A REASSESSMENT OF WAGE INEQUALITY IN ITALY

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Abstract

A job polarization explanation has been proposed in the last decade to relate the changes in wage inequality to the changes in the job quality distribution. In this paper we show that the Italian case represents an interesting outlier in this literature. Wage inequality decreased in the private sector from 1993 to 2006, both in the upper and in the lower part of the distribution. By applying a quantile decomposition procedure we find out that the decrease of wage inequality is driven by a negative coefficients component, related to falling educational wage premia. We argue that this evidence can be related to changes in the job quality distribution that have penalized top occupations and to patterns of over education. Furthermore, we show that residual inequality partly affects the changes in the lower part of wage distribution and that supply-demand explanations play only a negligible role.

JEL codes: I20, J24, J31, J45, J51

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1. Introduction

The analysis of changes in the distribution of wages has been an active research area in labour economics over the last thirty years, especially because of the steep increase of wage inequality and schooling premia in the United States and other Anglo-Saxon countries since the early 1980s (Bound and Johnson, 1992; Katz and Murphy 1992). To a less extent, increases of the educational wage premia (EWP, henceforth) and wage inequality are also documented for other OECD countries (Gottschalk and Smeeding, 1997).

In the last decade, a new and intriguing explanation for recent trends in wage inequality has been proposed by three influential papers (Autor et al, 2006, for the US, Goos and Manning, 2007, for the UK, and Dustmann et al., 2008, for Germany). Using detailed classification for occupations, these papers investigate the changes over time of the job quality distribution, i.e. the over time changes in employment shares along the occupation distribution (ranked by median wage). The main intuitions concerns the fact that new technologies are substitute to routine tasks, located in the middle of the wage distribution, complementary to non routine cognitive, and uncorrelated to manual tasks, located respectively at the top and at the bottom of the job quality distribution. Hence, the technological change favours the employment growth for cognitive tasks in high paid jobs, while it decreases the employment in middling jobs where routine tasks are used. The new technologies are then responsible for the polarization trends, i.e. the increase in the upper tail wage inequality (the 90/50 index) and for the decrease of the lower tail inequality (the 50/10).

In this paper we show that the Italian case emerges as an interesting outlier in the relation between changes in wage inequality, schooling premia, and the job quality distribution. Our analysis can be summarized in three main findings.

First, using the Survey of the Household Income and Wealth (SHIW) of the Bank of Italy for the period 1993-2006, we point out that in the private sector the 90/10 ratio of net wages decreased by 13%, from 2.77 to 2.42, due to a decrease in both the 90/50 and 50/10 indexes.

Second, to identify which forces have played a role for the decreasing wage inequality we implement a quantile decomposition methodology, developed by Machado and Mata (2005), Melly (2005), and Autor, Katz, Kerney (2005), which decomposes the changes of the wage distribution into changes in covariates, coefficients, and residual components. Applying a standard mincerian wage equation, where education, experience and gender are included as covariates, we point out that the decrease in wage inequality is mainly driven by the negative coefficients component and, to a lesser extent, by a negative residual-within component, while the effect of covariates is negligible. The negative

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coefficients component is consistent with the falling educational wage premia over the period, as pointed out by Naticchioni, Ricci, Rustichelli (2008).

Third, using INPS administrative data we provide evidence that the negative coefficients component, which is the driving force of the decreasing inequality, may be related to changes in the job quality distribution offered by firms between 1993 and 2002. In particular, we observe patterns that are against job polarization trends, since the increase in employment shares of top occupations is always lower than the increases in employment shares for middle and/or lousy jobs. Moreover, using both SHIW and LFS-ISTAT data we show that from 1993 to 2006 the share of educated workers increased more in the lower than in the upper tail of the job quality distribution, as also observed for the UK case (Goos and Manning, 2007). These over education patterns reinforce the explanation related to changes in the job quality distribution: educated workers entering the labour markets are willing to accept jobs at the bottom and at the middle of the job quality distribution because the shares of skilled occupations decreased over time, affecting negatively the dynamics of educational wage premia and through this channel reducing wage inequality.

Furthermore, we argue that supply-demand interactions cannot be considered as a leading explanation for the falling of EWP and wage inequality in the private sector. In particular, using the CES production approach (Card and Lemieux, 1999) we show that differences in relative supply can only partly affect differences in relative wages between groups with different human capital endowments. Finally, we show that residual inequality and changes in the tax regimes might have played a role in explaining the trends observed in the lower part of the distribution.

The paper is structured as follow. Section 2 presents a survey of the literature. Section 3 introduces the data used in the paper as well as descriptive statistics. Section 4 presents the decomposition analysis, while section 5 gives the results. Possible explanations for the inequality trends are investigated in section 6 and section 7 provide a wider discussion on the findings of the paper. Section 8 concludes.

2. A survey of the empirical Literature
Most of the theories proposed to explain observed trends in wage inequality for OECD countries emphasize the central role played by technical change and human capital accumulation (Acemoglu, 2002). Standard theories of skill biased technological change (SBTC, henceforth) predict that new technologies favour the relative demand for high educated workers and, as a consequence, are associated to an increase of wage inequality. Katz and Murphy (1992) and Bound and Johnson (1992), for instance, show that the relative demand for more educated workers increased steadily during the 1970s and the 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 SBTC is greater than the increase in the relative supply, entailing a raise of wages for graduates.1

Furthermore, recent empirical evidence shows that inequality trends are characterized by divergent patterns in the upper and in the lower tail of the wage distribution. An explanation for this evidence concerns the changes in the structure of the job quality distribution, as in Autor et al. (2006) and Goos and Manning (2007). Using detailed classification for occupations, these papers investigate the over time changes in employment shares along the occupation distribution, ranked by median wage per occupation. Moreover, using other data sources, for instance the Dictionary of Occupational Titles (DOT) for the US, they provide evidence that cognitive skills are concentrated at the top of the job quality distribution, routine skills are instead required at the middle, and manual skills are located at the bottom. Autor et al. (2006) and Goos and Manning (2007) argue that new technologies are substitute to routine tasks, located in the middle of the wage distribution, and are complementary to non routine cognitive and manual tasks, located respectively at the top and at the bottom of the job quality distribution. Hence, the technological change favours the employment growth for cognitive tasks in high paid jobs as well as for manual tasks in low paid jobs, while it decreases the employment in middling jobs where routine tasks are used. In this framework, the new technologies would be responsible for the increase in the upper tail wage inequality (the 90/50 index) and for the decrease of the lower tail inequality (the 50/10), observed for instance in the US case.

These interpretations have not been 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 and Smeeding, 1997). For instance, 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. They estimate quantile mincerian regressions studying the differences in educational wage premia along the wage distribution and over time. Four different patterns emerge: i) a positive increasing contribution of education on within wage inequality in Portugal; ii) a positive and stable effect of education on inequality in Austria, Finland, France, Spain, Sweden, Ireland; iii) a neutral role in Denmark and Italy; and iv) a negative impact in Greece.

Analogously, Barth and Lucifora (2004) provide a comparative study on the relationship between wage inequality, market forces and institutions for 12 European countries for the period 1984-2003. They show that the increase of educational levels closely matched the shifts of the relative demand for skilled workers driven by technological change, and this should explain why in some countries the wage premia for education rose moderately. In particular, they do not find evidence that the expansion of higher education have lead to an

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1 The supply demand technology paradigm remains the main theoretical framework also when the analysis takes into account the whole wage distribution, and not only the mean wage differentials by educational groups. 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.
erosion of graduate wages, nor evidence of increasing over-education in Europe. Further, they claim that labour market institutions have played a key role in compressing wage structure, even thought at different point of the wage distribution. Finally, a recent paper by Dustmann et al. (2008) challenge the view that SBTC is not a pervasive phenomenon in European countries, showing that job polarization is one the main explanations for the increase in wage inequality in the upper tail of the distribution in Germany, similarly to the US and UK cases.

As for the Italian case, the paper that addresses the issue of wage inequality for a very long time period is Brandolini, Cipollone and Sestito (2002), which use the survey SHIW of Bank of Italy to investigate the dynamics of inequality of net wages from 1977 to 1998.\(^2\) This paper points out that the distribution of net wages narrowed from 1977 to the end of the 1980s, mainly due to a wage indexation mechanism (the so-called “Scala Mobile”) that 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 concerning the abolition of the wage indexation mechanism (in 1992) generated an increase in earning inequality, which mainly took place between 1991 and 1993, as also stressed by Manacorda (2004). Then, from 1993 to 1998 Brandolini, Cipollone and Sestito (2002) argue that wage inequality remained basically unchanged.\(^3\)

More recent papers have extended the period of analysis to 2002, using SHIW data. Lilla (2005) argues that in the period 1998-2002 inequality indexes concerning net wages slightly increased, both in the between and within component. Another paper of Boeri and Brandolini (2005) investigates the evolution of inequalities in Italy, both of incomes and wage, using SHIW data. They claim that the distribution (both of incomes and wages) shifted, between 1993 and 2002, to the advantage of the households of self-employed, managers and retired persons, and to the disadvantages of households of production and clerical workers.

The dynamics of wage inequality in Italy has been also investigated using the social security contribution data, the INPS employer-employee dataset. This data source has the advantage to have information on gross wages, much more observations per year and a longitudinal dimension, while it has the drawback that there is no information concerning education and that it covers only the private sectors. Using this dataset, Devicienti (2003) shows that in the period 1985-1996 wage inequality increased slightly, especially in the period 1992-1993, as in the SHIW data. Applying the Juhn, Murphy and Pierce (1993) decomposition, Devicienti (2003) points out that inequality changes over time are mainly due to a positive coefficients component, while the residual and the covariates components are found to be quite negligible.

\(^2\) We will deepen in section 3 the details of the SHIW data.
\(^3\) In their analysis of wage 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 the trend for the whole population.
As far as the literature concerning education and wages, Brunello, Comi and Lucifora (2001) estimated the average returns to schooling by applying least square and instrumental variables techniques. Using SHIW (Bank of Italy) data they detect an increasing trend of educational wage premia from 1977 to 1995, mainly driven by the trend in the public sector. Naticchioni, Ricci and Rustichelli (2008) use the SHIW data for the period 1993-2004. By means of quantile regressions, they show that EWP in the private sector decline across the entire wage distribution, evidence that holds when different robustness checks are carried out in order to deal with sample selection issues. Other related papers are Giustinelli (2004) and Lilla (2005), which perform a quantile regression analysis on SHIW data from the beginning of the nineties to early 2000s, without addressing the issue of intertemporal comparison of EWP.4

Another remark concerns a brief description of the changes in the institutional setting of the Italian labour market. In 1992-1993 the wage setting in the private labour market was completely reformed. Two levels of bargaining were introduced, inducing wage moderation and a strengthening of the degree of centralization of the wage setting process. The first sectoral-national level sets wage floors for each occupation at the national level for each sector, in order to maintain over time a stable purchasing power. The second level of bargaining takes place at the company level, or at a territorial level, and it should relate wages to the productivity dynamics. This two level bargaining system still applies in the Italian labour market. Tronti (2007) shows that the incidence of the second level of bargaining has remained quite low over time, suggesting that wages has been only weakly related to productivity trends. Moreover, other reforms were introduced in the labour market in 1998 (“Pacchetto Treu”) and 2003 (“Legge 30 - Biagi”). These reforms did not concern the wage setting system, as they were mainly focused on the increase of the hiring flexibility in the labour market, introducing new types of atypical temporary contracts.

3. Data and Descriptive statistics

The empirical analysis is based on the Survey of the Household Income and Wealth (SHIW) of the Bank of Italy, from 1993 to 2006. This database represents the main source used in the literature to investigate inequality issues in Italy, as shown in the survey of the literature. We consider this time period for different reasons. First, because former periods have been widely covered in the literature. Second, because it is a homogenous institutional period, since the reforms in 1992 and 1993 represented a breaking point for the Italian labour market. Nonetheless, as robustness check we replicated our decomposition analysis considering the periods: 1995-2006, 1993-2002, 1993-2004. Results are very similar from a qualitative point of view, as also shown in Table 2 in the next sections.

The sample consists of employees aged 18-64. We focus on employees with permanent jobs or with fixed term contracts (“contratti a tempo determinato” or “apprendistato”),

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4 As for international comparisons, Peracchi (2006) uses ECHP data to compare EWP for European countries. By applying OLS estimates he finds out that Italy is in an intermediate position, EWP being higher than in Germany, Belgium, Denmark, UK, and lower than in France, USA, Ireland, Portugal.
while we do not consider atypical contracts introduced after the reforms in 1998 and 2003 ("collaborazioni coordinate e continuative", "contratti a progetto"), since we cannot identify these kind of contracts in 1993 and since formally these workers are to be considered as self-employed.\footnote{Formally these contracts are considered as self-employment contracts. However, they are often used by employers to replace dependent workers, because of the lower social security contributions. Note also that the share of these contracts is quite negligible in the SHIW data, being equal to 2.2\% in 2004 in the private sector. These atypical contracts are usually characterized by low durations (few months) and low average wages (in the SHIW data in 2006 the average wage for this kind of contracts was less than the 50\% of the average wage of permanent and fixed term contracts).} Further, we consider employees who have worked more than three months in the reference year. We refer to the real monthly net wage, obtained by dividing the yearly wage from employment (including overtime, bonuses, and fringe benefits\footnote{In the US literature the fringe benefits include life and health insurances, vacation and sick leave, and they can be very relevant as a share of total wage. In Italy they are less widespread. This is because some of the benefits mentioned for the US are supplied by the State (health insurance) and others are fixed by national contracts (vacation and sick leave). In Italy usually the fringe benefits are made by employer-paid cars, luncheon vouchers, and some additional health services, such as the dental expenses, a health sector that in Italy is basically private. The correspondent value of money related to these benefits are computed and self-declared by the employee. However, descriptive statistics do not change much when we do not consider this component of wages.}), net of taxes and social security contributions, by the number of months worked in that year, and deflating by the consumer price index (base year 2004). As all the papers for Italy using SHIW data we are forced to consider net wages, since information about gross wages is not available. This represents a drawback of the analysis, since our results might also be affected by changes in the tax regimes over time. We will address this issue in section \ref{sec:6.3}.\footnote{Note also that we drop 0.025\% of the observations in both the right and left tail to cancel out potential outliers. Results do not change including these observations in the sample.}

Furthermore, we consider full-time equivalent individuals, controlling 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.\footnote{We define as employee in the private sector who is not employed in the public sector. The public employee is defined using two variables in the database, APSETT and DIMAZ. APSETT provides us with self-declaration of the sector in which the individual works, including the public sector, while DIMAZ refers to the firm size, and it is specified when the employee declares that he/she is employed in the public sector. We consider as public employees those workers who declare for both questions that they are employed in the public sector. Results do not change much when we consider definitions of private employee based on APSETT and DIMAZ separately.}

Table \ref{tab:1} provides the descriptive statistics of the main variables in 1993, 1995, 2002, 2004, 2006, which are the years that we use in the analysis. The share of female increases monotonically over time, as expected. As for the educational levels, the share of graduates increases from 4\% in 1993 to 9\% in 2006, as well as the share of upper secondary workers increases from 33\% to 47\%. Instead, the shares of primary and lower secondary workers decrease over time. As far as the experience levels are concerned, the share of individuals with less than 15 years of experience decrease and, symmetrically, the share of those with more than 16 years of experience slightly increase. As for the wage dynamics, average wages slightly decrease in 1995 and 1998 and then increase again in 2006, similarly to the
trend of the median wages. Interestingly enough, the 10th percentile substantially increases over time (13%) and the 90th percentile decreases slightly.

As for the evolution over time of wage inequality in Italy, the literature argues that it has been quite stable from 1993 to 2002 (Brandolini, Cipollone, Sestito, 2002, Lilla 2005, Boeri and Brandolini, 2004). However, these papers do not investigate separately the patterns of public and private sector, and do not make use of the SHIW last waves for 2004 and 2006. In this section we point out that when considering only the private sector inequality trends change. As for the Gini index, it decreases by 15%, from 33.5 to 28.6, while for the whole set of employees, putting together public and private sector, it is actually very stable until 2004, as shown in other papers, and it starts decreasing in 2006 (-7.8%). Using another standard index of inequality, the ratio between the 90th and the 10th percentile, provides very similar evidence. The inequality index for the whole set of employee only slightly increases (1%) from 1993 to 2004, while it falls by 4% from 1993 to 2006. When focusing on the private sector, the 90/10 index decreases by 10% from 1993 to 2004 and by 13% from 1993 to 2006, from 2.77 to 2.42.

Useful insights can be also derived from the analysis of the changes in the different tails of the wage distribution. In particular, we can investigate the lower (upper) tail of the wage distribution analyzing the 50/10 (90/50) ratio. From Figure 1 it is possible to notice that the decrease in the 90/10 is associated to a decrease in both the 90/50 and the 50/10. The fall in the 50/10 from 1993 to 2006 is greater (9%) than the fall in the 90/50 (4.5%). Furthermore, from Figure 1 it is possible to investigate the dynamics of inequality trend in the private sector. Actually, inequality started to increase immediately, already in 1995, then from 1998 to 2002 it has remained quite stable, and it decreased again from 2002 to 2006.9

In order to identify what are the forces that have played a role in explaining inequality trends in the private sector between 1993 and 2006 we carry out a decomposition analysis.

4. Quantile Regression Decomposition

In this section we 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 contributions in 1973 by Oaxaca and by Blinder, and has seen great developments over 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. We make use of a methodology that has been recently developed by Machado & Mata (2005), and extended by Melly (2005) and Autor et al. (2005), papers that use the same general idea and slightly different techniques in the implementation. As stressed by Autor

9 Using INPS administrative data for the private sector we observe different patterns of wage inequality. In particular, wage inequality increased slightly from 1993 to 2002, by 3% (computed on full-time jobs, age 18-64). However, the differences in the nature of the two datasets (administrative data rather than survey data), the wage variable used (gross vs net yearly earnings), the way how the monthly wage is computed (worked days or weeks vs worked months), do not allow a direct comparison between these two data sources. It is worth noting that the findings concerning inequality trends in the SHIW data might be biased only if underreporting for wealthy employees had been increasing overtime, hypothesis that is not testable with any kind of data.
et al. (2005), the Machado-Mata method for calculating counterfactual densities is closely related to the kernel reweighting approach proposed by DiNardo, Fortin and Lemieux (1996) and improved by Lemieux (2002, 2005). Further, the Machado-Mata approach can be easily extended to provide a uniform and consistent treatment of both overall inequality and residual inequality. On the contrary, alternative approaches apply a hybridized set of methods (OLS regressions, parametric probability models, and kernel reweighting) to separately derive counterfactuals for overall and residual inequality.

This methodology takes as starting point the two quantile estimations in cross-section, for 1993 and 2006, using a Mincerian standard specification:

\[
\ln w_i^t = X_i^t \beta(\theta) + u_i^t
\]

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.\(^\text{10}\)

Once having derived the quantile parameters \(\beta(\theta)\), this methodology allows to estimate the marginal distribution of wages as function of both the matrixes of \(X\) and of \(\beta(\theta)\). See Appendix 1 for a detailed explanation of the estimate of the marginal distribution of wages.

We implement this methodology using the SHIW Bank of Italy data, in 1993 and 2006. We consider the monthly real wages (in log) as dependent variable, and as covariates education, experience and gender. Further, we implement 200 weighted quantile estimations on a regular grid, from 0 to 1 (0.005, 0.01, 0.015, …, 0.99, 0.995), deriving the coefficients \(\beta(\theta)\) along all the \(\theta\) distribution. We then derive the unconditional wage distribution 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 considered as drawn from the unconditional wage distribution.\(^\text{11}\) As for the fit of the estimation methodology, it is very accurate, as shown in Figure A1 in appendix 2.

This methodology derives the marginal distribution of wages as function of covariates and coefficients, which implies the possibility to generate counterfactual densities, using different sets of \(g(X)\) and \(\beta(\theta)\). For instance, it would be possible to compute a

\(^\text{10}\) Note that choosing this set of covariates leads to a human capital interpretation, which we argue have played a role in the last decades. Obviously, choosing different sets of covariates would shed light on other possible explanations. For instance, for an analysis focusing on a generational approach (age classes, and cohorts) see Rosolia and Torrini (2007).

\(^\text{11}\) Note that instead of drawing observations from \(g(X)\) we consider the whole \(X\) matrix, as in Autor et al. (2005). Further, we do not consider, as in Machado and Mata (2005), only the elements on the diagonal of the resulting matrix generated by \(\hat{w}_j \equiv \{X_i, \hat{\beta}(\theta)\}_{i=1, \ldots, N, j=1, \ldots, J}\), but all the matrix. This means that we produce a much larger set of simulated values for the unconditional wage distribution (200 times larger), as in Autor et al. (2005).
counterfactual distribution keeping the covariates at the 1993 level and coefficients at the 2006 level.\textsuperscript{12}

Furthermore, since the Machado and Mata (2005) methodology did not explicitly build up a direct measure for a within-residual component, i.e. between observationally equivalent individuals, our reference now moves on to Autor et al. (2005) and Melly (2005), who extend the Machado-Mata approach to identify three separate components in the computation of counterfactual distribution: covariates, coefficients and residuals.

Autor et al. (2005) and Melly (2005) define the coefficients component as a 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 2006):

\begin{equation}
\ln w_t^i = X_t^i \beta^t(0.5) + u_t^i, \quad t = 93, 06
\end{equation}

where $\beta^t(0.5)$ is the coefficients vector of the median regression in year $t$, which can be considered as a measure of between group inequality. To disentangle the effect of coefficients (between groups inequality) from the effect of residuals (within group inequality) it is important to note from (2) that the $\theta$th quantile of the residual distribution of $u_t^i$ conditionally on $X$ is consistently estimated by $X(\hat{\beta}^i(\theta) - \hat{\beta}^i(0.5))$.\textsuperscript{13} Accordingly, Melly (2005) defines the following vector of coefficients as a measure for the within component: $\hat{\beta}^{06,93}(\theta) = (\hat{\beta}^{06}(0.5) + \hat{\beta}^{93}(\theta) - \hat{\beta}^{93}(0.5))$, where the consistent estimate of the residual component given $X$, $(\hat{\beta}^{93}(\theta) - \hat{\beta}^{93}(0.5))$, is added to the between component, $\hat{\beta}^{06}(0.5)$, in 2006. In other words, we estimate the distribution that would have prevailed if the median return to characteristics had been the same as in 2006 but the residuals had been distributed as in 1993.

Using counterfactual distributions generated by applying different sets of covariates and coefficients, Melly (2005) computes how the variations over time of some quantile $q$ of the wage distribution is attributable to covariates, coefficients and residuals. In particular, denoting by $\hat{q}(\hat{\beta}^{06}, X^{06})$ the $q$ quantile of the estimated distribution generated using the vector of coefficients $\hat{\beta}^{06}$ and the set of covariates $X^{06}$, Melly (2005) estimates the residual component as the difference, at the quantile $q$, of the two following estimated distributions,

\begin{itemize}
\item \textsuperscript{12} Note that all this literature, for instance Autor et al. (2005), Melly (2005, 2006), Machado and Mata (2005), make use of the partial equilibrium assumption that aggregate quantities of covariates do not affect labour market prices and vice versa. This assumption represents the major drawback of this research field. As shown by Di Nardo, Fortin, Lemieux (2006), supply and demand adjustments can be quantitatively important, accounting for 21% to 33% of the growth of male 90/10 log hourly wage inequality between 1979 and 1988.
\item \textsuperscript{13} Note that it is possible to apply the conditional quantile process to (4), deriving: $Q_{u}(u | X) = Q_{u}(u | X) - X\beta(0.5) = X\beta(\theta) - X\beta(0.5)$.
\end{itemize}
\( \hat{q}(\hat{\beta}^{06}, X^{06}) \) and \( \hat{q}(\hat{\beta}^{06, r93}, X^{06}) \),\(^{14}\) where the \( X \) and the \( \beta^{(0.5)} \) are constant at the 2006 level while the residual component is the only one that changes over time.\(^{15}\)

Similarly, the difference between \( \hat{q}(\hat{\beta}^{06, r93}, X^{06}) \) and \( \hat{q}(\hat{\beta}^{93}, X^{06}) \) is due to changes in coefficients since characteristics and residual are kept at the 2006 level.\(^{16}\) Finally, the difference between \( \hat{q}(\hat{\beta}^{93}, X^{06}) \) and \( \hat{q}(\hat{\beta}^{93}, X^{93}) \) is due to changes of covariates.

To sum up, adding and subtracting \( \hat{q}(\hat{\beta}^{93}, X^{06}) \) and \( \hat{q}(\hat{\beta}^{06, r93}, X^{06}) \) it is possible to decompose the variation over time of an estimated quantile of the wage distribution into the three components (residuals, coefficients, covariates), as follow:\(^{17}\)

\[
\Delta \text{residuals (within)} = \hat{q}(\hat{\beta}^{06}, X^{06}) - \hat{q}(\hat{\beta}^{93}, X^{93})
\]

\[
\Delta \text{coefficients (between)} = \left\{ \hat{q}(\hat{\beta}^{06, r93}, X^{06}) - \hat{q}(\beta^{93}, X^{06}) \right\}
\]

\[
\Delta \text{covariates} = \left\{ \hat{q}(\beta^{93}, X^{06}) - \hat{q}(\beta^{93}, X^{93}) \right\}
\]

Similarly, it is also possible to decompose the variations of any inequality index we are interested in, such as the ratios 90/10, 90/50, 50/10.

It is worth noting that this decomposition analysis suffers from the standard critic related to the order of the decomposition, i.e. it would be possible to derive others counterfactual distributions ending up with different coefficients, covariates and residual effects. In other words, the order is arbitrary. We have chosen the same order as in Melly (2005) and Autor et al. (2005).

Other methodologies that compute the residual component have to assume independent error terms, as in the case of Juhn, Murphy and Pearce (1993). Methods based on quantile regressions can instead account for heteroscedasticity. This is actually crucial when the variance of the residuals expands as a function of education and experience (Lemieux, 2002) and when the population gets more educated and experienced, as in the Italian case.

\(^{14}\) Note that \( \hat{q}(\hat{\beta}^{06}, X^{06}) \) is different from \( Q_q(w | X_i) \), which represents the conditional quantile of the observed wage distribution.

\(^{15}\) It is worth noting that the difference for each quantile \( q \) between the two distributions \( \hat{q}(\hat{\beta}^{06}, X^{06}) \) and \( \hat{q}(\hat{\beta}^{06, r93}, X^{06}) \) can be easily rewritten in the following way: \[ \hat{q}(\hat{\beta}^{06}(0.5)+\hat{\beta}^{06}(\theta)-\hat{\beta}^{06}(0.5), X^{06})-\hat{q}(\beta^{06}(0.5)+\hat{\beta}^{93}(\theta)-\hat{\beta}^{93}(0.5), X^{06}) \], from which it comes out clearly that the only component that changes over time is the residual one.

\(^{16}\) As in the previous note: \[ \hat{q}(\hat{\beta}^{06, r93}, X^{06})-\hat{q}(\hat{\beta}^{93}, X^{06}) = \hat{q}(\hat{\beta}^{06}(0.5)+\hat{\beta}^{93}(\theta)-\hat{\beta}^{93}(0.5), X^{06})-\hat{q}(\beta^{93}(0.5)+\hat{\beta}^{93}(\theta)-\hat{\beta}^{93}(0.5), X^{06}). \]

\(^{17}\) Note that the sum of the three components exactly amounts to the estimated variation over time of that given quantile. This property is not shared with other methodology previously adopted.
5. **Quantile decomposition results**

As first remark, it is worth pointing out that it is possible to estimate the coefficients for education at all quantile of the distribution. This means that there are graduates in the lower part of the distribution and workers with low educational levels at the top. Table A1 in the appendix 2 gives some intuitions for these patterns, which are, in a sense, quite unexpected. In the left panel of the table we report the percentage of workers in the bottom 25% of the wage distribution, computed by educational level (primary, lower secondary, upper secondary and university), sector (agriculture, manufacture, services), and age (under 40 in the top panel, over 40 in the bottom panel). Symmetrically, the right panel reports the same descriptive statistics for the top 25% of the wage distribution. From the left panel it comes out that 62.9% of the workers in the bottom 25% of the wage distribution are under 40, and that the share of graduates (3.37%) is concentrated in the services sector (2.46%), a sector that has increased its employment share over time. The share of graduates over 40 in the bottom 25% of the distribution is instead lower than 1% (0.082%). As for the analysis of the right panel of table A1, it emerges that a high shares of workers over 40 (68%) are employed in the top 25% of the wage distribution, and that a high share of these over 40 workers (almost 20%) have a low educational levels (primary and lower secondary), confirming that in Italy experience careers can still provide high remunerations even when associated with low educational levels.

Table 2 displays the results of the quantile decomposition in the private sector, derived using a Mincerian equation with gender, education and experience as covariates. To interpret the figures of table 2 it is worth noting that the variation over time of selected quantiles (10, 25, 50, 75, 90) are to be considered as the differences of two logarithms, i.e. percentage change over the period. Panel A of table 2 shows that from 1993 to 2006 the median of the estimated distribution increases by 2.9% over time, the first decile increased by 12.5% while the 90th percentile decreased by 2.2%. Using the decomposition methodology we can identify the driving forces behind these changes of the wage structure. As for the covariates component, it is positive and constant across the wage distribution. This simply means that the increase in education and experience in the workforce would have shifted to the right the wage distribution, given fixed the other coefficients components. The coefficients (between) component turns out to be the one the changes the most along the wage distribution: from -2.5% at the 10th percentile to a -12% at the 90th, monotonically. Further, the within component displays an asymmetric impact on the wage distribution, being positive in the lower quantiles (4.7% at the 10th and 2.3% at the 25th) and negative in the upper quantiles (-1.7% at the 75th and -1% at 90th).18

The interplay between these forces determines the changes in the wage structure at selected quantiles. In particular, below the median wage the negative impact of the

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18 Note that the residual-within component has to be equal to zero at the median, by definition. Actually, our simulated counterfactual distributions allow to compute a within component not statistically different from zero at the median (we do not report standard errors). Also in Melly (2005) the residual effect is not significant different from zero (but very close to zero).
coefficients component is dominated by the positive impact of the covariates component, which is also strengthened by the positive within component. Above the median wage, on the contrary, the strong negative coefficients (between) component, which is also reinforced by the negative within component, dominates the positive covariates component.

In Panel B and C of Table 2 we report the same decomposition analysis for the periods 1993-2004 and 1993-2002, for mainly two reasons. First, to show that our analysis concerning the period 1993-2006 are robust to the choice of the period, i.e. the behaviour of the three decomposition components are qualitatively very similar in the three panels. Second, to have a better understanding of the dynamics of the different percentiles of the distribution. In particular, the 10\textsuperscript{th} percentile strongly increases over time, as already stressed in the descriptive statistics section. Table 2 shows that this increase in manly due to a change in the negative coefficients component (from -7.4\% in panel C to -2.5\% in panel A) and to an increase in both the covariates and residual components.

These over time variations at selected quantiles help to understand the dynamic of wage inequality. Actually, the standard inequality indexes (90-10, 90-50, 50-10) can be easily derived from Table 2, computing the related differences, both for the estimated variations and for the three decomposition components.

Table 3 shows the trends of the inequality indexes for the periods 1993-2002, 1993-2004 and 1993-2006. As for the period 1993-2006 the falling of the overall 90/10 index of wage inequality (-14.7\%) is concentrated more in the lower part of the distribution (-9.5\%) than in the upper tail (5.1\%). The analysis of the three components reported in table 3 shows that the 90/10 index reduction observed in the private sector is mainly driven by the negative coefficients (between) component (65\%), and to a less extent by the negative within components (39\%), while the covariates component is negligible. The 50/10 decrease is instead equally driven by the coefficients (48\%) and the residual components (49\%), while the 90/50 is strongly related to the negative coefficients component (95\%).

As far as the negative coefficients component is concerned, it is consistent with the dynamics of educational wage premia observed in Italy. Naticchioni, Ricci, Rustichelli (2008) show that educational wage premia decreased over the period 1993-2004 along the whole wage distribution. Since the coefficients component is derived comparing median coefficients in 1993 and 2006 for each group, it can be considered as a measure of the change over time of the coefficients of the chosen covariates, in our case mainly education. Returns to experience, on the other hand, have not changed much over time. Results for the period 1993-2002 and 1993-2004 (Table 3) are very similar from a qualitative point of view.

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19 Further, as expected, the covariates component increases from the period 1993-2002 to the period 1993-2006, since the share of educated and experienced workers raises.

20 The results of Naticchioni, Ricci, Rustichelli (2008) holds using both a continuous and a dummy specification for education, and are robust to several robustness checks (different econometric specifications, different population subgroups). Note that also Peracchi (2006) derived falling EWP for Italy, using ECHP data and OLS estimates.

21 Actually, from 1993 to 2006 returns to experience decreased but in a not significant way, as well as the intercept of the estimated equation, while the coefficient for the gender variable has increased over time.
To sum up, the decomposition analysis points out that the two driving forces of the inequality trend are the coefficient and residual components, which will be investigated in the next section.

6. Explanations for the coefficients and residual between components

6.1. What behind the negative coefficients component

6.1.1. The role played by the changes in the job quality distribution

In this paragraph we investigate whether the changes in the job quality distribution might have played a role in explaining the decreasing wage inequality in the private sector. Autor et al. (2006), Goos and Manning (2006), Dustmann et al. (2008) show that changes in the job quality distribution play a role in explaining the increasing wage inequality trends in the US, UK and Germany. Using detailed classification for occupations, these papers investigate the changes over time in employment shares along the occupation distribution, ranked by median wage. Moreover, using other data sources, for instance the Dictionary of Occupational Titles (DOT) for the US, they provide evidence that cognitive skills are concentrated at the top of the job quality distribution, routine skills are instead required at the middle, and manual skills are located at the bottom. Autor et al. (2006), Goos and Manning (2006), Dustmann et al. (2008) underline that job polarization trends are at work in the US, the UK and Germany. They claim that in the last decade technologies have been more substitute to routine jobs, which are located at the middle of the job quality distribution, and complement to non-routine jobs, both cognitive and manual, which are located at the top and the bottom, respectively. In this framework, the new technologies would be responsible for the increase in the upper tail wage inequality (the 90/50 index) and for the decrease of the lower tail inequality (the 50/10), observed for instance in the US case.

We apply the same kind of analysis as in Autor et al. (2006), Goos and Manning (2006), Dustmann et al. (2008) to the Italian case. We make use of the INPS database of social security contributions, because of the detailed classification for occupations. We derive a sample as close as possible to the one used in the SHIW data, including full-time and part-time (reconverted into full-time equivalent), men and women, workers in all private sectors, aged 18-64. As for the not-standard contracts we adopted the same selection criteria used for the SHIW data. We include apprenticeship contracts in the sample, because formally they are standard fixed term contracts, while we exclude contracts that formally have to be considered as self-employment (“collaborazioni coordinate and continuative”, “contratti a progetto”). Further, as in the SHIW data we restrict our sample to those individuals who

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22 We cannot use the Italian LFS since there is no information about wages.
23 We use the INPS data elaborated by ISFOL. The sample scheme of the INPS data is set up to follow individuals born on the 10th of March, June, September and December, and therefore the proportion of this sample in the population of Italian employees is approximately 1/90. Further, the self-employed and public employees are not included in INPS database, as well as the employees of the agricultural sector.
have worked at least 3 months per year. Unfortunately, we cannot cover exactly the same period as in the SHIW data, since our INPS data is available up to 2002. However, as shown in Table 3, the patterns occurred between 1993 and 2006 are not that different from the ones occurred between 1993 and 2002, suggesting common explanations for the two periods. Our final sample includes 171,665 observations for the two years of interest (1993 and 2002).

To derive a detailed classification for occupations we exploit the information related to the national-sectoral contracts ("contratti nazionali per settore"), signed by the employer association and unions. In these contracts the parties set the rules for all the working conditions in the related industry (or sub-industry), including all types of occupations that can be applied and the related contractual minimum wage for any given occupation (from blue collars to managers). For instance, a national contract for a given sub industry in the textile sector includes all the occupations (usually from 5 to 10) that can be used in that sector, and for each of these occupation the related contractual minimum wage. It means that in that given sub-industry only the foreseen occupations can be used, and that the decentralized bargaining between the employer and the employee has a lower bound, a contractual minimum wage, for any given occupation.

In the final sample of our INPS database we exploit information related to the 31 most important (in terms of employment shares) national contracts. Unfortunately, the number and the definitions of the occupational levels (the labels) within each national contract may change over time since the national contracts are renewed on average every two years. Hence, it is impossible to follow over time individual characterized by the same occupational level in a given national contract, which would represent our preferred analysis to carry out. In order to deal with this issue we adopt a procedure characterized by the following steps:

1) within each of the 31 national contract, we rank occupations by their contractual minimum wage, which represents a reliable proxy for the job quality;
2) we generate distributional measures, such as terciles, from the ranked occupational levels in each contract. For instance, if in a national contract 9 occupations are foreseen, they will be ranked in three terciles. Terciles can be followed over time, even if the number of occupations and/or their labels change every two years. This implies a loss of information, but it allows to carry out an over time analysis that would not be possible using the occupational levels;
3) our cells of analysis are then defined interacting the information concerning the 31 national contract with the one of the terciles of the ranked occupations (derived within each national contract), i.e. 93 cells.

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24 A drawback of this procedure is that since we do not have information for all the national contracts we can cover approximately 60% of the initial sample for the years 1993 and 2002 (similarly to Devicienti et al., 2008).
25 To compute the quintiles of occupations we use the STATA command xtile (default settings). Further, note that distributional measures (quintiles) are computed on occupations without considering their observed frequencies in the INPS sample, i.e. occupations are not weighted by their frequency. This is because our aim is to rank the quality of occupations.
4) from this step we go back to the standard procedure used in the literature (Autor et al., 2006, Goos and Manning, 2006, Dustmann et al., 2008). We rank on the x-axes the cells derived in step 3 according to their median observed wages in 1993, and we aggregate them in terciles and quintiles. On the y-axes the changes over time of the employment shares of that tercile and quintile are reported.

In panel A of figure 2 we display the results concerning the case in which: a) for each national contract we generate 3 terciles to aggregate the information about occupational levels (point 2 of the procedure); b) the cells are aggregate on the x-axis in terciles (left side) and quintiles (right side) using the median observed wages for each occupation (point 4 in the procedure). The evidence in Panel A shows that the changes in the job quality distribution are against patterns of job polarization, suggesting instead patterns of job compression. In particular, from the left side graph of panel A it is possible to observe that the share of occupations located at the top tercile decreased over time by 11.2%, the share of employment for occupations in the middle of the distribution increased (2.2%), and lousy jobs at the bottom of the distribution increased only by 1.2%. The analysis in quintiles (right side of panel A) goes in the same direction. In panel B and C of table 2 we carry out some robustness checks. In particular, instead of using terciles as distributional measure of the occupational levels in each national contract (point 2 of the procedure) we make use of quartiles (panel B – using 124 cells) and quintiles (panel C – using 155 cells). Results are still against evidence of job polarization, even if the emerging patterns are no longer in favour of a job compression, being more mixed.26

Another robustness check concerns the point 4 of the procedure. In particular, instead of using the observed median wages to rank the occupations along the x-axes, we can exploit the information of the contractual minimum wages in 1993, which represents a more reliable proxy for the job quality mainly because they are not affected by tenure profiles and by measurement errors.27 Hence, we rank on the x-axes the cells derived in step 3 according to their contractual wages in 1993, and we aggregate them in terciles and quintiles. On the y-axes the changes over time of the employment shares of that tercile and quintile are reported. Panel A, B, C of Figure 2A are derived as those in Figure 2. Patterns emerging from Figure 2A are still against patterns of job polarization. In particular, considering the left side of Panel A the employment share of lousy jobs increased over time by 2.7%, middle occupations decreased by 2% and top occupations decreased by 7%. The right side part of Panel A and Panel B and C confirm substantially this evidence.

These findings are also consistent with the decomposition analysis and inequality trends observed using SHIW data. In particular, the decrease of the employment share of workers at the top of the job quality distribution is consistent with a decrease of wages at the 90th percentile (the compression of the upper tail of the distribution). Furthermore, since

26 We carried out additional robustness checks: a) excluding part time jobs; b) considering separately men and women; c) excluding apprenticeship contracts; d) focusing on prime age workers; e) relaxing the rule of having worked for at least 3 months. Results are very similar.

27 Note however that median observed wages and contractual wages are highly correlated (0.80), as expected.
educated workers are concentrated in the right tail of the job distribution, the decrease of the demand for this kind of workers constitutes an explanation for the negative coefficients component observed in the decomposition analysis: EWP decreased over time because of a change in the job quality distribution.

Unfortunately, in the INPS data we do not have information about education, and it is not possible to investigate the changes in labour demand for educated workers. To deal with this issue we resort to the SHIW data. We carry out the same kind of exercise on the changes in job quality distribution with the INPS data. The SHIW data contains much less detailed information concerning occupations and industries. More specifically, the SHIW includes only five categories: blue collar, white collar, teachers, managers, directors. Since the teachers and directors cells are very thin, we are forced to aggregate these two categories with managers, ending up with three occupation categories. Moreover, in order to have greater dimension for each cell we collapse two consecutive surveys. In particular, we aggregate 1993 and 1995, and 2002 and 2004, to be as close as possible to the INPS data (1993-2002). We then exploit the sectoral information, as in Goos and Manning (2007). Interacting nine sectoral dummies with three occupational categories we end up with 27 sector-occupation cells. Hence, we rank these cells using the median wage by cell in 1993-1995, and then we aggregate these cells in 3 terciles. For each tercile we compute the changes in employment shares from 1993-1995 to 2002-2004. Further, we carry out also a robustness test considering the periods 1993-1995 and 2004-2006. From Table 4 it is possible to notice the share of graduates increase much more in the lower tail of the job quality distribution than in the upper tail, for both periods.

It could be argued that the classification for occupations is not enough detailed in the SHIW data, casting some doubts on the results. For this reason we carry out a robustness check using another database, the Labour Force Survey (LFS) data from ISTAT, and another classification for the quality of occupations, the well-known ISCO-88, which exogenously ranks the occupations from the top ones to the bottom ones. As in OECD (2008), ISCO 1-3 are categorized as skilled occupations, ISCO 4-8 as semi-skilled occupations, and ISCO 9 as unskilled occupations. We then compute how graduates are allocated in skilled, semi-skilled, and unskilled occupations, and the variations of these shares from 1993 to 2006.

28 Using the same procedure we have carried out an analysis of the dynamics of the job-quality distribution, similar to the one derived using the INPS data. Results are still against patterns job polarization. In particular, using a classification of occupations in terciles for the periods 1993-1995 and 2002-2004, it is possible to show that the share of workers at the middle of the job quality distribution is the one that increases the most (by 19%), the top tercile increases much less (7%) while to bottom tercile decreases (8%). Hence, there is evidence of job compression, since the middle tercile increase more than the two extreme terciles. Further, it is not worrying that these findings are not perfectly in line with the ones derived using INPS data, since the variables used to compute cells are different. Nonetheless, these two databases generate two pieces of evidence quite similar from a qualitative point of view, showing that the share of top occupations decreases, or increase less, with respect to those in middle and bottom occupations. However, we prefer to rely on the INPS data for such a kind of analysis, because of the sample size and of the much more detailed occupation classification.

29 Note that there has been a structural change in the LFS in 2004. However, the structural break should not produce any relevant bias when the analysis is focused on dependent workers, since the main differences between the old and the new survey regard the efficacy in capturing new forms of employment relations, mainly atypical contracts (not considered in our analysis). As a robustness check we computed the same
Table 5 shows that the share of graduates employed in skilled occupations decreased by 7.8%, from 78.6% to 73.34%, while it increases in the semi-skilled (30.1%) and unskilled occupations (33.3%). An even stronger evidence is derived when skilled occupations are computed using a stricter criterion, i.e. ISCO 1-2, translating the ISCO 3 category in the semi-skilled occupations: the share of graduates decreases by 27.3%, from 51.7% to 37.6%, and the shares of graduates increase in the semi-skilled (29.1%) and unskilled occupations (33.3%). The findings derived from SHIW and LFS data are, from a qualitative point of view, very close one-another.30

It is hard to believe that this evidence be related to a faster increase of the demand for skills (education) at the bottom than at the top of the job quality distribution. A wide and robust international evidence shows that educated workers are more complementary to skilled than to unskilled jobs. Ruling out this explanation, we claim that graduates entering the labour markets might be willing to accept jobs at the bottom of the job quality distribution because the shares of skilled occupations decreased over time, as shown using INPS data. Similar patterns of over education are observed by Goos and Manning (2007) in the UK, in which “some educated workers are forced into the low-skill jobs at the bottom end of the distribution”.31

To sum up, we claim that the dynamics in the changes of the job quality distribution, derived from INPS data, and the over education patterns, derived from SHIW and LFS data, can be considered as convincing explanations for the falling educational wage premia and, in turn, for the decreasing wage inequality. In particular, the reduction over time of the share of skilled occupations might have forced skilled individual to shift to the middle and/or to the bottom of the distribution, affecting negatively the dynamics of educational wage premia and through this channel reducing wage inequality.

6.1.2. The role of supply and demand

The interaction between supply and demand represents another possible candidate for the between groups inequality associated with the negative coefficients component. Put it differently, one might argue that the increase in educational levels of the labour supply from 1993 to 2006 might have generated the reduction in the EWP. In particular, the share of workers with an upper secondary degree increased from 33% to 47% and the share of graduates from 4% to 9%.

To address this possible explanation we implement the methodology proposed by Card and Lemieux (2001), which makes use of aggregate CES production function where the two

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30 To the best of our knowledge there are no other databases in Italy that relate the information on occupations and on education, and their variation over time.

31 Pag. 4 of the working paper version (2003).
types of labour inputs, skilled and unskilled labour, are paid their marginal product. The aggregate output in period $t$ is given by:

$$Y_t = \left( \theta_{H,t} \cdot H_t^\rho + \theta_{L,t} \cdot L_t^\rho \right)^{1/\rho}$$

where the parameters $\theta_{H,t}$ and $\theta_{L,t}$ represent the efficiency of college graduates and secondary school graduates, respectively, $H_t$ is the aggregate labour input of skilled (graduates) and $L_t$ is the aggregate labour input of unskilled labour (less than graduates degrees) in year $t$. The elasticity of substitution $\sigma_E$ between the two educational groups is given by $\sigma_E = \frac{1}{1 - \rho}$.

We also exploit the experience and gender information in our dataset, dividing for each educational level the sample into 14 groups (7 experience classes and gender), for each year (1993, 1995, 1998, 2000, 2002, 2004, 2006). We hence also assume that aggregate inputs depend on two nested CES of skilled and unskilled labour:

$$H_t = \left[ \sum_j \left( \alpha_j \cdot H^\eta_{j,t} \right) \right]^{1/\eta}$$

$$L_t = \left[ \sum_j \left( \beta_j \cdot L^\eta_{j,t} \right) \right]^{1/\eta}$$

where the index $j$ represents each experience-gender group, the parameters $\alpha_j$ and $\beta_j$ are efficiency parameters, which are assumed to be time invariant, $H_{j,t}$ and $L_{j,t}$ are group specific supplies of skilled and unskilled labour in each period $t$. The elasticity of substitution among different experience-gender groups $j$ is equal to $\sigma_{A} = \frac{1}{1 - \mu}$. In this framework it is then possible to take into account two different elasticities of substitution, the one between skilled and unskilled and the one among experience-gender groups (within each educational level).

The firm profit maximization requires that the relative wages of different skill groups are equal to their relative marginal products, i.e., the (log) ratio of the skilled/unskilled wage rate in each gender experience group $j$ (i.e., $w^H_{j,t} / w^L_{j,t}$) satisfies the following condition:

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32 With respect to the 8 experience groups used so far, we only drop those with experience higher than 35 years, because for them the share of graduate individuals is often very close to zero.
where \( e_{j,t} \) reflects sampling variation in the measured gap in the experience-gender wage premia. According to this model, the skilled-unskilled wage gap for a given gender-experience group \( j \) depends on both the aggregate relative supply of college labour \( (H_t/L_t) \) in period \( t \), and on the experience-gender specific relative supply of skilled labour \( (H_{j,t}/L_{j,t}) \). Further, as in Card and Lemieux (2001) we approximate the term \( \log(\theta_t/\theta_t) \) with a linear trend, since it does not depend on \( j \), and the terms \( \log(\beta/\alpha) \) with experience-gender dummies, since they do not depend on \( t \).

It is worth pointing out that, on the one hand, equation (8) nests the conventional specification used by Katz and Murphy (1992) that assumes perfect substitution across groups with the same level of education \( (\sigma_A \rightarrow +\infty) \). More specifically, in this latter case the term \( [\log(H_{j,t}/L_{j,t}) - \log(H_t/L_t)] \) drops and the skilled-unskilled wage gap depends only on the aggregate relative supply of skilled workers in \( t \) \( (H_t/L_t) \), the time trend and the group dummies. On the other hand, we also estimate equation (6) by assuming imperfect substitution between experience-gender groups, regressing the relative wage of college workers for each gender-experience group on the aggregate supply index, \( \log(H_t/L_t) \), and on the deviation between the gender-experience group specific relative supply of college workers and aggregate supply index, i.e. \( [\log(H_{j,t}/L_{j,t}) - \log(H_t/L_t)] \), always including time trends and group dummies. The coefficient associated to this variable provides an estimate of \( 1/\sigma_A \), while the coefficient associated to the \( \log(H_t/L_t) \) is the elasticity of substitution between the two educational groups, i.e. \( \sigma_E \).

Table 6 gives the estimates of (6). More specifically, we define as skilled the graduates and as unskilled all these workers with less than a university degree. In column (1) we give the results for the case where the elasticity of substitution across experience-gender groups be infinite, i.e. they are perfect substitutes. In column (2) we allow for the groups to be imperfect substitutes. Actually \( \sigma_E \) does not change much in the two estimations, probably because the elasticity across groups is not statistically different from zero in column (2). The value of \( \sigma_E \) is hence equal to 3 in column (2) and to 2.8 in column (1).33

33 Actually we implement this methodology as in Autor, Katz, Kearney (2008), using a one step estimation. Instead, Card and Lemieux (2001) make use of a two steps procedure to estimate in the first step the parameters \( \alpha, \beta, \sigma_A \) in such a way to derive the amount of \( H_t \) and \( L_t \) in terms of efficiency units, as in equation (4) and (5). Using the two steps procedure the estimate of \( \sigma_E \) is slightly higher, around 4. Furthermore, in our analysis we define \( H_{t,b}, H_{j,t,b}, L_{t,b} \) and \( H_{j,t,b} \) using the absolute number of workers. Actually, Card and Lemieux (2001) exploit also the information concerning the worked hours. For this reason we implement a further robustness check in which we weighs the number of workers by the number of months and hours worked in that years. The estimate of \( \sigma_E \) is still around 4. Finally, we also implemented the methodology of Manacorda, Manning, Wadsworth (2006), which allows us to have three separate elasticities of substitution, one between skilled and
This value for $\sigma_E$ is very high when compared to the US case, where it ranges between 1.4 and 2 (Katz and Krueger, 1998), while it is lower than the value of 5 for Germany (Dustmann et al., 2008).\textsuperscript{34} Dustmann et al. (2008) claim that this high value of $\sigma_E$ might depend on the presence of unions and other institutions in the labour market, which are still much stronger in Germany than in the US, that make wages less responsive to supply and demand shocks. A similar explanation might hold for the Italian case as well. Furthermore, the R-square is also low (0.44), meaning that the explicative power of differences in supply can explain only less than half of the total variance of relative wages.

These findings suggest that the supply-demand interactions can hardly be considered as the leading explanation for the falling of EWP and wage inequality: differences in relative supply can only partly affect differences in relative wages between groups.

6.2. An explanation for the residual within component

As shown in panel A of Table 2, the residual component was positive at the 10\textsuperscript{th} percentile (4.7\%), equal to zero at the median, and slightly negative at the 90\textsuperscript{th} percentile. Table 3 pointed out that 49\% of the reduction of 50/10 inequality index was related to the residual-within component.

To provide an interpretation for the residual-within component, we resort to Lemieux (2002, 2006), which underlines two main possible forces.

On the one hand, using the “skill price theory” Lemieux (2002) argues that the changes in the coefficients component can have an impact on the dynamics of the residual component along the wage distribution: “when the return to years of schooling increases, it is reasonable to expect that the returns to (unmeasured) school quality would increase too.” (p. 664).

On the other hand, Lemieux (2002, 2006) claim that the residual component is also related positively to the covariates component, i.e. to the share of educated and experienced workers in the labour force: “The composition effects are due to the fact that the working age population is getting older and more educated. Increasingly more weight is thus put on groups with higher residual variances” (p.676).\textsuperscript{35}

\textsuperscript{34} Actually, Dustmann et al. (2008) carry out an analysis based on three types of skills (low, medium and high). However, they show that when imposing the same elasticity of substitution between high vs. medium skills and medium vs. low skills the value of $\sigma$ is equal to 5.5.

\textsuperscript{35} The residual components computed using the two methodologies of Melly (2005), Autor et al. (2005) and Lemieux (2002, 2005) are not actually exactly the same. Autor et al. (2005) argue that the two methodologies are similar except that the Lemieux methodology sets the between coefficients $\beta(0.5)$ to zero when computing the residual component. This means that the Lemieux methodology exclusively analyses the contribution of labour force composition to changing residual inequality, abstracting from the role played by between-group prices. For this reason, Autor et al. (2005) claim that the Lemieux methodology has to be considered as a ‘subcomponent’ of their methodology. Nevertheless, when Autor et al. (2005) compute the inequality decompositions using the Lemieux methodology derive similar results.
In this paper we have emphasized the role of a negative coefficients component and the increasing share of educational and experience attainments in the workforce. We hence expect two effects on the residual-within inequality: a negative effect due to negative coefficients component and a positive one related to the increase in the share of educated and experienced workers. The estimated residual-within inequality, reported in Table 2, shows that under the median the positive effect related to the covariates component dominates the negative effect related to the coefficients component, generating a positive within component. On the other hand, above the median, we observe a negative within component, meaning that the unobserved effect related to the negative coefficients component, which becomes more and more important along the distribution, dominates the effect related to the covariates component.

Furthermore, we claim that the over education patterns derived in Table 4 and 5 reinforce this interpretation. According to the Lemieux’s framework (2002, 2006), the increase of educated workers at the bottom of the job and wage distribution is associated to an increase in the dispersion of earnings, which cannot be captured by covariates and coefficients. This holds under the assumption that even if employed in unskilled jobs, high-educated workers maintain those unobserved characteristics that generate higher residual wage dispersion.

6.3. The potential role of changes in tax regimes
As already stressed, SHIW data contains only information about net wages. Under the hypothesis that tax regimes have not strongly changed over time our results would remain unaffected. However, this hypothesis can hardly hold, since from 1998 various tax reforms have been implemented in Italy. In particular, the declared purpose of the legislator in the last decade was to favour the individuals at the bottom of the distribution, by means of changes in the income brackets, household oriented policies and especially with the introduction in 2003 of a no-tax area.36 Martone (2008) computed simulations of the effective average tax rates for two widespread typologies of dependent earners in the labour market: single individual and married worker with two children (table A2 in appendix 2). The time span considered by Martone (2008) is 1998-2006, since before 1998 changes in the tax system had been marginal. The analysis of Martone (2008) confirms that tax reforms have mainly affected the lower tail of the distribution. In particular, according to the simulation concerning a married individual with two children the effective average tax rate decreased strongly, especially for labour incomes lower than 25000 euros, while for individual in the upper tail of the wage distribution differences over time in effective average tax rate are much lower, especially for earners beyond 40.000 euros. As for single individuals similar patterns applies: effective average tax rates decreased especially in the lower tail of the wage

36 The no-tax area is structured such that a dependent workers earning less than 7.500 euros does not pay taxes. For income between 7.500 and 33.500 there is decreasing tax deduction.
distribution (below 20,000 euros) while their reduction is very small in magnitude at the top of the wage distribution.

This set of simulations suggests that the impact of tax reforms might have affected the wage structure in the lower tail of the distribution. More specifically, the increase in the 10th percentile from 1993 to 2006 might at least partially be related to a reduction in the effective average tax rate, while changes in the upper tail of the distribution should not be affected by changes in tax regimes.

To sup up, in this section we claim that the main explanation for the negative coefficients effect is related to changes in the job quality distribution that have penalized top occupations and to over education patterns, while we explain the trends in the residual-within component using the Lemieux (2002, 2006) approach. Moreover, we argued that changes in tax regimes might have played a role only in the lower tail of the wage distribution.

7. Theoretical and institutional interpretations of our findings: a discussion

Which are the main forces that have generated the observed changes in the job quality distribution, over education, falling educational wage premia and decreasing wage inequality? In this section we sketched out and discuss some theoretical and institutional interpretations.

The starting point is that the Italian evidence is in sharp contrast with the available evidence on the polarization of labour markets observed in other developed countries (Autor, Katz and Kearney, 2005, for US; Goos and Manning, 2007, for UK; Dustmann et al. 2008 for Germany). In particular, the model presented by Autor, Katz and Kearney (2006), formalizes the idea that the impact of new technologies (i.e. computerization) strongly complement the cognitive tasks typically exerted in high wage jobs, directly substitute for routine tasks found in middle wage jobs, and have little direct impact on non-routine tasks in relatively low wage jobs.

By applying this theoretical framework to our findings, one may then argue that in Italy there has not been a pervasive technological change substitutive of labour input employed in routine tasks and complementary to labour input in non-routine tasks. Indeed, empirical evidence supports the thesis that Italy is a slow adopter of new technologies, when compared to other developed countries. For instance, the OECD (2001) states that in 1996 the share of capital stock accounted for by ICT goods was about 2% in Italy, 3% in West Germany and France, 5% in UK and more than 7% in the US. Moreover, the gap with fast adopter countries increased over time, since the 1990s: the yearly growth rate of ICT investments in the period 1996-1999 was 23% in US, 22% in France and only 15% in Italy and Germany. Further, the expenditures in R&D in the private sector, as a percentage of the production at current prices, decreased from 0.98% in 1991 to 0.68% in 2003 in the Italian
manufacturing sector, while in France the same ratio have been stable around 2.3%, in Germany around 2.7%, and about 3% in the US and Japan (OECD STAN database).

However, an explanation based on an exogenous theory of technological change, as in Autor et al. (2006), cannot account for incentives related to firm technological choices, which typically interacts with both the quality of the labour force and search frictions in a highly regulated labour market, as in the Italian case.

In this perspective, the model of endogenous job composition developed by Acemoglu (1999) enriches the set of the possible interpretations for Italy. Acemoglu (1999) considers an economy with frictions, where workers are heterogeneous in terms of human capital endowment, and where firms choose the level of their capital stock before matching the worker. The basic idea is that when either the productivity gap between skilled and unskilled worker is limited or when the share of skilled workers in the labour force is small, it will be profitable for firms to choose only one capital-level to employ both skilled and unskilled workers. Conversely, when the productivity gap is large or when there is a sufficient high share of skilled workers, it may become profitable for firms to create higher quality (higher capital) jobs, specifically targeted to skilled workers. Thus, there can be two different types of equilibria in this economy: a pooling equilibrium, in which firms choose the same level of capital and use it with both skilled and unskilled; a separating equilibrium, in which firms target the skilled and choose a higher level of capital, and in which wage inequality is higher. In this context, it is straightforward to think about the Italian labour market as characterized by a pooling equilibrium, due to either a low productivity gap between skilled and unskilled worker (i.e. low and falling educational wage premia, as in the Italian case) or to the low incidence of skilled workers in the labour force (only 4% of graduates in 1993 and 9% in 2006).\footnote{We cannot identify the causality effect, i.e. whether low and falling educational wage premia are the cause or the consequence of low productivity gap.}

The model of endogenous job composition (Acemoglu, 1999) and the model of technical change biased against routine tasks (Autor et al., 2006) provide two different explanations though which rationalizing the existence of a compressed (pooling) equilibrium in Italian labour market: the low productivity gap between skilled and unskilled workers (and/or the low share of skilled workers) and the low incidence of investments in computer technologies. However, these two explanations are exogenous in the two models. What can have generated a low productivity gap between skilled and unskilled, and/or low incidence of investments in computer technologies? We argue that they might be related either to factors internal to the labour market, such as labour market institutions, or to factors external to the labour market, related to macroeconomic issues.

As for the explanation based on the role of institutions (employment protection legislation, unions power, centralized wage setting), it does not seem to be very convincing, because of the waves of flexibility policies introduced in the European labour market in the nineties and in the early 2000s. Actually, as shown by the OECD index of employment
protection (OCED, 1994, 2004), the rigidity of the Italian labour market decreased in the last fifteen years, and this should have exerted a pressure toward the widening, rather than a compression, of inequality, especially at the bottom of the wage distribution. This is also confirmed by Manacorda (2004) who shows that the abolition of the wage indexation mechanism (in 1992) generated an increase in wage inequality, which mainly took place at the beginning of the nineties.

The second explanation refers to factors external to the labour market. Tronti (2007) shows that in 1995 the Italian hourly productivity were 5% higher than the EU-15 average, while in 2005 it was equal to 90% of the corresponding EU-15 average, a fall of 15% in 10 years. Furthermore, many authors stressed the relevance of the specialization patterns of the production system based on traditional industries. Faini and Sapir (2005) shows that Italian comparative advantages in international trade stem from traditional sectors, while high-tech sectors are strongly penalized. Faini and Sapir (2005) also show that these relative advantages in traditional sectors increases over time, in spite of the rising competition from developing countries. Other related peculiar factors characterizing the Italian economy are the small size of firms, also in a within industry dimension (Pagano and Schivardi, 2006), and the corporate governance often based on familiar structure. All these factors might have contributed to generate the macroeconomic conditions such that to favour the three main stylized facts derived in the private labour market: falling educational wage premia, job compression, decreasing wage inequality.

8. Conclusion

This paper shows that the Italian case is an outlier in the literature concerning the relation between the changes over time of wage inequality, schooling premia and job quality distribution.

The starting point of the analysis is that wage inequality decreased from 1993 to 2006 in the Italian private sector, both in the upper and the lower parts of the distribution. To investigate the forces that have generated these inequality trends we carry out a quantile decomposition analysis to identify three main components, related to coefficients, covariates and residuals.

We find out that the driving force of the decreasing wage inequality is the falling over time of educational wage premia that, in turn, we associate to the changes in the job quality distribution that have penalized top occupations, and to over education patterns. Furthermore, we show that residual inequality affects the changes in the lower part of wage distribution and that supply-demand explanations play only a negligible role.

---

38 The small size issue might play a role because usually big firms employ more skilled workers, pay higher wage differentials, and invest more in ICT and R&D (Bernard et al, 2007). One possible reason for the small size of the firm might refer to the family based corporate governance system.
References


<table>
<thead>
<tr>
<th>Table 1: SHIW Sample descriptives. Private Sector</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share of Female</td>
</tr>
<tr>
<td>Education</td>
</tr>
<tr>
<td>Primary - no school</td>
</tr>
<tr>
<td>Lower secondary</td>
</tr>
<tr>
<td>Upper secondary</td>
</tr>
<tr>
<td>Univ. Degree or higher</td>
</tr>
<tr>
<td>1.00</td>
</tr>
<tr>
<td>Experience (year)</td>
</tr>
<tr>
<td>eps1 - 0-5</td>
</tr>
<tr>
<td>eps2 - 6-10</td>
</tr>
<tr>
<td>eps3 - 11-15</td>
</tr>
<tr>
<td>eps4 - 16-20</td>
</tr>
<tr>
<td>eps5 - 21-25</td>
</tr>
<tr>
<td>eps6 - 26-30</td>
</tr>
<tr>
<td>eps7 - 31-35</td>
</tr>
<tr>
<td>eps8 - &gt;36</td>
</tr>
<tr>
<td>1.00</td>
</tr>
<tr>
<td>Net Wages (Monthly)</td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>10th percentile</td>
</tr>
<tr>
<td>50th percentile</td>
</tr>
<tr>
<td>90th percentile</td>
</tr>
<tr>
<td>Observations</td>
</tr>
</tbody>
</table>

Note: 0.025% of the observation in the right and left tails dropped. Weight: pesofl.
Table 2. Total observed variations (in %) at selected quantiles and quantile decomposition into the coefficients, covariates and residuals components in the private sector

<table>
<thead>
<tr>
<th>Panel</th>
<th>1993-2006</th>
<th>Variations at selected quantiles</th>
<th>Δ p10</th>
<th>Δ p25</th>
<th>Δ p50</th>
<th>Δ p75</th>
<th>Δ p90</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total estimated variation</td>
<td></td>
<td></td>
<td>12.5</td>
<td>7.4</td>
<td>2.9</td>
<td>-1.2</td>
<td>-2.2</td>
</tr>
<tr>
<td>Coefficients</td>
<td></td>
<td></td>
<td>-2.5</td>
<td>-4.5</td>
<td>-7.1</td>
<td>-9.8</td>
<td>-12.0</td>
</tr>
<tr>
<td>Covariates</td>
<td></td>
<td></td>
<td>10.3</td>
<td>9.6</td>
<td>10.0</td>
<td>10.2</td>
<td>10.7</td>
</tr>
<tr>
<td>Residual (within)</td>
<td></td>
<td></td>
<td>4.7</td>
<td>2.3</td>
<td>0.0</td>
<td>-1.7</td>
<td>-1.0</td>
</tr>
</tbody>
</table>

Panel B  1993-2004

| Total estimated variation | 6.3 | 3.4 | 0.0 | -3.7 | -5.5 |
| Coefficients             | -4.8 | -6.2 | -8.6 | -10.7 | -13.4 |
| Covariates               | 8.5 | 8.7 | 8.7 | 9.0 | 9.2 |
| Residual (within)        | 2.6 | 1.0 | -0.1 | -2.0 | -1.2 |

Panel C  1993-2002

| Total estimated variation | 3.6 | -0.5 | -2.7 | -5.0 | -4.9 |
| Coefficients             | -7.4 | -7.6 | -10.0 | -11.3 | -14.0 |
| Covariates               | 7.6 | 6.8 | 7.0 | 6.7 | 7.5 |
| Residual (within)        | 3.4 | 0.3 | 0.3 | -0.3 | 1.5 |

Source: SHIW data.
Table 3. Decomposition of the inequality indexes into the between, within and covariates component in the private sector (in percentage points)

<table>
<thead>
<tr>
<th></th>
<th>Period - 1993-2006</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>90/10</td>
<td>50/10</td>
<td>90/50</td>
</tr>
<tr>
<td>Total estimated variation</td>
<td>-14.7</td>
<td>-9.6</td>
<td>-5.1</td>
</tr>
<tr>
<td>Coefficients contribution</td>
<td>-9.5</td>
<td>-4.6</td>
<td>-4.8</td>
</tr>
<tr>
<td></td>
<td>64%</td>
<td>48%</td>
<td>95%</td>
</tr>
<tr>
<td>Covariates contribution</td>
<td>0.5</td>
<td>-0.3</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>-3%</td>
<td>3%</td>
<td>-15%</td>
</tr>
<tr>
<td>Residual contribution</td>
<td>-5.7</td>
<td>-4.7</td>
<td>-1.0</td>
</tr>
<tr>
<td></td>
<td>39%</td>
<td>49%</td>
<td>19%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Period - 1993-2004</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>90/10</td>
<td>50/10</td>
<td>90/50</td>
</tr>
<tr>
<td>Total estimated variation</td>
<td>-11.7</td>
<td>-6.3</td>
<td>-5.4</td>
</tr>
<tr>
<td>Coefficients contribution</td>
<td>-8.7</td>
<td>-3.8</td>
<td>-4.8</td>
</tr>
<tr>
<td></td>
<td>74%</td>
<td>61%</td>
<td>89%</td>
</tr>
<tr>
<td>Covariates contribution</td>
<td>0.6</td>
<td>0.2</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>-5%</td>
<td>-4%</td>
<td>-8%</td>
</tr>
<tr>
<td>Residual contribution</td>
<td>-3.73</td>
<td>-2.69</td>
<td>-1.04</td>
</tr>
<tr>
<td></td>
<td>32%</td>
<td>43%</td>
<td>19%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Period - 1993-2002</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>90/10</td>
<td>50/10</td>
<td>90/50</td>
</tr>
<tr>
<td>Total estimated variation</td>
<td>-8.5</td>
<td>-6.4</td>
<td>-2.2</td>
</tr>
<tr>
<td>Coefficients contribution (between)</td>
<td>-6.5</td>
<td>-2.6</td>
<td>-4.0</td>
</tr>
<tr>
<td></td>
<td>77%</td>
<td>41%</td>
<td>183%</td>
</tr>
<tr>
<td>Covariates contribution</td>
<td>-0.1</td>
<td>-0.6</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td>1%</td>
<td>10%</td>
<td>-26%</td>
</tr>
<tr>
<td>Residual contribution (within)</td>
<td>-1.9</td>
<td>-3.1</td>
<td>1.2</td>
</tr>
<tr>
<td></td>
<td>22%</td>
<td>49%</td>
<td>-57%</td>
</tr>
</tbody>
</table>

Source: SHIW data.
### Table 4. Evidence of a over education patterns from SHIW data

<table>
<thead>
<tr>
<th>Terciles</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share of workers per tercile in 1993-1995</td>
<td>64.15</td>
<td>22.37</td>
<td>13.48</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.81</td>
<td>5.17</td>
<td>175%</td>
<td>220%</td>
</tr>
<tr>
<td></td>
<td>2.24</td>
<td>10.24</td>
<td>98%</td>
<td>122%</td>
</tr>
<tr>
<td></td>
<td>175%</td>
<td>98%</td>
<td>54%</td>
<td>57%</td>
</tr>
</tbody>
</table>

Source: SHIW Bank of Italy data. Weight:peso

### Table 5. Over education: how graduates are allocated in skilled, semi-skilled and unskilled jobs.

<table>
<thead>
<tr>
<th>Classification for occupations</th>
<th>Unskilled ISCO 9</th>
<th>Semi-skilled ISCO 4-8</th>
<th>Skilled ISCO 1-3</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share of graduates</td>
<td>Shares 1993</td>
<td>Shares 2006</td>
<td>Shares 2006</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.2</td>
<td>19.3</td>
<td>79.5</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>1.6</td>
<td>25.1</td>
<td>73.3</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>3.3%</td>
<td>30.1%</td>
<td>-7.8%</td>
<td></td>
</tr>
</tbody>
</table>

Table 6. The role of the supply-demand explanation

<table>
<thead>
<tr>
<th>Covariates</th>
<th>(1) perf. Substitut. among groups</th>
<th>(2) imperfect Substitut. among groups</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(Ht/Lt)</td>
<td>Coef</td>
<td>p-value</td>
</tr>
<tr>
<td></td>
<td>-0.358</td>
<td>0.003</td>
</tr>
<tr>
<td>[log(Hj,t/Lj,t) -log(Ht/Lt)]</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Time trend</td>
<td>0.023</td>
<td>0.114</td>
</tr>
<tr>
<td>Groups effects</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.43</td>
<td></td>
</tr>
<tr>
<td>Elast.Sub.(σₑ)</td>
<td>2.8</td>
<td></td>
</tr>
</tbody>
</table>

Sample size: 98 observations

Figures

Figure 1. 90/10, 50/10, 90/50 indexes in the private sector
Period 1993-2006
Figure 2. Job compression patterns - median observed wages. Private sector, INPS data, 1993-2002.

PANEL A: 3 terciles for each national contract

PANEL B: 4 quartiles for each national contract

PANEL C: 5 quintiles for each national contract
Figure 2A. Job compression patterns - median contractual wages. Private sector, INPS data, 1993-2002.

**PANEL A: 3 terciles for each national contract**

**PANEL B: 4 quartiles for each national contract**

**PANEL C: 5 quintiles for each national contract**
APPENDIX 1: The Machado-Mata decomposition

This methodology takes as starting point the two quantile estimations in cross-section, for 1993 and 2006, using a Mincerian standard specification:

\[
\ln w^t_i = X^t_i \beta^t (\theta) + u^t_i \theta
\]

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. As standard in this literature (Koenker and Basset, 1978), \( \beta(\theta) \) can be estimated minimizing the following expression:

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

where
\[
\rho_\theta (u) = \begin{cases} 
\theta u & \text{if } u > 0 \\
(\theta - 1)u & \text{if } u < 0
\end{cases}
\]

Once having derived the quantile parameters \( \beta(\theta) \), this methodology allows to estimate the marginal distribution of wages as function of both \( X \) and \( \beta(\theta) \), and to derive counterfactual distributions of wages.

Estimation of the marginal distribution of wages

This methodology is essentially developed in two main parts. In the first part, the conditional quantile distribution 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 defined as:

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

where \( X_i \) is a vector for the set of covariates. For instance, \( X_i \) might stand for male graduates with less than 5 years of experience. Basset and Koenker (1982) showed that,

---

39 Note that choosing this set of covariates leads to a human capital interpretation, which we argue have played a role in the last decades. Obviously, choosing different sets of covariates would shed light on other possible explanations. For instance, for an analysis focusing on a generational approach (age classes, and cohorts) see Rosolia and Torrini (2007).

40 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.
under some regularity conditions, the estimated conditional quantile function is a consistent estimator of the population conditional quantile function, uniformly in $\theta$.

It is then 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 distribution $F$. In our case, if $\theta_1, \theta_2, \ldots, \theta_j, \ldots, \theta_J$ are drawn from a uniform (0,1), the corresponding $j$ estimates of the conditional quantile at $X_i$, $\hat{\theta}_i = \{X_i, \hat{\theta}(\theta_j)\}_{j=1}^J$, constitute a random sample from the estimated conditional distribution of wages given $X_i$. Using this procedure, we can estimate the conditional 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, $Q_\theta(w \mid X_i) = X_i, \hat{\beta}(\theta_j)$ for given $X_i$ and $\theta_j$, and the distribution of the covariates, $g(X)$. In order to derive a random sample from the 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 $j=1,\ldots,J$, in which the different $\theta_j$ are randomly chosen from the uniform (0,1) distribution. In this setting, each observation of the resulting matrix, $\hat{w}_i = \{X_i, \hat{\beta}(\theta_j)\}_{j=1}^J$, can be considered as drawn from the estimated marginal distribution of wages.

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 considered 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. $\int \int \hat{Q}_\theta(w \mid X)g(X) \theta d\theta dX$, integral that produces a consistent estimator of the marginal distribution of wage, $f(w)$, which can be written as (Melly, 2005, 2006):

$$f(w) = \int f(w, x) dx = \int \underbrace{f(w \mid x)}_{x \theta} g(x) dx = \int \int Q_\theta (w \mid x) g(x) d\theta dx$$

$$\int Q_\theta (w \mid x) d\theta$$

$^{41}$ To validate the heteroscedasticity hypothesis, i.e. the fact that ‘slope coefficients’ are different for the same covariate across quantiles, we successfully test that the estimates of the coefficient vectors at different quantiles are statistically different from one another (Buchinsky, 1995, Koenker and Basset, 1978).

$^{42}$ Note that $\theta$ is uniformly distributed on the [0,1] interval, implying that the relative density $f(\theta)$ is equal to 1.
The insights behind the comparison between the Machado & Mata approach and the integral procedure are quite intuitive. More specifically, 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 seen 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 both the sample size and the number of quantiles chosen in (0,1) are sufficiently large.

APPENDIX 2

Figure A1. Fit of the estimation methodology of Machado and Mata (2005): estimated vs observed distribution in 2006.
Table A1. Descriptives statistics concerning the composition of the labour force (by sector, education and age) in the bottom 25% (left panel) and the top 25% (right panel) of the wage distribution in 2006.

<table>
<thead>
<tr>
<th>Bottom 25% of the distribution</th>
<th>Top 25% of the distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agric.</td>
<td>Indus.</td>
</tr>
<tr>
<td>Under 40</td>
<td>Under 40</td>
</tr>
<tr>
<td>Primary</td>
<td>0.27</td>
</tr>
<tr>
<td>Low.Sec.</td>
<td>2.64</td>
</tr>
<tr>
<td>Upp.Sec.</td>
<td>0.73</td>
</tr>
<tr>
<td>University</td>
<td>0.09</td>
</tr>
<tr>
<td>Total</td>
<td>3.74</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Over 40</th>
<th>Over 40</th>
</tr>
</thead>
<tbody>
<tr>
<td>Primary</td>
<td>1.28</td>
</tr>
<tr>
<td>Low.Sec.</td>
<td>2.37</td>
</tr>
<tr>
<td>Upp.Sec.</td>
<td>0.82</td>
</tr>
<tr>
<td>University</td>
<td>0.00</td>
</tr>
<tr>
<td>Total</td>
<td>4.47</td>
</tr>
</tbody>
</table>

Total number of workers in the bottom and top 25%: 1097. The percentages expressed in the table are computed dividing the frequency for each education, sectoral and age level by 1079 (*100). Hence, the sum of all the percentages for the left (right) panel is equal to 1.

Table A2. Trends in effective average tax rate from 1998 to 2006

<table>
<thead>
<tr>
<th>Dependent employees</th>
<th>Single</th>
<th>Married with 2 children</th>
</tr>
</thead>
<tbody>
<tr>
<td>10000</td>
<td>11.6</td>
<td>7.1</td>
</tr>
<tr>
<td>15000</td>
<td>17.0</td>
<td>14.7</td>
</tr>
<tr>
<td>20000</td>
<td>20.0</td>
<td>18.4</td>
</tr>
<tr>
<td>25000</td>
<td>22.7</td>
<td>20.7</td>
</tr>
<tr>
<td>30000</td>
<td>24.7</td>
<td>22.9</td>
</tr>
<tr>
<td>40000</td>
<td>27.7</td>
<td>27.1</td>
</tr>
<tr>
<td>50000</td>
<td>30.2</td>
<td>29.5</td>
</tr>
<tr>
<td>75000</td>
<td>33.6</td>
<td>32.6</td>
</tr>
<tr>
<td>100000</td>
<td>35.9</td>
<td>34.2</td>
</tr>
</tbody>
</table>

Simulations computed in Martone (2008), using real wages.