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THE ROLE OF SUPPLY AND DEMAND FOR EDUCATION

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DECREASING WAGE INEQUALITY IN ITALY: THE ROLE OF SUPPLY AND DEMAND FOR EDUCATION

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Abstract

In this paper we show that wage inequality decreased in the Italian private sector, both in the upper and in the lower tail of the distribution, in the period 1993-2006. By applying a quantile decomposition procedure we find that the decrease of the 90/50 ratio is almost totally related to a negative coefficients component. As for the reduction of the 50/10 ratio, the quantile decomposition shows that it can be related to both the negative coefficients component and the residual component. We claim that that supply and demand for education have to be considered as the main explanation for the falling educational wage premia that represent the driving force of the falling 90/50 ratio. The reduction of the 50/10 ratio can be instead associated to the changes in the residual component -related to compositional effects-, to the changes in the occupation distribution and to changes in tax regimes.

JEL codes: J24, J3, O3.

Keywords: Inequality, Educational Wage Premia, Quantile Decomposition, supply-demand of education, Italy.

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 lesser extent, increases of the educational wage premia (EWP, henceforth) and wage inequality are also documented for other OECD countries (Gottschalk and Smeeding, 1997). One of the most prominent explanation for inequality trends in the last decades is related to skill-biased technical change, i.e. demand for skilled workers increases because of technological change (Acemoglu, 2002). Further, Autor et al (2006) and Goos and Manning (2007) have proposed a refinement of the skill-biased technical change explanation to address the trends in wage polarization observed in the US and the UK since the nineties. The main intuition concerns the fact that new technologies are substitute to routine tasks, located in the middle of the wage distribution, complementary to non routine cognitive tasks and *a priori* uncorrelated to manual tasks, located respectively at the top and at the bottom of the job quality distribution. The new technologies are then responsible for the polarization trends, i.e. for the increase in the upper tail wage inequality (the 90/50 ratio) and for the decrease of the lower tail inequality (the 50/10). Other explanations have also been considered in the literature, such as the role of institutions (unions and minimum wages, as in Di Nardo, Fortin, Lemieux, 1996) and the role of the interactions between changes in the supply and the demand of education (Katz and Murphy, 1992; Card and Lemieux, 2001, among others).

In this paper we show that the Italian labour market emerges as an interesting case in the analysis of wage inequality. 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

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ratios. As far as we know, Italy is the only OECD country where wage inequality decreased over time.

Second, to identify which forces have played a role for the decreasing wage inequality we implement a quantile decomposition procedure, 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 the 90/50 inequality ratio is mainly driven by the negative coefficients component, while the decrease in the 50/10 ratio is related to both a negative coefficients component and a residual component. For both the 90/50 and the 50/10 ratio the impact of the covariate component is negligible. The negative coefficients component is consistent with the falling educational wage premia observed over the period, as pointed out by Naticchioni, Ricci, Rustichelli (2009).

Third, we provide explanations for the wage inequality trends and for the findings derived by means of the quantile decomposition. For the decrease of the 90/50 inequality ratio we show that it is mainly related to supply-demand interactions. Using the CES production approach (Card and Lemieux, 2001), we point out that the increase in relative supply of education has exerted a negative impact on relative wages, while the impact of the changes of the technical change –proxy for the demand for workers- is not statistically different from zero. As for the decrease in the 50/10 ratio, we identify three main explanations. First, the quantile decomposition pointed out that the decrease in the 50/10 ratio is largely accounted for by the residual component (49%). We explain the impact of the residual component in the lower part of the wage distribution by means of a composition effect (Lemieux, 2002, 2006): the increase of educated workers at the bottom of the wage distribution have increased the dispersion of earnings, affecting the residual component. Second, we show that the changes in the job quality distribution offered by firms have played a role, since the demand for unskilled jobs decreased less than the demand for medium-skilled jobs. Third, we show that changes in tax regimes have had an effect on the lower part of the wage distribution, because of a reduction in tax effective rates.

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. Explanations for the inequality trends are investigated in section 6 and section 7 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 highly 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, such as 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, complementary to non routine cognitive tasks and a priori 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. In this framework, the new technologies would be responsible for the increase in the upper tail wage inequality (the 90/50 ratio) and for the decrease of the lower tail inequality (the 50/10 ratio), 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

[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).

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. By means of quantile regressions, four different patterns emerge: i) a positive increasing contribution of education on 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 either rose moderately or remained basically stable.

However, recent papers have challenged the view that SBTC is not a pervasive phenomenon in European countries. Dustmann et al. (2008) showed 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. This finding is also consistent with Goos et al (2009), who point out that job polarizations trends are occurring in most of the European countries in the period 1993-2006.

As for the Italian case, the paper that addresses wage inequality trends for a very long time period is Brandolini, Cipollone and Sestito (2002), which use the survey SHIW of the Bank of Italy to investigate the dynamics of inequality of net wages from 1977 to 1998. 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. 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 (2004) investigates the evolution of inequalities in Italy, both of incomes and wage, using SHIW data. They claim that the distribution 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.

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 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 (2009) use the SHIW data for the period 1993-2004 and quantile regressions to show that EWP in the private sector decline across the entire wage distribution, evidence that holds even when different robustness checks are carried out in order to deal with sample selection issues. Other related papers is Giustinelli (2004), which performs 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.

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 data 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 of the wage setting in the private labour market in 1992 and 1993 represented a breaking point for the Italian labour market.[2]

[2] In 1992-1993 the reforms established two levels of collective bargaining, aiming at 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. 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

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"), 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 kinds of contracts in 1993 and since formally these workers are to be considered as self-employed.[3] Further, we consider employees who have worked more than three months in the reference year and we drop 0.025% of the observations in both the right and left tail to cancel out potential outliers. We refer to the real monthly net wage, obtained by dividing the yearly wage from employment (including overtime, bonuses, and fringe benefits[4]), 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).[5] 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.[6]

Table 1 provides the descriptive statistics of the main variables in 1993, 1995, 2002, 2004, 2006, which are the waves 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

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] 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 less than the 50% of the average wage of permanent contracts).

[4] 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.

[5] Using hourly wages inequality trends are similar from a qualitative point of view. We prefer not to use hourly wages since the variable 'hours worked' is not totally reliable when compared to the one of the Labour Force Survey data (Istat).

[6] 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 SHIW database, APSETT and DIMAZ.

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. Table 1 also shows that average wages slightly decrease in 1995 and 1998 and then increase again in 2006, similarly to the trend of the median wages. Interestingly, 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 pointed out 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 the ratio between the 90th and the 10th percentile decreases 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 and the upper tail of the wage distribution analyzing the 50/10 and the 90/50 ratios. 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.

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. One of 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.

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

(1) $$\ln w_i^t = X_i^t \beta^t(\theta) + u_{i,\theta}^t$$

where $i=1,\ldots n$ is the number of observations in each year t, θ is the quantile being analyzed, u_i is an idiosyncratic error term, and X represents our set of explanatory variable.

Once having derived the quantile parameters $\beta(\theta)$, this methodology allows to estimate the marginal distribution of wages as function both of the matrix X and of $\beta(\theta)$.[7] 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.[8] The fit of the estimation methodology is very accurate, as shown in Figure A1 in appendix. Since the marginal distribution of wages is now a function of the covariates and coefficients, it is possible to generate counterfactual densities, using different sets of X and $\beta(\theta)$. For instance, it would be possible to compute a counterfactual distribution keeping the covariates X at the 1993 level and coefficients $\beta(\theta)$ at the 2006 level.[9]

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

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[7] See Appendix 1 for a detailed explanation of the estimate of the marginal distribution of wages.

[8] We implement 200 weighted quantile estimations on a regular grid, from 0 to 1 (0.005, 01, 015,…, 0.99, 0.995), deriving the coefficients $\beta(\theta)$ along all the θ 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.

[9] 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.

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):

$$(2) \qquad \ln w_i^t = X_i^t \beta^t(0.5) + u_i^t, \quad t = 93,06$$

where $\beta^t(0.5)$ is the coefficients vector of the median regression in year t. To disentangle the effect of coefficients (between groups over time) from the effect of residuals (within group inequality) it is important to note from (2) that the θth quantile of the residual distribution of u_i^t conditionally on X is consistently estimated by $X(\hat{\beta}^t(\theta) - \hat{\beta}^t(0.5))$. Accordingly, Melly (2005) defines the following vector of coefficients as a measure for the within component: $\hat{\beta}^{m06,r93}(\theta) = (\hat{\beta}^{06}(0.5) + \hat{\beta}^{93}(\theta) - \hat{\beta}^{93}(0.5))$, 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. So doing 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 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, $\hat{q}(\hat{\beta}^{06}, X^{06})$ and $\hat{q}(\hat{\beta}^{m06,r93}, X^{06})$, where the X and the $\beta^t(0.5)$ are constant at the 2006 level while the residual component is the only one that changes over time.[10]

Similarly, the difference between $\hat{q}(\hat{\beta}^{m06,r93}, X^{06})$ and $\hat{q}(\hat{\beta}^{93}, X^{06})$ is due to changes in coefficients since characteristics and residual are kept at the 2006 level.[11] 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.

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[10] It is worth noting that the difference for each quantile q between the two distributions $\hat{q}(\hat{\beta}^{06}, X^{06})$ and $\hat{q}(\hat{\beta}^{m06,r93}, X^{06})$ can be easily rewritten in the following way: $\left\{\hat{q}(\hat{\beta}^{06}(0.5) + \hat{\beta}^{06}(\theta) - \hat{\beta}^{06}(0.5), X^{06})) - \hat{q}(\hat{\beta}^{06}0.5) + \hat{\beta}^{93}(\theta) - \hat{\beta}^{93}(0.5), X^{06})\right\}$, from which it comes out clearly that the only component that changes over time is the residual one.

[11] As in the previous note: $\hat{q}(\hat{\beta}^{m06,r93}, X^{06})$ - $\hat{q}(\hat{\beta}^{93}, X^{06})$ = $\hat{q}(\hat{\beta}^{06}(0.5) + \hat{\beta}^{93}(\theta) - \hat{\beta}^{93}(0.5), X^{06})$ $- \hat{q}(\hat{\beta}^{93}(0.5) + \hat{\beta}^{93}(\theta) - \hat{\beta}^{93}(0.5), X^{06})$.

To sum up, adding and subtracting $\hat{q}(\hat{\beta}^{93}, X^{06})$ and $\hat{q}(\hat{\beta}^{m06,r93}, X^{06})$ 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:[12]

$$\hat{q}(\hat{\beta}^{06}, X^{06}) - \hat{q}(\hat{\beta}^{93}, X^{93}) = \overbrace{\left\{ \hat{q}(\hat{\beta}^{06}, X^{06}) - \hat{q}(\hat{\beta}^{m06,r93}, X^{06}) \right\}}^{\Delta residuals\ (within)}$$
$$+ \overbrace{\left\{ \hat{q}(\hat{\beta}^{m06,r93}, X^{06}) - \hat{q}(\hat{\beta}^{93}, X^{06}) \right\}}^{\Delta Coefficients\ (between)} + \underbrace{\left\{ \hat{q}(\hat{\beta}^{93}, X^{06}) - \hat{q}(\hat{\beta}^{93}, X^{93}) \right\}}_{\Delta \text{Covariates}}$$

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.[13]

5. Quantile decomposition results

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.[14] 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. The coefficients component turns out to be the one that changes the most along the wage distribution: from -2.5% at the 10th percentile to a -12% at the 90th, monotonically. 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

[12] 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.

[13] 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). Moreover, note also that 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] It is worth pointing out that it is possible to estimates the coefficients for education at all quantile of the distribution, meaning that there are graduates in the lower part of the distribution and workers with low educational levels at the top of the wage distribution.

workforce would have shifted to the right the wage distribution, given fixed the two other components. Further, the within component displays an asymmetric impact on the wage distribution, being positive in the lower quantiles (4.7% at the 10^{th} and 2.3% at the 25^{th}) and negative in the upper quantiles (-1.7% at the 75^{th} and -1% at 90^{th}).

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 coefficients component is dominated by the positive impact of the covariates component, which is also strengthened by the positive residual component. Above the median wage, on the contrary, the strong negative coefficients component, which is also reinforced by the negative residual 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, in order to show that our analysis concerning the period 1993-2006 is robust to the choice of the period, i.e. the behaviour of the three decomposition components are qualitatively very similar in the three panels.[15] Second, to have a better understanding of the dynamics of the different percentiles of the distribution.[16]

These over time variations at selected quantiles help to understand the dynamic of wage inequality. Actually, the standard inequality ratios (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 ratio 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 ratio reduction observed in the private sector is mainly driven by the negative coefficients component (65%), and to a lesser extent by the negative residual component (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%).

[15] 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.

[16] The 10th 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.

As far as the negative coefficients component is concerned, it is consistent with the falling educational wage premia observed in Italy over the period 1993-2004 along the whole wage distribution (Naticchioni, Ricci, Rustichelli 2008).[17] 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.[18] Results for the period 1993-2002 and 1993-2004 are very similar from a qualitative point of view (Table 3).

6. Explanations for the Italian wage inequality trends

6.1. Explanations for the trends of the upper tail of the wage distribution (the 90/50)

In this section we set out to address the explanations for the changes in the upper tail of the wage distribution and for the related findings of the decomposition analysis. We showed that the decrease of the 90/50 ratio is associated to the negative coefficients component, and this is in turn related to the falling EWP observed in Italy. As a first possible explanation we analyses whether the changes in the job quality distribution might have played a role in explaining the decreasing 90/50 ratio. Autor et al. (2006), Goos and Manning (2006), Dustmann et al. (2008) show that changes in the job quality distribution can at least partially account for the increasing wage inequality trends in the US, the UK and Germany. Autor et al. (2006), Goos and Manning (2006), Dustmann et al. (2008) 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, complement to non-routine tasks, and uncorrelated to manual tasks, which are located at the top and the bottom of the wage distribution, respectively. In this framework, the new technologies can account for the increase in the upper tail wage inequality (the 90/50 ratio) and for the decrease of the lower tail inequality (the 50/10 ratio). Further, Goos et al. (2009) find out job polarization trends in most of the European countries, using data from the European Labour Force Survey data (ELFS).

We apply the same kind of analysis as in Autor et al. (2006), Goos and Manning (2006), Dustmann et al. (2008), Goos et al (2009), to the Italian case, in order to verify whether the

[17] The results of Naticchioni, Ricci, Rustichelli (2009) 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.

[18] 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.

changes in wage inequality can be related to changes in the quality of jobs offered by firm. We use the same data as Goos et al (2009), the ELFS, for the same years (1993 and 2006) for Italy. Consistently with our analysis, we focus on the private sector, while Goos et at (2009) considered both public and private sector employees. As in Goos et al (2009) employment is measured as usual weekly hours worked, but similar results can be obtained when using the alternative definition of persons employed. According to the ISCO classification we divide the occupations in three main categories: skilled (ISCO 1-3), medium-skilled (ISCO 4-8), unskilled (ISCO 9).[19]

In Table 4 we report the shares of the amount of hours worked in skilled, medium-skilled and unskilled occupations in 1993 and 2006, and the related variation over time. It is worth noting that skilled occupation increase by 5.8 percentage points, medium-skilled occupations (proxy for routine occupations) decrease by 5.0 percentage points, and unskilled occupations decrease only slightly (-0.8 percentage points).[20] These findings are consistent with the polarization patterns observed by Goos et al (2009) for Europe: the share of routine occupations decreased more than those of unskilled and, especially, of skilled occupations.

Nonetheless, these polarization patterns contribute only partially to explain our wage inequality patterns. The increase in the 10^{th} percentile of wages, with respect to the median, can be related to the greater drop in the share of routine occupations -located in the middle of the wage distribution- with respect to the basically stability of the share of unskilled occupations. Hence, the changes in the occupations shares can address –at least partially- the evolution of the 50/10 ratio, as we will discuss in the next paragraph. However, the decrease in the 90/50 ratio can hardly be related to the increase in the share of skilled occupations and to the drop in the demand for medium-skilled occupations. To investigate further this issue we go on to analyse the labour demand for educated workers, to check whether the increase in skilled occupations has matched the increase in the supply of educated workers. We then compute how graduates are allocated in skilled, medium-skilled, and unskilled occupations, and the variations of these shares from 1993 to 2006. Table 5 shows that the share of graduates employed in skilled occupations

[19] Goos et al (2009) compute the three categories ranking the occupations by average wages. Comparing our classification to the one of Goos et al (2009), the occupations included in the skilled category are basically the same, while the occupations in the medium-skilled and the unskilled differs slightly.

[20] Note that there has been a structural change in the Italian 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 mainly 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 analysis for the period 1993-2003, and results are very similar.

decreased by 6.2%, from 79.8% to 73.6%, while it increases in the medium-skilled (4.7%) and unskilled occupations (1.5%).[21]

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 in recent years might have been willing to accept jobs at the bottom or at the middle of the job quality distribution because the demand for graduate workers has not increased over time at the same pace as the supply of education.

6.1.1. The role of supply-demand interactions

The findings of the previous section suggest that the interactions between demand and supply can account for wage inequality patterns in Italy. Put it differently, one might argue that the increase in educational levels of the labour supply from 1993 to 2006 has been faster than the increase in the demand for education, and this might have generated the reduction in the EWP that in turn represents the driving force of the fall in wage inequality, especially in the upper tail of the distribution. It is worth noting that actually the increase in the supply of education has been impressive, since the share of workers with an upper secondary degree increased from 33% to 47% and the share of graduates - although still very low when compared to OECD countries- more than doubled, from 4% to 9%.

To address if and how much the interactions between demand and supply have played a role we implement the methodology proposed by Card and Lemieux (2001), which makes use of aggregate CES production function with two types of labour inputs, skilled and unskilled labour. The aggregate output in period *t* is given by:

$$Y_t = \left(\theta_{H,t} \cdot H_t^{\rho} + \theta_{L,t} \cdot L_t^{\rho}\right)^{\frac{1}{\rho}} \qquad (3)$$

where the parameters $\theta_{H,t}$ and $\theta_{L,t}$ represent the efficiency of skilled and unskilled, respectively, H_t is the aggregate labour input of skilled and L_t is the aggregate labour

[21] Similar patterns of 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 job quality distribution.

input of unskilled labour in year t. The elasticity of substitution σ_E between the two educational groups is given by $\sigma_E = \dfrac{1}{1-\rho}$.

We also exploit the experience and gender information in our dataset, dividing the sample of skilled and unskilled workers into 14 groups (7 experience classes and gender), for each wave (1993, 1995, 1998, 2000, 2002, 2004, 2006).[22] As in Card and Lemieux (2001) we assume that aggregate inputs depend on two nested CES of skilled and unskilled labour:

$$H_t = \left[\sum_j \left(\alpha_j \cdot H_{j,t}^{\eta}\right)\right]^{\frac{1}{\eta}} \tag{4}$$

$$L_t = \left[\sum_j \left(\beta_j \cdot L_{j,t}^{\eta}\right)\right]^{\frac{1}{\eta}} \tag{5}$$

where the index j represents each experience-gender group, the parameters α_j and β_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 $\sigma_A = \dfrac{1}{1-\eta}$. 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. $w_{j,t}^{H} / w_{j,t}^{L}$, satisfies the following condition:

$$\begin{aligned} \log\left(\frac{w_{j,t}^{H}}{w_{j,t}^{L}}\right) &= \log\left(\frac{\theta_{H,t}}{\theta_{L,t}}\right) + \log\left(\frac{\beta_j}{\alpha_j}\right) - \left(\frac{1}{\sigma_E}\right)\log\left(\frac{H_t}{L_t}\right) \\ &\quad - \left(\frac{1}{\sigma_A}\right)\left[\log\left(\frac{H_{j,t}}{L_{j,t}}\right) - \log\left(\frac{H_t}{L_t}\right)\right] + e_{j,t} \end{aligned} \tag{6}$$

[22] 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 $e_{j,t}$ is the error term in the empirical specification of the firm-maximization condition. According to this model, the skilled-unskilled wage gap for a given gender-experience group *j* depends on both the aggregate relative supply of skilled labour (H_t/L_t) in period *t*, and on the experience-gender specific relative supply of skilled labour ($H_{j,t} \backslash L_{j,t}$). As in Card and Lemieux (2001) we approximate the term $log(\theta_{Ht}/\theta_{Lt})$ with a linear trend, since it does not depend on *j*, and the terms $log(\beta_j/a_j)$ 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 ($\sigma_A \to +\infty$). 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* ($H_t \backslash L_t$), 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 supply and the aggregate supply, i.e. $[log(H_{j,t}/L_{j,t}) - log(H_t/L_t)]$, always including time trend 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 inverse of the elasticity of substitution between the two educational groups, i.e. σ_E.

In the empirical specification we define as skilled the graduates and as unskilled all workers with less than a university degree. In column (1) of Table 6 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 σ_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 σ_E is hence equal to 3 in column (2) and to 2.8 in column (1).[23]

[23] 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 a, β, σ_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 σ_E is slightly higher, around 4. Furthermore, in our analysis we define H_t, $H_{j,t}$, L_t, and $H_{j,t}$, using the (weighted) absolute number of workers. Actually, Card and Lemieux (2001) exploit 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 year. The estimate of σ_E is still around 4. Finally, we also implemented the methodology of Manacorda, Manning, Wadsworth (2006), which allows to have three separate elasticities of substitution, one between skilled and unskilled labour, one among the experience groups, and another one between men and women

This value for σ_E is very high when compared to the US case, where it ranges between 1.4 and 2 (Acemoglu, 2002), while it is lower than the value of 5 for Germany (Dustmann et al., 2008).[24] These findings suggest that the changes over time in relative supply affect negatively relative wages, entailing a fall in the EWP that in turn drives the fall of the 90/50. Even more importantly, the linear trend coefficient, which is the proxy for the skill-biased technical change -and hence in a sense for the demand for skilled workers- is not statistically different from zero. Combining the two effects, it is possible to claim that relative wages between skilled and unskilled decreased over time because they are negatively affected by the changes in the supply of education.

According to these findings, one might wonder why demand for skilled has not increased in Italy at the same pace as in other OECD countries. This analysis is beyond the goals of this paper. Nonetheless, it does not represent an unexpected finding once one takes into account the data concerning technology improvements in the OECD countries. 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, 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). Moreover, it is also important to take into account other related peculiar factors characterizing the Italian economy, i.e. the specialization in traditional sectors (Matano and Naticchioni, 2008), the family based corporate governance system and the incidence of small size firms (Pagano and Schivardi, 2006).

(in each experience group). However, results do not change much, since the additional elasticity of substitution between men and women is very high (higher than 10).

[24] 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 σ is equal to 5.5. Dustmann et al. (2008) claim that this high value of σE 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 equal to 0.44 suggesting that the supply demand explanation explain almost half of the total variance of relative wages.

6.2. Explanations for the lower part of the distribution (the 50/10 ratio)

The 50/10 ratio decreased by 9% from 1993 to 2006, and the decomposition analysis pointed out that this reduction can be accounted for by the negative coefficients component (48%) and by the residual component (49%). The negative coefficients component can be related to supply-demand interactions, as shown in the previous section. To provide an interpretation for the residual-within component, we resort to Lemieux (2002, 2006), which argue that educated and experienced workers display higher levels of wage dispersion and that their employment share increase over time in all OECD countries. Hence, according to Lemieux (2002, 2006) the increase of the residual component at the 10th percentile of the wage distribution can be related to the increase of the shares of educated and experienced workers, characterized by a higher dispersion: the so called composition effect.

Moreover, we also claim that other two factors have at least partially affected the decrease in the 50/10 ratio. The first factor concerns, as already stressed in the previous paragraph, the changes in the job quality distribution offered by firms, since the demand for medium-skilled occupations decreased more than the demand for unskilled workers, and this is consistent with a decrease in the 50/10 ratio.

The second factor regards the fact that SHIW data contains only information about net wages. Under the hypothesis that tax regimes have not 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.[25] 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 7). The time span considered by Martone (2008) is 1998-2006, since before 1998 changes in the tax system had been negligible. 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

[25] 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.

40.000 euros. As for single individuals similar patters applies: effective average tax rates decreased especially in the lower tail of the wage distribution (below 20.000 euros) while their reduction is very small in magnitude at the top of the wage distribution. In accordance with this evidence it is then possible to argue that the increase in the 10th percentile of net wages from 1993 to 2006 is at least partially related to a reduction in the effective average tax rate, while changes in the upper tail of the distribution are not affected by changes in tax regimes.

It is also worth noting that in this section we do not rely on explanations based on the role of institutions (employment protection legislation, unions power, centralized wage setting) because of the waves of flexibility policies introduced in Italy in the nineties and in the early 2000s. 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.[26]

7. Conclusion

This paper shows that the Italian case is an outlier in the literature concerning wage inequality trends. 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 part 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. The decomposition analysis shows that the decrease in the 90/50 ratio is mainly driven by the negative coefficients component, while the decrease in the 50/10 ratio is related to both a negative coefficients components and a residual component.

As for possible explanations for our findings we claim that the decrease in the 90/50 ratio has to be mainly related to the decrease over time in EWP, in turn caused by supply-demand interactions, and not to the changes in the quality distribution of jobs offered by firms. As for the decrease in the 50/10 ratio, we identify three main explanations: a) the composition effect (Lemieux, 2002, 2006), which drives the residual components derived

[26] 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 tooks place at the beginning of the nineties.

using the decomposition analysis: the increase in the share of educated workers at the bottom of the wage distribution might have increased the residual component that is one the driving force of the increase of the wages at the 10^{th} percentile; b) the changes in the job quality distribution offered by firms since the reduction in demand in medium-skilled occupations is much stronger than the one occurred for unskilled occupations; c) the changes in the tax regimes: Martone (2008) shows that in the period of analysis the effective tax rate decreased strongly for workers at the bottom of the wage distribution, while they remained stable (or slightly decreasing) for the rest of the distribution. Hence, the reduction in the 50/10 ratio might at least partially be related to changes in the tax regimes.

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Tables

Table 1: SHIW Sample descriptives. Private Sector.					
	1993	1995	2002	2004	2006
Share of Female	0.33	0.35	0.38	0.38	0.39
Education					
Primary - no school	0.18	0.16	0.09	0.09	0.05
Lower secondary	0.45	0.40	0.38	0.38	0.38
Upper secondary	0.33	0.39	0.44	0.45	0.47
Univ. Degree or higher	0.04	0.04	0.08	0.08	0.09
	1.00	1.00	1.00	1.00	1.00
Experience (year)					
eps1 - 0-5	0.18	0.18	0.16	0.14	0.13
eps2 - 6-10	0.13	0.16	0.12	0.13	0.13
eps3 - 11-15	0.14	0.12	0.13	0.14	0.13
eps4 - 16-20	0.13	0.13	0.16	0.17	0.17
eps5 - 21-25	0.13	0.13	0.15	0.14	0.15
eps6 - 26-30	0.11	0.11	0.11	0.11	0.12
eps7 - 31-35	0.09	0.09	0.10	0.09	0.09
eps8 - >36	0.08	0.08	0.07	0.09	0.09
	1.00	1.00	1.00	1.00	1.00
Net Wages (Monthly)					
Mean	1318	1255	1295	1304	1356
10th percentile	723	722	750	775	822
50th percentile	1177	1104	1165	1195	1224
90th percentile	2006	1930	1916	1933	1994
Observations	4052	3798	4195	4341	4386

Note: 0.025% of the observation in the right and left tails dropped. Weight: pesofl.

Table 2. Total observed variations (in percentage points) at selected quantiles and quantile decomposition into the coefficients, covariates and residuals components in the private sector.

	Δ p10	**Δ p25**	**Δ p50**	**Δ p75**	**Δ p90**
Panel A	**Variations at selected quantiles - 1993-2006**				
Total estimated variation	12.5	7.4	2.9	-1.2	-2.2
Coefficients	-2.5	-4.5	-7.1	-9.8	-12.0
Covariates	10.3	9.6	10.0	10.2	10.7
Residual	4.7	2.3	0.0	-1.7	-1.0
Panel B	**Variations at selected quantiles - 1993-2004**				
Total estimated variation	6.3	3.4	0.0	-3.7	-5.5
Coefficients (between)	-4.8	-6.2	-8.6	-10.7	-13.4
Covariates	8.5	8.7	8.7	9.0	9.2
Residual	2.6	1.0	-0.1	-2.0	-1.2
Panel C	**Variations at selected quantiles - 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	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 covatiates component in the private sector (in percentage points).

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

Source: SHIW data.

Table 4: Shares of the total number of hours worked in skilled, medium-skilled, and unskilled occupatons, in 1993 and 2006, and the related variation. Private Sector.

	Unskilled ISCO 9	**Semi-skilled ISCO 4-8**	**Skilled ISCO 1-3**
Share 1993	0.12	0.69	0.19
Share 2006	0.11	0.64	0.25
Variation in % points	**-0.8%**	**-5.0%**	**5.8%**

Data: Italian Labour Force Survey.

Table 5: Share of the hours worked by graduates in skilled, medium-skilled, e unskilled occupations in 1993 and 2006, and the related variation (in percentage points). Private Sector.

	Unskilled ISCO 9	**Semi-skilled ISCO 4-8**	**Skilled ISCO 1-3**
Share 1993	0.013	0.189	0.798
Share 2006	0.028	0.236	0.736
Variation in % points	**1.5%**	**4.7%**	**-6.2%**

Data: Italian Labour Force Survey

Table 6. The role of the supply-demand explanation

	(1) perf. Substitut. among groups		**(2) imperfect Substitut. among groups**	
Covariates	Coeff	p-value	Coef	p-value
log(Ht/Lt)	-0.358	0.003	-0.337	0.004
[log(Hj,t/Lj,t) –log(Ht/Lt)]	-	-	-0.076	0.269
Time trend	0.023	0.134	0.020	0.160
Groups effects	Yes		Yes	
R^2	0.43		0.44	
Elast.Sub.(σ_E)	2.8		3.0	

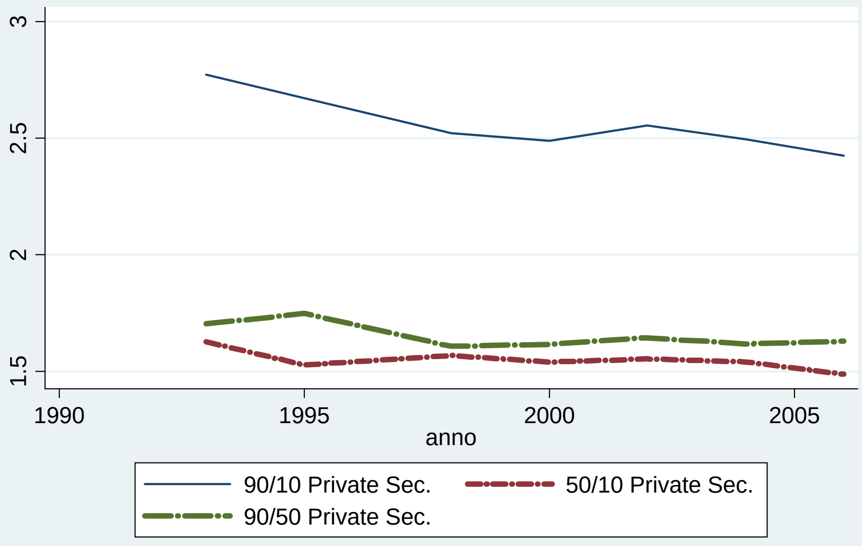
SHIW Bank of Italy data. Sample size: 98 observations.

Table 7. Trends in effective average tax rate from 1998 to 2006				
	Dependent employees			
	Single		Married with 2 children	
Euros	1998	2006	1998	2006
10000	11.6	7.1	-29.5	-30.1
15000	17.0	14.7	-5.6	-16.3
20000	20.0	18.4	8.1	-0.3
25000	22.7	20.7	15.8	9.9
30000	24.7	22.9	20.2	14.6
40000	27.7	27.1	24.5	20.9
50000	30.2	29.5	28.2	26.0
75000	33.6	32.6	32.3	31.9
100000	35.9	34.2	35.0	34.2

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

Figures

Figure 1. 90/10, 50/10, 90/50 indexes in the private sector
Period 1993-2006



APPENDIX: 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:

(1A) $$\ln w_i^t = X_i^t \beta^t(\theta) + u_{i,\theta}^t$$

where $i=1,\ldots n$ is the number of observations in each year t, θ 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:

(2A) $$\min_{\beta}\left[n^{-1}\left(\sum_{i=1}^{n}\rho_\theta(\ln w_i^t - X_i^t\beta)\right)\right] \quad \text{where } \begin{cases}\rho_\theta(u)=\theta u \text{ if } u>0\\ \rho_\theta(u)=(\theta-1)u \text{ if } u<0.\end{cases}$$

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, $Q_\theta(w\,|\,X_i)$, for all θ 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:

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

where X_i is a vector for the set of covariates. Basset and Koenker (1982) showed that, under some regularity conditions, the estimated conditional quantile function is a consistent estimator of the population conditional quantile function, uniformly in θ.[27]

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, $\hat{w}_i \equiv \{X_i\hat{\beta}(\theta_j)\}_{j=1}^{J}$, 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,

[27] To validate the heteroscedasticity hypothesis, i.e. the fact that 'slope coefficients' are different for the same covariate across quantiles, we successfully test in this paper that the estimates of the coefficient vectors at different quantiles are statistically different from one another (Koenker and Basset, 1978).

$Q_\theta(w \mid X_i) = X_i \hat{\beta}(\theta_j)$ for given X_i and θ_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 θ_j are randomly chosen from the uniform (0,1) distribution. In this setting, each observation of the resulting matrix, $\hat{w}_i \equiv \left\{X_i \hat{\beta}(\theta_j)\right\}_{\substack{j=1,\ldots,J\\ i=1,\ldots,N}}$, can be considered as drawn from the estimated marginal distribution of wages.[28]

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 θ, i.e. $\int_X \int_\theta \hat{Q}_\theta(w \mid X) g(X) \partial\theta\, \partial X$, integral that produces a consistent estimator of the marginal distribution of wage, $f(w)$, which can be written as (Melly, 2005, 2006):[29]

$$f(w) = \int_x f(w,x)dx = \int_x \underbrace{f(w \mid x)}_{= \int_\theta Q_\theta(w|X)d\theta} g(x)dx = \int_x \int_\theta Q_\theta(w \mid x) g(x) d\theta dx$$

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 θ ranging from 0 to 1, and this can be considered as the internal integration over the support of θ. 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.

[28] 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 $\hat{w}_i \equiv \left\{X_i \hat{\beta}(\theta_j)\right\}_{\substack{i=1,..,N\\ j=1,..,J}}$, 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). In this paper we implement 200 weighted quantile estimations on a regular grid, from 0 to 1 (0.005, 01, 015,…, 0.99, 0.995), deriving the coefficients $\beta(\theta)$ along all the θ 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.

7 *Note that* θ is uniformly distributed on the [0,1] interval, implying that the relative density $f(\theta)$ is equal to 1.

APPENDIX

Figure A1. Fit of the estimation methodology of Machado and Mata (2005): estimated vs observed distribution in 2006.