analysis are the two quantile estimations in cross-section, for 1993 and 2004, using a mincerian standard specification:

(1) $$\ln w_i^t = X_i^t \beta_\theta^t + u_i^t$$

where $i=1,\ldots N$ is the number of observations in each year $t$, $\theta$ is the quantile being analyzed, $u_i$ is an idiosyncratic error term, and $X$ represents our set of explanatory variable that, according to the mincerian specification, includes education, experience and gender.[7] As standard in this literature (Koenker and Basset, 1978), $\beta(\theta)$ can be estimated minimising the following expression:[8]

$$\min_{\beta}\left[ n-1\left( \sum_{i=1}^{n} \rho_{\theta}(w - X\beta) \right) \right] \tag{2}$$

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

4.1 Estimation of the marginal distribution of wages

Once having derived the quantile parameters $\beta(\theta)$, we introduce the methodology to estimate the marginal distribution of wages as function of both X and $\beta(\theta)$, methodology that is then used to derive counterfactual distribution of wages. This methodology is essentially developed in two main parts, which we will briefly describe in the following.

In the first part, the conditional quantile distribution of wages is estimated, $Q_\theta(w \mid X_i)$, for all $\theta$ given the set of covariates $X$. More specifically, quantile regression theory has shown that, using a linear specification, the conditional quantile distribution of wages can be expressed as:

$$Q_\theta(w \mid X_i) = X_i \beta(\theta) \quad \text{for all } \theta \in (0,1) \tag{3}$$

where $X_i$ is a vector for the set of covariates. For instance, $X_i$ might stand for men graduated with less than 5 years of experience. Further, in this framework, the quantile regression coefficients can be interpreted as rates of return to the different characteristics at the specified quantile of the conditional distribution. Basset and Koenker (1982, 1986) showed that, under some regularity conditions, the estimated conditional quantile function is a consistent estimator of the population conditional quantile function, uniformly in θ.

Hence, it is possible to use the estimated parameters to simulate the conditional distribution of $w$ given $X$, using an application of the probability integral transformation theorem: if $V$ is a uniform random variable on [0,1], then $F^{-1}(V)$ has the density $F$. In our case, if $\theta_1, \theta_2,..,\theta_j$ are drawn from a uniform (0,1), the corresponding $j$ estimates of the conditional quantile at $X_i$, $\hat{w}_i \equiv \{X_i \hat{\beta}(\theta_j)\}_{j=1}^{J}$,

[7] In the empirical analysis, we do not take into account any relationship between ability and education, as well as the effects of their interaction on wage determination. Actually, the unobserved ability may induce heterogeneity in the conditional distribution of wages and, as a consequence, causes inconsistency of the regression estimates (Card, 2001). However, assuming that the distribution of individual ability is invariant over time, an hypothesis that seems to be quite reasonable, the comparison of the *quantile treatment effect* of education at two different time periods is unaffected by the ability bias (see also Arias, Hallock, Sosa-Escudero, 2001).

[8] To validate the heteroscedasticity 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, 1978).

constitute a random sample from the estimated conditional distribution of wages given $X_i$. Using this procedure, we can estimate the distribution of wages for all the different combination of $X$.

The second part of the procedure consists in deriving an estimation of the marginal distribution of wages. Following Machado & Mata (2005) and Autor, Katz, Kerney (2005), the marginal density of wages depends upon both the conditional quantile function, $X_i\hat{\beta}(\theta_j)$ for given $X_i$ and $\theta_j$, and the distribution of the covariates, $g(X)$. In order to derive a random sample from marginal density of wages, it is possible to multiply the matrix containing random observations (or all the observations) from $g(X)$ times the matrix of $\beta(\theta_j)$, with $j=1,\dots,m$, in which the different $\theta_j$ are randomly chosen from the uniform (0,1) distribution. In this setting, each observation of the resulting matrix, $\hat{w}_i$, can be thought as drawn from the marginal distribution of wages implied by the model, $\hat{w}_i \equiv \left\{X_i\hat{\beta}(\theta_j)\right\}_{j\in(0,1)}$.

By applying this procedure, it is possible to draw an arbitrarily large random sample from the marginal distribution of wages. Autor, Katz, Kearney (2005) claim that this procedure can be thought as equivalent to numerically integrating the estimated conditional quantile function $\hat{Q}_\theta(w \mid X)$ over the distribution of $X$ and $\theta$, i.e. $\int_X\int_\theta \hat{Q}_\theta(w \mid X)g(X)\partial\theta\,\partial X$.[9] The idea is quite intuitive. Any given random observation of $X_i$ is multiplied by all the possible $\beta(\theta)$, with $\theta$ ranging from 0 to 1, and this can be considered as the internal integration over the support of $\theta$. Then, $X$ is repeatedly drawn from the whole support $g(X)$, and this can be thought as the external integral in $X$. Melly (2006) shows that the Machado and Mata (2005) estimator and the integration procedure produce the same results when the sample size is sufficiently large as well as the number of chosen quantiles in (0,1).

Concretely, we use SHIW Bank of Italy data, in 1993 and 2004. We focus on subordinate workers (full time equivalent) 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 variables usually included in the standard mincerian equation, such as education and experience (and gender). Further, we implement 200 weighted quantile estimations, from 0 to 1 (0.005, 01, 015,…, 0.99, 0.995), deriving the coefficients along all the $\theta$ distribution separately for 1993 and 2004. Then, we derive the unconditional wage distribution, for each year, multiplying the full matrix of $X$ by the matrix containing all quantile regression coefficients, as in Autor et al. (2005). Each element of the resulting matrix can be thought as drawn from the unconditional wage distribution.[10]

[9] Note that $\theta$ is uniformly distributed on the [0,1] interval, implying that $f(\theta)=1$.

[10] 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).

## 4.2 Counterfactual wage distributions: covariates, coefficients and residual effects

As already stressed, this methodology derives the marginal distribution of wages as function of covariates and coefficients. This means that it allows generating counterfactual densities, using different *g(X)* and *β(θ)*. For instance, it would be possible to compute a counterfactual distribution keeping the covariates at the level of 1993 and coefficients at the one of 2004.[11]

Furthermore, the Machado and Mata (2005) methodology did not directly take into account a within-residual component. Two recent papers, Autor et al. (2005) and Melly (2005), extended the Machado-Mata approach in order to estimate this additional component, in this way identifying three separate effects in the computation of counterfactual distribution: covariate, coefficient and residual.

Autor et al. (2005) and Melly (2005) defines the coefficient effect as the measure of between group inequality. In particular, following the notation of Melly (2005) and taking the median as a measure of the central tendency of the data, it is possible to derive the following wage equation for each year (1993 and 2004):

$$\ln w_i^t = X_i^t \beta^t(0.5) + u_i^t, \quad t = 04, 93 \tag{4}$$

where $\beta^t(0.5)$ is the coefficient vector of the median regression in year *t,* which represents a measure of between group inequality. To disentangle the effect of coefficients (between group inequality) from the effect of residuals (within group inequality) it is important to note from (4) that the $\theta^{th}$ quantile of the residual distribution of $u_i^t$ conditionally on $X$ is consistently estimated by $X(\hat{\beta}^t(\theta) - \hat{\beta}^t(0.5))$. Accordingly, Melly (2005) defines the within component using the following vector of coefficients: $\hat{\beta}^{m04,r93}(\theta_j) = (\hat{\beta}^{04}(0.5) + \hat{\beta}^{93}(\theta_j) - \hat{\beta}^{93}(0.5))$. Using these coefficients Melly (2005) computes the variation over time of some quantile $q$ attributable to the residual component as the difference of the related quantile of the two following distributions, $\hat{q}(\hat{\beta}^{04}, X^{04}) - \hat{q}(\hat{\beta}^{m04,r93}, X^{04})$, where the X and the $\beta^t(0.5)$ are constant at the 2004 level while the residual inequality is the only one the changes over time.[12]

Similarly, the difference between $\hat{q}(\hat{\beta}^{m04,r93}, X^{04})$ and $\hat{q}(\hat{\beta}^{93}, X^{04})$ is due to changes in coefficients since characteristics and residual are kept at the 2004 level. Finally, the difference between $\hat{q}(\hat{\beta}^{93}, X^{04})$ and $\hat{q}(\hat{\beta}^{93}, X^{93})$ is due to changes of covariates.

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[11] Note that all this literature, for instance Autor et al. (2006), Melly (2005, 2006), Machado and Mata (2004), make use of the partial equilibrium assumption that aggregate quantities of covariates do not affect labour market prices.

[12] Note that $\hat{\beta}^{m04,r04}(\theta_j) = (\hat{\beta}^{04}(0.5) + \hat{\beta}^{04}(\theta) - \hat{\beta}^{04}(0.5)) = \hat{\beta}^{04}(\theta)$.

Hence, adding and subtracting $q(\hat{\beta}^{93}, X^{04})$ and $q(\hat{\beta}^{m04,r93}, X^{04})$ it is possible to decompose the variation over time of an estimated quantile of the wage distribution in the three components (residual, coefficients, covariates) :[13]

$$\hat{q}(\hat{\beta}^{04}, X^{04}) - \hat{q}(\hat{\beta}^{93}, X^{93}) = \left\{\hat{q}(\hat{\beta}^{04}, X^{04}) - \hat{q}(\hat{\beta}^{m04,r93}, X^{04})\right\} + \left\{\hat{q}(\hat{\beta}^{m04,r93}, X^{04}) - q(\hat{\beta}^{93}, X^{04})\right\}$$
$$+ \left\{\hat{q}(\hat{\beta}^{93}, X^{04}) - q(\hat{\beta}^{93}, X^{93})\right\}$$

In this framework, it is possible to decompose the variations of all the estimated quantiles we are interested in, such as the median, the 10th, the 90th, etc, as well as the inequality indexes 90/10, 90/50, 50/10 and so on.

Other methodologies that compute the residual component have to assume independent error terms, like Juhn, Murphy and Pearce (1993). On the contrary, methods based on quantile regressions can account for heteroscedasticity. This is really crucial when the variance of the residuals expands as a function of education and experience (Lemieux, 2002). The fact that the population is getting more educated and experienced puts more weight on groups with higher within-group inequality. This might entail a composition effect and not an increase in the price of unmeasured skills as traditionally argued. Autor et al. (2005) and Melly (2005) allow taking into account these issues.

## 5. Decomposition results

We apply the described procedure to decompose the changes of the wage structure between 1993 and 2004 into changes attributable to covariates (individual workers' attributes), to coefficients (remuneration of these attributes) and to a residual component.

As in the related literature concerning decomposition analysis, such as Lemieux (2002) and Autor et al. (2005), we use a simple mincerian specification including educational dummies (in four classes), experience dummies (in eight dummies) and the gender dummy.

Table 4 shows the decomposition results. In particular, we report the estimated variation over time of some selected quantiles (10, 25, 50, 75, 90), and the related decomposition into the three components.[14] From the first row of able 4 it is possible to note that the lower tail of the distribution remains quite stable (the 10th and the 25th percentile), as well as the 90th percentile, while the median and the 75th percentile decrease substantially over time.

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[13] Note that the sum of the three components exactly amounts to the variation over time of that given quantile. This property is not shared with other methodology previously adopted.

[14] It is worth noting that the estimated variations at the selected quantiles fit well the observed variations, as well as the inequality indexes. This provides additional evidence if favour of the quantile decomposition method.

As for the decomposition components, it comes out that the coefficients component (between) is always negative and it increases in magnitude along the wage distribution, ranging from -0.489 at 10th percentile to -0.0773 at the 90th percentile.[15] This implies that the decline of the price of human capital would have generated a shift to the left of the wage schedule, mainly concentrated in the right tail of the distribution, for constant covariates and residual components. This negative coefficient component is consistent with the dynamics of educational wage premia in Italy. Naticchioni, Ricci, Rustichelli (2007) show that educational wage premia decreased over the period 1993-2004, and across the whole wage distribution.[16]

As for the covariates component, it is always positive and slightly decreasing along the wage distribution, while the residual contribution is quite negligible from the 10th to the 75th quantiles, and becomes quite relevant at the 90th percentile.

| | diff_p10 | diff_p25 | diff_p50 | diff_p75 | diff_p90 |
|---|---|---|---|---|---|
| Total estimated variation | 0.0054 | 0.0023 | -0.0226 | -0.0332 | 0.0027 |
| Coefficients contrib. (between) | -0.0489 | -0.0579 | -0.0699 | -0.0763 | -0.0773 |
| Covariates contribution | 0.0612 | 0.0551 | 0.0500 | 0.0487 | 0.0479 |
| Residual contribution (within) | -0.0069 | 0.0051 | -0.0027 | -0.0056 | 0.0321 |

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

Indeed, these findings on the variations of selected quantiles of the wage distribution help to understand the dynamic relationship between the human capital attainments of the workforce and wage inequality (Autor et al., 2005, Melly, 2005). Actually, the standard inequality indexes (90-10,90-50,50-10) can be easily derived from table 4, computing the related ratios, both for the estimated variations and for the three components.

From table 5 we observe that the upper tail (90/50) of the wage distribution increases, while a wage compression is observed in the lower tail, i.e., the 50/10 index decreases since wages of low skilled group (10th) declined less than wages of individuals around the median wage level.

Considering the impact of the decomposition components on wage inequality, from table 5 we show that the coefficients (between) effect is negative for the changes of both the 90/10 and the 50/10 log wage ratios, while it is negligible for the 90/50 wage ratio. This negative price effect is reinforced by a less relevant

[15] Note that these variations are computed as differences of log wages of the estimated (or of the counterfactual) distributions. This means that the variations over time are given by the difference of two logarithms, i.e. a growth rate.

[16] The results of Naticchioni, Ricci, Rustichelli (2007) holds both using a continuous and a dummy specification for education, and are robust to several robustness checks (different econometric specifications, different population subgroups).

negative covariates component, which is very close to zero for the 90/50 ratio. As for within component, we observe a significant positive impact on both the 90/10 and 90/50 inequality indexes, while it is negligible in the lower tail of the wage distribution.

The extent to which the positive residual component offset both the negative coefficients and covariates components depends on their relative magnitude across the wage distribution. Actually, the falling 50/10 ratio is mainly explained by the negative covariates and coefficients components, while the residual inequality drives the increases in wage inequality at the top of the wage distribution.[17] In particular, the 90/50 index increases is only related to the residual component, while the stability of the 90/10 index is explained by negative coefficients and covariates effects that are counterbalanced by a positive residual component.

In order to provide an interpretation of the within component, we resort to the "skill price theory" (Juhn, Murphy and Pierce, 1993, and Lemieux, 2002), which basically underlines two main effects. On the one hand, the positive (negative) changes in the coefficients component exert a positive (negative) impact on the residual component, along the wage distribution, providing a measure for "unmeasured price skills" On the other hand, the residual component is also related positively to the trends in the covariates component, i.e. to the share of educated and experienced workers in the labour force. Our results reported in table 4 and 5 suggest that up to the 75th percentile these two forces cancel out one another, involving a within component close to zero, while at the 90th percentile the positive effect related to the increase of educated and experienced workers seems to prevail to the negative effect induced by the coefficients component. In terms of wage inequality, this implies that the within inequality plays a role only in the upper tail of the distribution, as already stressed. Anyway, since the within component plays a role only at the 90th percentile, we do not further investigate any related issue.

To sum up, the picture we get from these decomposition exercises could be explained by the fact that labour demand might have increased less that the labour supply: in 2004 individuals employed in the labour market are more educated than those in 1993 but receive lower wages for the same level of education. In other words, this evidence suggests that in Italy we do not observe the standard features related to a skill-biased change, which is usually defined as an increase of the relative demand of skilled workers stronger than the increase in its labour supply. This also means that in Italy the choice of schooling could have been crowded out by the contents of the productive process, where high skilled workers are employed.

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[17] These results are also consistent with other analysis concerning Europe, such as Lucifora and Barth (2006), which document an increasing trend in within-group wage inequality, especially for tertiary education.

| | 90/10 | 50/10 | 90/50 |
|---|---|---|---|
| Total estimated variation | -0.0027 | -0.0281 | 0.0253 |
| Coefficients contribution (between) | -0.0285 | -0.0210 | -0.0074 |
| Covariates contribution | -0.0133 | -0.0113 | -0.0021 |
| Residual contribution (within) | 0.0390 | 0.0042 | 0.0348 |

Table 5. Decomposition of the inequality variation in the between, within and covatiates component

## 6. Descriptive evidence on labour demand

In previous sections we showed that the main distinctive feature of the dynamics of wage structure in Italy is the negative coefficients (between price) component across quantiles.

Several explanations could be proposed for this evidence. One possible explanation is that skill-biased technical change has not been so pervasive in Italy as in other countries. That is, the shifts of relative labour demand favouring more skilled workers (over less skilled workers) have not caused the expected increase of the wage differentials between groups characterized by different human capital endowments. A second explanation suggests that shifts in product demand associated with trade have led to a shift in employment share toward sectors that were not skill intensive. A third alternative explanation focuses on labour market institution, such as unions and employment protection legislation, which are supposed to compress wage differentials among groups of workers with different schooling and experience levels.

Though technology, trade and institutions could have jointly played a role in explaining the observed pattern in wage inequality, we claim that technical change theories appears to be particularly useful to interpret our decomposition results, while explanations related to institutions and trade seem to be less convincing.

As for the institutional explanation, various reforms took place during last decade, such as the abolition of the wage indexation mechanism ("scala mobile"), the introduction of so called "pacchetto Treu" in 1997 and the "Legge 30" in 2003. These reforms increased the degree of flexibility[18] as well as they presumably reduced the strength of the unions role in the wage bargaining process. This in turn should have exerted a pressure toward both a rise of wage inequality and a positive coefficients (between) effect, rather than a wage compression. That is, if institutional channels effectively were at work, we would have expected increasing educational wage premia rather than a decline.

As far as the trade explanation is concerned, empirical literature for Italy shows that the impact of trade on wage inequality is significant although quite negligible

[18] In particular, in 2004 the OECD index of employment protection legislation placed Italy in an intermediate position, while in 1999 it came second to last, just above Portugal, meaning that in the nineties the Italian labour market was ranked by OCSE as one of the strictest.

in magnitude.[19] Further, there is not evidence of between industry workers reallocation induced by trade patterns specialization.

These reasons justify our focus on technological change theories to interpret the patterns observed in the Italian case, providing a set of descriptive statistics concerning the demand side of the market.

To compute these descriptive statistics we make use of four waves for each year (1993, 1998 and 2003) of the Italian Labour Force Survey,[20] for a total of about 2,400,000 observation and 605,000 employees. This dataset provides more detailed classifications of industries and occupations with respect to SHIW dataset as well as much greater sample size. For our purpose we limited our analysis to employees in public and private sectors, excluding self-employment from the analysis, so to get as close as possible to the sample used in the SHIW dataset. Then, we aggregated NACE 2-digit classification into 21 major industries categories. Besides, in order to define skill levels, we exploited the hierarchical nature of the Italian Classification of Occupations (CPI1999), which is quite similar to ISCO-88 classification.[21] 1-digit level codes of CPI1999 provide an adequate taxonomy of the workforce into skill groups, as occupations are ranked according to complexity and range of tasks involved. In particular, we define as high skill jobs occupations ranked with codes 1 and 2 in CPI1999 1-digit level classification (e.g. Legislators, senior officials and managers, Professional), as medium skill jobs occupations listed with codes 3 to 5 (Technicians and associate professionals, Clerks, Service workers and shop and market sales workers), and as low skill jobs occupations coded from 6 to 9 (Skilled agricultural and fishery workers, Craft and related trades workers, Plant and machine operators and assemblers, Elementary occupations). At this level of aggregation CPI1999 is perfectly equivalent to ISCO, thus we will refer to ISCO in the following of this paper.

The first descriptive statistics we provide is a shift share analysis. The basic idea is to verify whether changes in the structure of product demand may shift the relative labour demand function for high skilled workers. A standard index of the impact of product demand shifts on the relative labour demand functions is the average employment share growth by industry, weighted by the initial employment distribution of each educational group (Katz and Murphy, 1992, Autor, Katz and Krueger, 1998). In particular, following Autor, Katz and Krueger (1998) we decompose the change in the employment share of group $j$ (university graduates, upper secondary graduates, lower secondary, primary) between years $t$

[19] See Matano and Naticchioni (2007) for a survey on the impact of trade variables on wage structure and inequality. This paper also provide estimates concerning these issues, using INPS and ISTAT data.

[20] Differently from previous analysis carried on SHIW dataset, we here use 2003 instead of 2004 because of a break in Italian LFS series.

[21] See www.ilo.org/public/english/bureau/stat/isco/index.htm for further details about the ISCO classification.

and $\tau$, $\Delta E = E_{jt} - E_{j\tau}$, into a term reflecting the reallocation of employment share across industries and a term reflecting changes in the shares of each group within industries. This index is given by:

$$\text{(5)} \qquad \Delta E_{jt} = \sum_k \left(\Delta E_{kt} \cdot \alpha_{jk.}\right) + \sum_k \left(\Delta \alpha_{jkt} \cdot E_{k.}\right)$$

where $k$ indexes industries, $\alpha_{jkt} = \frac{E_{jkt}}{E_{kt}}$ is the employment share of group $j$ in industry $k$ in year $t$, $\alpha_{jk.} = \frac{\alpha_{jkt} + \alpha_{j\tau t}}{2}$ and $E_{k.} = \frac{E_{kt} + E_{k\tau}}{2}$ are the average over time of $\alpha_{jk.}$ and $E_{k.}$. The first term in (5) reflects the change in aggregate employment share of group $j$ attributable to changes in employment share between industries, while the second term reflects within industry skill upgrading. More specifically, within sector components presumably reflects factor (education) specific shocks, such as changes in the relative productivity of skilled workers due to skill-biased technical change, while between components reflect industry specific shocks altering relative market shares, such as changes in consumer tastes. Table (6) depicts such a between and within industry decomposition of the growth in the employment share from 1993 to 2003 for university graduates, upper secondary graduates, lower secondary and primary, using a two digit classification for industries. We have also considered two distinct time sub periods (1993-1998, 1998-2003), in order to verify whether there are different trends over time.

| | | **Primary** | **Lower Secondary** | **Upper Secondary** | **Graduates** |
|---|---|---|---|---|---|
| 1993-1998 | Total | -0.069 | -0.003 | 0.053 | 0.019 |
| | *Between* | *-0.006* | *-0.002* | *0.005* | *0.003* |
| | *Within* | *-0.063* | *-0.001* | *0.047* | *0.016* |
| 1998-2003 | Total | -0.032 | -0.031 | 0.048 | 0.016 |
| | *Between* | *-0.001* | *0.000* | *0.002* | *-0.001* |
| | *Within* | *-0.031* | *-0.031* | *0.046* | *0.017* |
| 1993-2003 | Total | -0.101 | -0.034 | 0.100 | 0.035 |
| | *Between* | *-0.006* | *-0.002* | *0.007* | *0.002* |
| | *Within* | *-0.094* | *-0.032* | *0.093* | *0.033* |

Table 6. Within-between decomposition of employment share variation by education

The overall changes of the employment share for upper secondary and university graduates are explained by the positive contributions of within and between components, as well as the decrease in the share of low educated is related to the negative change of both between and within components. In particular, the increase of 0.035 in the employment share for graduates over the period is the result of a negligible 0.002 rise between sector and a more important 0.033 rise within sector. To the extent that within variations reflects skill biased technical change (Berman, Bound and Johnson, 1992; Autor, Katz and Krueger, 1997), one could argue that this evidence encourages a skill-biased interpretation for the Italian case, since the within effect dominates the between effect. However, three issues are in contrast with this provisional interpretation.

First, the skill-biased interpretation seems not to be coherent with the negative coefficients (between) component derived in the quantile decomposition analysis. Second, the share of graduates raised at a lower rate with respect to other developed countries, and this partly reduce the implication of a skill bias theory for Italian labour market. This remark is further reinforced by the fact that not only the growth rate but also the stock of graduates in Italy is among the lowest in the context of developed countries.[22] According to the endogenous technical change theory (Acemoglu, 2002), the low levels of both stock and growth rate of human capital imply that the size of the market of high educated workers might be not enough to provide incentives for technological innovations.

Third, using education as a proxy for the technological content of labour demand, as in the shift share analysis carried in table 6, may be misleading. This is because the share of graduates employed in high skill occupation (as defined by ISCO 1-2, table 7) strongly reduced between 1993 to 2004, while the share of graduates increased in the medium skilled occupations (ISCO 3-5) as well as in low skill occupations (ISCO 6-9). This evidence suggests the presence of a "mismatch" between the technological content of occupations and the workers' educational level.

| | ISCO 1-2 | ISCO 3-5 | ISCO 6-9 |
|---|---|---|---|
| 1993 | 70.4 | 26.8 | 2.8 |
| 1998 | 65 | 32.3 | 2.7 |
| 2003 | 55.9 | 40.8 | 3.3 |

Table 7. College graduates workers distribution across occupations

To deepen this critical point, we replicate the previous shift share exercise by dividing the workforces into high skilled, medium skilled and low skilled groups (table 8), rather than into educational attainments. Comparing findings in table 8 and table 6, we observe two basic differences between the changes of skills contents of occupations and the changes of educational attainments of the workforce.

[22] As already stressed, OECD (2004) states that 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.

First, the within component related to changes for high-skilled occupations is much less pronounced than the one derived for graduates, and it decreased over the period, being slightly positive from 1993 to 1998 and slightly negative, and very close to zero, from 1998 to 2003. This implies that, if any, the skill-biased change has slowed down during the period. Furthermore, it is worth noting that both the between and the within components are quite negligible in magnitude in the period 1993-2004 (both are equal to -0.001), meaning that the shift share analysis does not detect any evidence in favour of neither a between industries reallocation nor a skill-biased interpretation (within).

Second, the share of high skilled occupations remains quite stable over time (+0.05%) while the share of graduates increased by 3.5%, suggesting that the technological content of the relative labour demand for skilled labour, proxied by occupational groups, has not increased at the same pace of the increase in the supply of skilled workers, proxied by education groups.

This evidence confirms the presence of a "mismatch" between the technological content of occupations and the workers' educational level. Such a mismatch could have played a role in explaining why the increased relative demand for high educated workers has not translated in an increase of wage differentials, i.e. a positive coefficients (between) component across the wage distribution.

| | | High skilled | Medium skilled | Low skilled |
|---|---|---|---|---|
| 1993-1998 | Total | 0.007 | 0.029 | -0.035 |
| | *Between* | *0.002* | *0.014* | *-0.016* |
| | *Within* | *0.004* | *0.015* | *-0.019* |
| 1998-2003 | Total | -0.002 | 0.038 | -0.036 |
| | *Between* | *-0.001* | *0.012* | *-0.011* |
| | *Within* | *-0.001* | *0.026* | *-0.025* |
| 1993-2003 | Total | 0.005 | 0.066 | -0.072 |
| | *Between* | *0.001* | *0.026* | *-0.027* |
| | *Within* | *0.004* | *0.040* | *-0.044* |

Table 8. Within-between decomposition of employment share variation by skill level

To sum up, according to the quantile decomposition results and to the set of descriptive statistics, we point out that the Italian case is characterized by features that are not completely in line with a skill-biased technological change explanation, suggesting that the relative supply of skilled labour increases more than the demand for high-skilled occupations, generating a mismatch penalizing the premia for human capital accumulation.

## 7. Conclusion

In this paper we investigate the relation between wage structure, inequality and skill-biased change for the Italian case. Using a quantile decomposition methodology we show that the driving force of the changes in wage structure is given by a negative coefficients (between) component. This result is consistent with the evidence of falling educational wage premia in Italy (Naticchioni, Ricci, Rustichelli, 2007). When relating to the literature on this topic, this finding does not support a skill-biased change interpretation of changes in wage structure.

We also provide descriptive evidence suggesting that the technological content of the relative labour demand for skilled labour, proxied by occupational groups, has not increased at the same pace as the increase in the supply of skilled workers, proxied by education groups. This evidence suggests the presence of a "mismatch" between the technological content of occupations and the workers' educational levels, which might in turn represents a partial explanation of the negative coefficients component of the decomposition analysis.

## References


Acemoglu, D. (2002), "Technical Change, Inequality, and the Labor Market", *Journal of Economic Literature*, 40, pp.7-72.

Arias, O., Hallock, K.F., Sosa-Escudero, W. (2001), "Individual Hererogeneity in the returns to schooling: instrumental variable quantile regression using twins data", *Empirical Economics*, vol.26, pp.7-40.

Autor, D.A, Katz, L.F., Kearney, M.S. (2005), "Rising Wage Inequality: The Role of Composition and Prices", NBER no. 11628.

Autor, D., Katz, L., Krueger, A. (1998), "Computing Inequality: Have Computers Changed the Labor Market?" *Quarterly Journal of Economics* 113, 1169-1213.

Blinder, Alan (1973) 'Wage Discrimination: Reduced Forms and Structural Estimation,' *Journal of Human Resources*, 8, pp.436-455.

Barth E., Lucifora C. (2006), Wage Dispersion, Markets and Institutions: The Effects of the Boom in Education on the Wage Structure, IZA DP 2181.

Bound, J. and G. Johnson, (1992), "Changes in the Structure of Wages in the 1980s: An Evaluation of Alternative Explanations", *American Economic Review,* 82, pp. 371-92.

Brandolini, A., Cipollone, P., Sestito, P. (2001), "Earnings dispersion, low pay and household poverty in Italy, 1977-1998", Discussion Paper 427.

Bratti, M., Matteucci, N. (2004) "Is There Skill Biased Technological Change in Italian Manufacturing: Evidence from Firm-Level Data", Quaderni di Ricerca, Universit`a Politecnica delle Marche, No. 202.

Brunello G., Miniaci R., (1999), "The Economics Returns to Schooling for Italian Men. An Evaluation Based on Instrumental Variables", *Labour Economics*, vol. 6, n. 4, pp.509-519.

Buchinsky, M. (1994), "Changes in the U.S. Wage Structure 1963-1987: Application of Quantile Regression", *Econometrica* 62, pp.405-458.

Buchinsky, M. (1995), "Estimating the Asymptotic Covariance Matrix for Quintile Regression Models: a Montecarlo study", *Journal of Econometrics*, 68, pp.303-338.

Burtless, G. (1995), "International Trade and the Rise in Earnings Inequality," *Journal of Economic Literature*, American Economic Association, vol. 33(2), pages 800-816.

Card, D. (2001), Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems, *Econometrica*, vol. 69(5), pp. 1127-60.

Caroli, E., Van Reenen, J. (2001), "Skill-Biased Organizational Change? Evidence From A Panel Of British And French Establishments," *The Quarterly Journal of Economics*, MIT Press, vol. 116(4), pages 1449-1492.

Casavola P., Gavosto A., Sestito P. (1996), "Technical Progress and Wage Dispersion in Italy: Evidence from Firms' Data", *Annales d'Economie et de Statistique*, 41/42.

Di Nardo, J., N.M. Fortin, and T. Lemieux (1996) 'Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach', *Econometrica* 65, pp.1001-46.

Fitzenberger, B, and Kurz, C., (2003), ""New insights on Earnings Trends across Skill Groups and Industries in West Germany", 2003, *Empirical Economics*, Vol. 28, pp. 479-514.

Giustinelli, P. (2004), "Quantile Regression Evidence on Italian Education Returns", *Rivista di Politica Economica*, XI-XII.

Gottschalk, P. and T.M. Smeeding (1997), "Cross-National Comparisons of Earnings and Income Inequality", *Journal of Economic Literature*, 35, 633-687.

Juhn, C., Murphy, K.M, and Pierce, B. (1993) 'Wage Inequality and the Rise in Returns to Skill,' *Journal of Political Economy*, 101, pp.410-42.

Katz, L.F. and K.M. Murphy, (1992), "Changes in Relative Wages, 1963-87: Supply and Demand Factors", *Quarterly Journal of Economics*, 107, pp.35-78.

Koenker, R., Basset, G. (1978),"Regression Quantiles", *Econometrica*, vol. 46, pp. 33-50.

Koenker, R., Basset, G. (1982), "Robust test for Heteroscedasticity Based on Regression Quintiles", *Econometrica*, 50, pp.43-61.

Koenker R., Bassett G., (1986), "Strong consistency of regression quantiles and related empirical processes." *Econometric Theory* 2: 191–201.

Krueger, A.B. "How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984-1989", *The Quarterly Journal of Economics*, February 1993, 108(1), pp.33-60.

Lee, David S, (1999), "Wage Inequality in the U.S. during the 1980s: Rising Dispersion or Falling Minimum Wage?", *Quarterly Journal of Economics,* 114, pp. 977-1023.

Lemieux, T. (2002). "Decomposing Changes in Wage Distributions: A Unified Approach", *Canadian Journal of Economics*, 35(4), 646-688.

Lilla, M. (2005), "Disuguaglianze salariali en italia: nuove evidenze dai microdati SHIW", *Politica economica*, no.1, pp. 71-102

Machado, J. and J. Mata. (2005), "Counterfactual Decompositions of Changes in Wage Distributions Using Quantile Regression", *Journal of Applied Econometrics*, 20(4), pp. 445-65.

Manacorda, M. (2004), "Can the Scala Mobile Explain the Fall and Rise of Earnings Inequality in Italy? A Semiparametric Analysis, 1977-1993", *Journal of Labor Economics* 22, no. 3 , pp. 585-613.

Matano, A., Naticchioni, P. (2007), "Trade and wage inequality: Do local comparative advantages matter?", forthcoming as DSE-ISFOL working paper.

Naticchioni, P., Ricci, A., Rustichelli, E., (2007), "Far away from a skill-biased change: falling educational wage premia in Italy", forthcoming as working paper, University of Rome "Tor Vergata".

Melly, B. (2005), "Decomposition of Differences in Distribution Using Quantile Regression", *Labour Economics*, 12, (4), pp. 577-590.

Melly, B. (2006), "Estimation of counterfactual distributions using quantile regression", University of St. Gallen, Discussion Paper.

Oaxaca, R. (1973), "Male-Female Wage Differential in Urban Labour Market", *International Economic Review*, 14, pp. 693-709.

Peracchi, F. (2004), "Educational wage premia and the distribution of earnings: an international perspectives", in E.Hanushek and F.Welch (eds.), *Handbook of the Economics of Education*, North-Holland, Amsterdam, forthcoming.

Pereira, P., Martins, P. (2004), "Does Education Reduce Wage Inequality? Quantile Regression Evidence From 16 Countries", *Labour Economics*, 11(3), pp. 355-371.

OECD (2004), *Education at a glance*, Paris.

OECD (2005), *Education at a glance*, Paris.

OECD, (2004), "Employment protection regulation and labor market performance", in *Employment Outlook*, Paris.