# An exploration of recent wage structure changes in Italy, 1995-2002

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**Abstract**

The aim of this paper is to provide a picture of recent wage structure changes in Italy. The analysis, performed on the Structure of Earning Surveys, on the basis of a novel technique by Lemieux (2002), account for the change in wage distribution, highlighting the contribution of prices and composition, in both the components of between and within groups (or residual) inequality. The work documents a slight increase in overall inequality and in the residual inequality, between 1995 and 2002, that is mostly explained by a change in the composition of the workforce.

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## 1. Introduction

In recent years, a vast American literature has documented and tried to explain the changes in wage distribution. The contribution of this literature is twofold. On one side, it has explored the dynamic of wage inequality along several dimensions such as education, experience, gender and inequality within groups (also called as residual inequality) trying to distinguish changes due to compositional effects to changes due to price effects. On the other side, the analysis has aimed to discriminate between different kinds of explanations. As is often the case, when a problem is studied deeply, as new data became available and new techniques were employed, the evidence has grown up and become more complex. Accordingly, to describe this evidence, theories had to be changed to fit the more detailed picture that was being emerging. Thus the first set of theories which assigned a prevalent role to the progress of technological change in shaping the education related wage gap and the within groups inequality have been modified to explain different patterns in different zones of the wage distribution. More recent views of the change in wage differentials have stressed the importance of two factors. First, the changes in institutional settings (especially in the minimum wage) have been found related to the changes over the lower wages. Second, changes in composition have been found to explain much of the residual inequality. While there is no agreement yet on an encompassing theory that interpret the whole picture (see for instance the debate between Lemieux (2005, 2006a) and Autor Katz and Kearney (2005a, 2005b, 2006) the main elements of a theory are largely accepted.

In contrast, in Italy the evidence on wage structure changes has been quite fragmented. In particular, there lacks a picture of recent changes. This work contributes to build evidence on these topics through the use of a recently available new data source, the Structure of Earnings Survey of the 2002. Combined with the previous wave of 1995, it serves the scope of examining the changes that have occurred in recent time.

The scope of the paper is, basically, to document the changes in the wage distribution from 1995 to 2002 evaluating 1. the role of between vs. within groups differentials 2. the role of composition and prices. To this aim, I use a recent technique due to Lemieux (2002). As a secondary scope, it tries to qualify the evidence related to the increase in the university premium.

The plan of the work is as follows. In section 2 I briefly recall some important findings of the American literature in the last 15 years along with the proposed explanations of this evidence. The

section aims to serve as guidelines for the techniques used and the theories proposed to interpret the evidence. In section 3, it is reported a short discussion on recent changes of some Italian labour market institutions which can be directly or indirectly relevant for the discussion on the wage differentials. Section 4 describes the data source. Section 5 presents some basic descriptive statistics together with an analysis based on quantile regressions of the structure of wages. In section 6, the decomposition due to Lemieux (2002) is explained in a simplified way. In section 7 the decomposition is applied to the changes in the wage distribution from 1995 and 2002. Section 8 completes the analysis by examining closely the differentials between the groups. Section 9 tries to assess if the movement in the education differentials are linked to the changes in the industrial/work composition or they can be related to the changes in the quantities of labour force. Section 10 reports some conclusions.

## 2. A look at the theories and evidence from the USA

The scope of this section is to briefly review the main works that, since the 90's, have shaped the discussion over the rise in the wage inequality in the USA. Far from being exhaustive, it is only meant to address the main points of the debate in the USA that in turn serve as motivation and guidelines for the analysis of the Italian situation.

Since the early 90's up to the present days there has been quite an intense flourishing of literature, mainly American, aimed at measuring and explaining the rising wage differentials that were being measured. In particular, this literature has showed that in the USA a striking increase in the wage gap associated to education occurred during the 80's followed by a slowing down of this trend during the 90's. If the return to education has been a primary parameter of interest other dimensions of inequality have been added to the study with the result of a more interesting but also more complex view of what was happening. The other two dimensions that have received particular attention are the gap due to the labour market experience and the within groups inequality. Card and Dinardo (2002) show that the change in the wage-experience profile during the 80's and the 90's has been different for different groups of workers (defined by gender and education). Summarizing, while the steepness of the profile has remained substantially unchanged for men with a high school level education, it seems to have become steeper for less experienced workers and flatter for the

more experienced workers with college education. For women the return to experience has increased especially for young to middle-age workers.

As for the change in the within group inequality, also referred to as residual inequality (since it is measured on the residual of wage regression), it has risen in the 80's and remained roughly constant in the successive decade. A similar pattern has been registered by the overall inequality.

The attempt to explain, with a unique theory, the changes in the wage structure along the various dimensions has started with the path breaking article by Juhn, Murphy and Pierce (1993). Their conclusion was that the inequality was rising along all dimensions and they attributed these changes to an increase in the price of skills, both observable and unobservable. Specifically the rise in the residual wage inequality was traced back to an increase in the price of unobservable skills such as the personal ability. Although this article was not about the causes of these enlarging differentials they suggested that an important role could have been played by skill bias technological change and/ or a change in the global economy trends. While part of the following literature has kept on pointing out the increase in the pace of technological change as the most likely cause of the increase in inequality, another part has showed that to explain the changes to the wage distribution as a whole a role had to be assigned to the changes in institutional factors as the union density and the minimum wage. Dinardo, Fortin and Lemieux (1996) (hereafter DFL) using a novel technique that allows to compare the changes in the entire distribution of wages removing the changes in the composition of the workforce, showed, for instance, that the fall of the real value of the minimum wage explained a considerable share of the increase in wage inequality, by increasing the dispersion in the left tail of the distribution. These types of analysis have greatly enhanced the view about changes in the wage distributions showing that possibly different factors are behind the growth in wage inequality along its dimensions. An important contribution to understand the change in the residual inequality has been given by Lemieux (2002 and 2006a). Extending the analytical method of DFL in a way that allows disentangling the effect of composition from the effect of prices, his analysis has showed that the observed rise in residual inequality has to be related to compositional changes of the workforce. His argument is that the variance of outcome rises with the level of skills. Quite interestingly, as is akwnloledged in his work, this point was first made clear in a former work by Mincer and it's related to the human capital theory. Mincer sustained that at higher levels of

education and experience, due to a more dispersed investment in human capital, an increase in the variance of earnings is likely to be observed. Lemieux argument proceeds by pointing out that with a secular rise in the educational endowment of the workforce and with the ageing of population this leads to more dispersed within group earnings. In other words the observed rise in residual inequality is due not to the rise of the prices of unobservable skills, as sustained by Juhn, Murphy and Pierce (1993), but to compositional effects associated to socio-demographic factors. According to his measurement the contribution of these factors to the residual inequality explains a large share of the residual inequality growth in the 80's and almost all of it thereafter. The view by DFL and Lemieux (2002 and 2006a), among others, has been recently named "revisionist" in that it down-weights the importance of technological change in explaining the residual inequality, and hence of the overall inequality, and points out towards compositional effect and the change in institutions. The revisionist view has been challenged by recent works of Author Katz and Kearney (2005a, 2005b, 2006). Their main finding is that during the 90's inequality in the top half of the distribution has risen but has been largely compensated by a contraction of the inequality in the bottom half. This dynamic was different from the one observed for the 80's where the inequality increased both for the higher wages and for the lower ones. To this evidence on wages, they add evidence that the employment growth has been concentrated for occupations at both ends of a wage scale during the 90's while the rate of growth had risen almost monotonically with the wage level in the previous decade. This dual behaviour of wages and employment that occurred during the 90's has been referred to with the term of "polarization of work" by Goos and Manning (2003) and it has been related to an impact of technology differentiate by jobs. Technology, as Goos and Manning (2003) and Autor Levy and Murname (2003) argue, has the effect of replacing jobs that require routine tasks, either manual or non manual, that are typically jobs which pay a wage in the middle of the wage distribution, that is middle skilled jobs. At the same time it enhances the demand of jobs which involve higher cognitive skills, such as professionals, engineers researcher and so on, while it has little impact on the low skilled jobs whose content consist mainly of non routine manual tasks (cleaners, servers etc.).

## 3. Wage inequality and the Italian Labour market institutions

The American labour market is usually depicted as a market, that, due to a decentralized wage settings system, is characterised by a high degree of wage flexibility. In contrast, continental European wage setting institutions are considered more centralized with the effect of designing a labour market where wages are relatively rigid. The Italian labour market institutions, however, have undergone some relevant changes in the last decades that can have affected the way wages are determined and react to market forces. In this section I recall and discuss the main modifications to the institutions with the aim of highlighting if, in principle, the labour market can have gained wage flexibility in recent years. First of all it has been affected by a secular trend of decline of the union density. Second, it has gone through the gradual dismantlement of the wage indexation system (Scala Mobile) at the end of the 80's. As Borgarello and Devicienti (2002) report, these two factors have been pointed out as probable causes of the increasing wage dispersion that has characterised Italy from the mid 80's. Lately, two main strands of reforms of the labour market could have had some impact on the wage flexibility and thus contribute, at least indirectly, to shape wage differentials. The first, which specifically affected the wage settings mechanism, is the reform signed with the *Accordo di Luglio 1993* (July 1993 Agreement) between the social institutions (Government, Employer Federations and Trade Unions) whose scope was to establish a new wage bargaining system composed of two stage of bargaining. The first stage, at sectoral national level has the scope of defending the purchasing power of workers linking the wage to the inflation targeted by the government. The second stage, at the firm level, has the scope to integrate the wages with bonuses linked to the "economic performance of the firm".

The effect of the new wage setting mechanism on inequality is uncertain. On one hand, the principle that wages increases, set up with the sectoral national bargaining, have to follow the rate of target inflation, by introducing a mechanism of coordination, should reduce the wage dispersion between sectors. On the other hand the effect of firm level contracts can be twofold: it should increase the wage differentials between otherwise similar workers of different firms but, by establishing a payment equal for all workers in a firm, can reduce the inequality within the firm. More important to this discussion is the extension of the coverage of the firm level contracts and the effectiveness of

these contracts on the actual level of pay. According to Casadio (2003)[2] the share of workers in firms with at least 10 employees which is covered by these integrative contracts was in the mid 90's about the 40% and this share is increased only slightly up to the 2001. Moreover, the extent to which these bonuses add to the basic pay is still to be clearly understood. However results from the manufacturing firms with over 50 employees showed that they were discontinuous and of reduced amount.

The second important reform of the labour market regards the employment flexibility. The so-called Treu Law[3] in the mid 90's has regulated several non-standard work arrangements. The steady growth of the employment registered in the second half of the 90's is largely associated to the diffusion of atypical labour contracts (that is non full time/non permanent jobs) which in turn is changing quickly the employment composition. For most of the contracts as wage employees, other things being equal, non-standard employees should not get a (full time equivalent) monthly remuneration different from the standard workers[4]. The actual effects on a comprehensive measure of hourly wage, again, is not clear. On one side, it depends on the number of hours worked by the atypical workers respect ot the typical ones (for instance it depends whether non-standard and standard workers have the same probability of accessing overtime hours, which receive an higher remuneration). On the other side, it depends on the coverage to these atypical contracts of parts of the remuneration integrative of the basic pay (such as individual premia). Moreover, the availability of new forms of contracts may have triggered the creation of jobs (or favoured the emersion from the underground economy) that are different (also in the remuneration) from the jobs usually available under the typical arrangements.

Concluding, the recent evolution of the Italian labour market institutions has no clear expected effect on wage flexibility and inequality. If on one side there are elements that could have made the wages more flexible and responsive to the changes in the labour demand and supply (such as the decreasing importance of the trade unions or the availability of new forms of contracts) other elements could play an opposite role (such as the increased degree of coordination between sectors).

[2] All the discussion on the wage setting is summarized from this article.
[3] More recently it has been extended and modified by the Biagi Law.
[4] One exception is the contract of apprenticeship for the newly employed worker that can be paid less than the contractual minimum for a worker in that category.

## 4. Features of the data

The data used in this work are individual data from the Italian Structure of Earning Survey of 1995 and 2002. This survey is a European Union harmonized survey provided for by the EU Council Regulation 530/1999. It has to be conducted once in four year. The survey for 1995 was a first attempt to set up a regular and common survey among the member states. The Italian survey for 2002 covers all firms with at least 10 persons employed in the sectors from C to K of the classification NACE rev.1.1.[5] The scope of the survey is to collect information on wage and hours worked of individual workers alongside with personal characteristics (sex, age, education), characteristics of the job (occupation, tenure, type of contract) and characteristics of firm at which the worker is employed (economic activity, size, geographical location). The sampling design is composed by two stages: in the first stage a sample of firms is selected according to a stratified random sampling where the strata were defined respect to economic activity sector, 7 classes of firm size and 5 geographical areas. In the second stage, firms are requested to select a random sample of their workers. This second stage sample size varies according to the size of the firm. The operational criteria of the survey for the 1995 were quite similar. One important difference is that the first stage sampling unit in this first survey was the local unit of the firm (a concept more similar to that of establishment) instead of the firm. A second important difference is about the educational classification used: while the first survey used a national classification of educational attainment and vocational training, the survey for the 2002 has adopted the International classification of Education (ISCED 97). To deal with this second problem the educational categories of the two surveys have been reclassified in order to get a single classification. The final breakdown contains 4 educational categories Primary education, Lower secondary education, Upper secondary and post secondary education and Tertiary education. I will also refer to the four levels respectively as Elementary school, Middle school, High school and University.

Another important point that is to be discussed refers to the representativeness of the workforce composition of this kind of surveys. Being business surveys, they are basically meant to be representative of the composition of the firm population not of the workers. Sampling design and

[5] These are: Mining and quarrying (C), Manufacturing (D), Electricity, gas and water supply (E), Construction (F), Wholesale and retail trade, repair of motor vehicles, motorcycles and personal and household goods (G), Hotels and restaurants (H), Transport, storage and communications (I), Financial intermediation (J), Real estate, renting and business activities (K)

sampling weights have to ensure that the composition of firm by size, economic activity and geographical location mirrors that of the population. As for the workforce composition, there is no guarantee that it is well represented. This can cause undesirable results especially when looking at the change in composition over time. To deal with this problem I have previously reweighed the two waves of SES to better represent the population composition by sex, age, education and geographical area as measured by the Labour Force Survey of the same years. The details of the reweighting procedure are given in appendix A1. This procedure has provided the new individual weights used in what follows.

The sample used in the following analysis is restricted to the individuals aged 20 to 64.

## 5. Descriptive analysis and evidence from quantile regression

This section explores the data with descriptive statistics and using quantile regressions.

The wage variable used here as in the rest of the paper is the (log of) real hourly wages (including overtime and bonus payments). Wages are expressed in 2002 value, using the consumer price index for the households of blue and white collar workers[6].

All the calculations of this paper are weighted using as weights the number of hours worked, obtained by multiplying the individual weight and the number of hours worked by the observation.

Table 1 shows mean and median wages for the two years for all workers and for aggregated groups. The period considered has been one of declining real wages: on average on all workers there has been a reduction of 1.1 log points. The analysis by groups reveals some important differences. For instance while the average wage of men has decreased by 2.5 points, that of women has increased by 3.9 indicating a reduction in the raw gender wage gap. Among the educational groups the workers with a high school or university degree experienced the highest decline. One thing to note is that when the change is measured between the median wages the Universities graduates have had a higher fall of the real wage: the difference between mean and median in this group points out to a heterogeneous behaviour along the wage distribution. Breaking down the analysis by gender shows that different behaviour of mean and median for the universities graduates is especially evident for

[6]Originally the values of the survey for 1995 are expressed in liras while the values for 2002 are expressed in euros. Thus before transforming the data in constant values, the values for 1995 have been transformed in current ECU. Then the constant value transformation has been operated.

the female workers. In fact, this group registered an increase of the average wage of 5.2 points and a decrease of 4 points in the median wage. This can be due to an increase in the wage concentrated at the extreme right of the distribution i.e. among the high wage workers. It's worth noticing that, although not as striking as for the female workers, a remarkable difference is also registered for men. Finally the analysis by experience groups shows that the losses are concentrated among the more experienced workers. The median wage confirms the same pattern.

Table 2 moves the analysis to the measures of inequality. I follow most of the works in this literature concentrating the attention on two simple measures of inequality: the variance of the log wages and the difference between the $90^{th}$ quantile and the $10^{th}$ quantile of the wage distribution, referring to it as the 90-10 wage gap. The variance of the wage distribution has increased from 1995 to 2002 from 0.141 to 0.149 log points with an increase of 5.7% over the whole period and an average annual change of 0.8%. The rate of increase is not far from that accounted for by Borgarello and Devicienti (2002) for the population of workers in the private sector aged 15 to 64[7]. They measure an average annual change in the variance of log earnings of 0.4% over the period 1990-1996 and a change of 1.1% over the longer period 1985-1996. Considering the present analysis as an ideal follow up of their work, the results confirm a slight increase in the earnings inequality. The average change in inequality in Italy is however far lower than the one registered from the estimates obtained for the USA. For instance, Lemieux (2006c) reports that, over a thirty years period from the 1973-1975 to the 2003-2005, the variance of log has increased at an average annual rate of 1.43%. It must be also pointed out, however, that in recent years the rate of change has significantly slowed down[8].

Turning to the 90-10 wage gap, the other measures of inequality, it shows also an increase of dispersion. Among the groups, the female workers wage variance has registered a considerable increase, hence reducing the difference with the male workforce which is the high variance group.

[7] It must be kept in mind that Borgarello and Devicienti paper differ from the present one for a number of aspects. First the data they use come from the Social Security Database sample of individuals. Second, the wage variable is the monthly wage where the data are normalized to get a wage that measures the remuneration of a 26 days long working month. Third, their working sample is trimmed at the 1st and 99th percentiles. Despite these differences the results seems quite connected. Even the level of wage inequality is very similar: for 1995, the year where the two works overlaps, the variance of log wages measured by Borgarello and Devicienti is 0.136 while in the present work is 0.141.

[8] Autor, Katz and Kearney (2005°, appendix Table1a) report an increase in the variance of log hourly earnings measured as 100*change of 2.3 over the period 1994-2003. The measurement is referred to the March CPS. The same statistics measured on the data of May and Outgoing Rotation Group is 0. In contrast the same measure calculated here for the 1995-2002 period is 0.7.

Thus the gender gap shows signs of reduction not only on the first moment but also in the second moment. The description is strengthened by the 90-10 gap.

The descriptive analysis can be misleading since there is little control over other covariates. To enhance the view I perform a quantile regression analysis of the log wage. The quantile regression can be summarized as a way of extending the common regression. While the latter is meant to estimate how the mean of the conditional distribution varies with the covariates, the former estimates the effect of covariates on selected quantiles of the conditional distribution of the dependent variable. The analysis at the median can be seen as the counterpart of the common regression in that it focus on a measure of location and, in the same way as the mean regression, can serve to measure the differences between groups. The analysis at different quantiles instead can highlight the differences in the return of a human capital variable along the wage distribution. In particular the difference between the effect at the $90^{th}$ quantile and the $10^{th}$ quantile is a measure of the dispersion within the groups. The quantile regression is estimated separately by gender. As for the specification, it includes: no intercept, four dummies that span the educational dimension and a quadratic polynomial in potential experience.

The use of educational categories instead of the number of years spent in education, although forced by data limitations, is to be considered by no means restrictive. In fact, recent results have shown that education has a differential impact according to the reached level of education. This feature of the return to education would be lost if the regression specification included only a linear trend in the number of years. Lemieux (2006b), along with a discussion of recent findings on this issue, use a quadratic polynomial in the years of education. Thus the use of dummies that span the educational attainment categories can highlight differential impact of different degree of education. Table 3 provides the results of the estimation exercise. However, to summarize these results four sets of graph are reported. Figure 1 plots the wages of educational categories evaluated at the median of the distribution. Both for male and female the figure shows the usual result that wages are increasing with the level of education. Less evident, but equally important, is that the major gains are obtained when passing from the middle school to the high school and from the high school to the university. The implied returns, that can be retrieved from the table of coefficients, for the middle school, high school and university over the respective preceding degree of education, for the 2002 are for males

respectively 10%,31%,44% and for the females 8%,30%,33%. Third, the graphs show that while the return to high school compared to the middle school has been stable over time, the return to university has expanded from 1995 to 2002 significantly.

Turning to experience, figure 2 shows the median experience earnings profile of a high school worker for the two years. The values reported are indexes in the sense that the wage for a worker with no experience has been set to 1 and other values are indexed at it. The figure shows that over time there has been little effect for male workers while the profile of female has slightly steepened for younger workers and has flattened for older workers.

The second set of graph shows the behaviour of the inequality within groups as measured by 90-10 effect of education and experience. As for education the main result is that the inequality is increasing with the level of education. It hints at the fact that the return to higher level of education, far from being constant over the wage distribution, grows with the wage level. This is emerging as a new stylized fact in the literature of wage differentials that have used quantile regressions (see Budria and Pereira (2005) and Martins and Pereira (2004)). In particular Martins and Pereira's that provide evidence for 16 countries in mid 90's conclude that: "…returns to schooling increase over the wage distribution. Or, to put it differently, the earnings increment associated with to schooling is higher for those individuals whose unobservable characteristics place them at the top of the conditional wage distribution" Martins and Pereira (2004 p. 367). They explain that, in general, this can be due to some unobserved factor heterogeneously distributed across the population whose value is correlated with wage and that interacts with education. One such factor can be the level of ability. If pay differentials due to different levels of ability grows with the level of education or, alternatively, if higher education trigger the inequality due to different ability this would result in an increasing dispersion of wages at higher level of education. Another possible explanation is that the return to education is just a synthetic measure of an array of returns to education associated, for instance, to different university degrees (e.g. Humanities, Scientific and so on). Since this range of educational possibilities is wider the higher the level of education this would explain why the inequality is higher at higher levels of education. Figure 3 add to this fact the evidence for Italy that while the inequality within the level of schooling up to the high school has narrowed from 1995 to 2002, that associated to universities graduates has widened.

On the experience side, the figure uncovers similar findings. The level of inequality is rising with the level of experience but the relationship appears to be less pronounced in the most recent year. The patterns described in this section are very important to gain insights into the changes in wage distribution. In particular the increase in wage inequality linked to higher level of education and job market experience may trigger an increase in overall inequality due to compositional effect. Generally speaking advanced countries are experiencing two socio-demographic phenomena: the increase in the share of the population and of the workforce with higher level of education and the aging of the population. If this is the case part of the increase in inequality can be due to compositional changes and thus explained by a mechanical effect.

The extent of compositional changes occurred in Italy is illustrated in table 4, where the structure of the employment is defined both as number of employees and as number of hours worked. The nature of the shifts is common to most developed countries even if some specificities arise for Italy[9]. There have been compositional shifts toward women, more educated workers and workers with middle experience. The expected result on the overall inequality is unclear because while the shift toward more educated workers is going to produce higher inequality, the shift toward women will tend to reduce it and the experience structure is only gradually moving toward the classes with higher experience.

To measure the impact of compositional shifts the next sections will use a technique due to Lemieux (2002). He applied this technique to the change in the American wage distribution, in particular trying to explain the rise in residual wage inequality observed in the USA in the 80's and in 90's. According to his measurement the contribution of these factors to the residual inequality explains a large share of the residual inequality growth in the 80's and almost all of it thereafter.

[9]One thing to be noted is that the proportion of workers with university degree is very low compared to most OECD countries. Beside the structural gap in education achievements the figure is probably also explained with the fact that a disproportionate share of university educated people find a job either as self employed or as employee in the public sector. These sectors are excluded in the reference population in the present paper.

## 6. The Lemieux decomposition

In this paragraph, I illustrate the decomposition presented in Lemieux (2002) who extended a methodology due to DFL. The exposition closely follows that of Lemieux (2002) and it use intuition more than formalized demonstration[10].

In the last 15 years, part of the literature has designed new techniques to give a broader view of the change in earnings distributions. The effort has been that of finding a way to account for three aspects:

i. To disentangle the changes due to composition from those due to changes in price of skills
ii. To account for changes between the socio-demographic (or skill) groups and changes within them
iii. To account for changes of the entire wage distributions so that different moments and different inequalities measures can be analyzed.

All these attempts can be seen as generalizations of the Oaxaca (1973) and Blinder (1973) (hereafter OB) decomposition of the difference of mean wage between two groups (where the two groups can be the same population observed in two points in time). The OB decomposition realizes the task of separating the effect due to different skills composition of the groups from the one due to the fact that the same skill or characteristics can be differently remunerated from group to group. In simpler terms, it decomposes the difference in mean wages in a composition effect and a price effect. The way the OB decomposition accomplishes its task is by building a counter factual situation where one group is paid for its skills according to the return schedule of the other group. To see this in a more formal way let us assume that the wage of individual *i* at time *t* is determined by the following generic earnings function:

$$w_{it} = x_{it} b_t + e_{it} \qquad [1]$$

where $w_{it}$ represents the (log of ) the wage, $x_{it}$ is a vector of observable personal characteristics (e.g education, experience, gender etc), $b_t$ a vector of return to the characteristics, the prices of them, and $e_{it}$ a residual obtained from the regression.

A similar equation can be estimated for the time *s* ($s < t$)

$$w_{is} = x_{is} b_s + e_{is} \qquad [2]$$

[10]For a more formalized way to expose it, refer to Dinardo, Fortin and Lemieux (1996). See also Dinardo (2002) for a simplified one.

To build the wage of individual *i* at time *t* that would have prevailed if the price of the skills had remained those of time *s* the coefficient of the regression for the time *s* can be plugged into equation 1 to get:

$$w_{it}^{\ a} = x_{it} b_s + e_{it} \quad [3]$$

The difference between the 2 and the 1 is only due to a different vector of prices. The mean wage difference due to the change in price is simply obtained by averaging the two equations and subtracting to obtain:

$$(\bar{w}_t - \bar{w}_t^{\ a}) = (b_t - b_s)\bar{x}_t \quad [4]$$

Here the bar over the symbols represents the operation of averaging. The effect of composition cannot be calculated in the same way since it's not possible to simply replace the *x* for each individual *i* due to the fact that the two samples are composed by both different units and a different number of them. The problem is simply overcome when the statistics of interest is the mean by inverting the operations of averaging and substituting. Averaging over equation 1 and 2 produce respectively:

$$\bar{w}_t = \bar{x}_t b_t \quad [5]$$

$$\bar{w}_s = \bar{x}_s b_s \quad [6]$$

By substituting $\bar{x}_t$ in equation 6 we obtain:

$$\bar{w}_s^{\ b} = \bar{x}_t b_s \quad [7]$$

And subtracting 6 from 7 we obtain:

$$(\bar{w}_s^{\ b} - \bar{w}_s) = (\bar{x}_t - \bar{x}_s) b_s \quad [8]$$

If we sum the 4 and 8 we obtain the final formula of the OB decomposition:

$$(\bar{w}_t - \bar{w}_s) = (\bar{w}_t - \bar{w}_t^{\ a}) + (\bar{w}_s^{\ b} - \bar{w}_s) = (b_t - b_s)\bar{x}_t + (\bar{x}_t - \bar{x}_s) b_s \quad [9]$$

where the first term represent the price effect and the second term the composition effect.

The OB method is a useful tool to decompose the wages at the mean. A consequence is that, since by construction of the OLS estimates the residual mean is 0, the decomposition can focus only to between groups decomposition and it's not suitable to understand the source of within groups changes and cannot provide results at any other moment or statistic of the distribution. To extend it to decompose the entire distribution, Lemieux (2002) uses the technique due to DFL.

Let's recall that, empirically, a wage distribution of a population is defined by the vector of wages of the sample units and the vector of sampling weights (or grossing factor) associated to each unit. The weight of a sample observation can be roughly defined as the number of units of the population represented by the sample observation. In this way, for instance, the wage distribution a time *t* is defined by the couple [$w_{it}$ , $f_{it}$] where $f_{it}$ represent the weight of the observation *i* at time *t* and $\sum_i f_{it} = 1$. Every moment of the distribution can be estimated using the couple defined above. For instance the mean is defined as

$$\bar{w}_t = \sum_i w_{it} f_{it} \qquad [10]$$

And the variance as:

$$v(w_t) = \sum_i (w_{it} - \bar{w}_t)^2 f_{it} \qquad [11]$$

In the same way also the order statistics and the density can be estimated using the couple [$w_{it}$,$f_{it}$]. Now if it was possible to associate to $w_{it}$ a weight $f_{it}^a$ which defines the number of individuals that observation *i* would represent in the population of time *s*, it would be possible to build the counterfactual distribution, and all the counterfactual statistics, of $w_t$ had the composition of the population remained the same of time *s*. For instance the density of a counterfactual wage distribution can be estimated plugging into the kernel density estimators the counterfactual weights instead that the actual weights.

If the weights $f_{it}^a$ could be defined as proportional to true weights at time *t*, as follows

$$f_{it}^a = \psi_i f_{it} \qquad [12]$$

the problem would become how to calculate the reweighting factor $\psi_i$ ?

The solution proposed by DFL consists in calculating the probability that an observation with determined characteristics belongs to the population of time *s* vs the probability that it belongs to the population of time *t*. To exemplify, suppose that between time *s* and *t* the number of female workers and of universities graduates is increased. Thus, the probability to observe a woman with college degree among the workers of time *s* would be lower than observing it at time *t*. The ratio of these two probabilities, opportunely rescaled to represent the change in size of the population, is the reweighting factor for an individual with specified characteristics. The proposal of DFL is to estimate the ratio of probability simply by a binary regression model (probit or logit) on the pooled

sample of the two years in which the dependent variable is an indicator (1/0) which represent if the observation belongs to the year *s* or *t*.

Thus the new weights allow building a counterfactual distribution of wages at time *t*, where the composition has been held constant at that of time *s*. In this sense, the new weights, $f_{it}^{a}$, represent for the composition effect what the $w_{it}^{a}$ represent for the price effect. Together they allow building some counterfactual distributions that are needed in the decomposition.

A schematic view of the distributions that can be built is as follows:

1) $[w_{it}, f_{it}]$ The actual (raw) distribution at time *t*
2) $[w_{is}, f_{is}]$ The actual (raw) distribution at time *s*
3) $[w_{it}, f_{it}^{a}]$ The counterfactual distribution at time *t* had the composition been stable at time *s*
4) $[w_{it}^{a}, f_{it}]$ The counterfactual distribution at time *t* had the prices been stable at time *s*
5) $[w_{it}^{a}, f_{it}^{a}]$ The counterfactual distribution at time *t* had prices and composition been stable at time *s*

Intuitively for a specified statistic, the difference between the statistic calculated on distribution 1) and 2) is the total effect; that between 1) and 3) is the effect due to change in composition; that between 3) and 5) is the effect due to prices changes; that between 5) and 2) the effect due to unexplained factors. The table permits to point out one problematic issue with this kind of decompositions: the price effect can be also calculated as the difference between 4) and 1) and the composition effect as the difference between 5) and 4). In other words, the decomposition is sequential and to be sure that the sequence does not influence the results one has to perform the decomposition in the inverted sequence. A second problem with it is the choice of the reference distribution. In the previous table the reference distribution is the one at time *s*, but one could chose to distribution of time t. Also in this case there is no certainty that the choice of the reference distribution does not matter unless the substitution of the reference distribution does not change the results.

## 7. The change in wage structures in Italy: 1995-2002

The purpose of this section is to overview the changes in the wage distribution between the 1995 and the 2002 using the SES data. The tool I use is the Lemieux decomposition described in the

previous paragraph. Since one of the main concerns of the literature is to accurately taking into accounts the change in composition due to socio-demographic reasons, I apply the method to control for sex-education-potential experience changes.

The propensity score is calculated by running a logit to the pooled sample of the waves for 1995 and 2002 to model the probability that an observation belongs to the more recent year. Here, as elsewhere, I use as weights the number of hours worked calculated by multiplying the average number of hours worked by the sampling weight. The model includes a dummy of gender, dummies of educational attainment that spans the following groups: elementary school, middle school, high school, universities +; dummies of potential experience that, with the exception of the last open class, represents 5 years intervals from 0-4 to 40 and over. Moreover it includes the interactions between gender and education, gender and potential experience and education and potential experience. The probability of belonging to the 1995 is adjusted by a factor equal to the total number of hours worked in 1995 divided by the total number of hours worked in 2002, to take into account the change in the size of workforce.

To measures the prices of the skills I perform a regression of the (log of) real hourly wages (including overtime and bonus payments) on the same covariates of the specification of the logit model above.

Table 5 presents the main results of the decomposition where the reference distribution is that of 1995. Column 1 and 2 presents the main descriptive statistics of the distributions respectively of 1995 and 2002 along with the contributions explained by the regression model and that explained by the residuals. The mean wage, shown in the first row, has declined in real terms of 1.1 log points. The following three rows of the table depict the variance of the distribution in its three aspects: the overall variance, the variance of the explained part of the regression and the variance of the unexplained part (or residual variance). They show that the rise in inequality is due to the rise in residual inequality: in fact, it has increased from 0.084 log points to 0.095 log points with an increase of 13 percent whereas the change in the variance due to the explained part of the model has decreased. In other words the increase in the overall variance is accounted for the increase in the within groups inequality that has been somewhat counterbalanced by a fall in the between groups inequality. The remaining rows show the value of the wage variable at the $90^{th}$ percentile, the $50^{th}$

percentile and the $10^{th}$ percentile and the corresponding measures of wage dispersion. Over the considered period the inequality measured by the change in 90-10 wage gap has increased by 1.2 log points. A more detailed inspection shows that this measure hides the change that have happened in the left and right tails of the distribution: the increase in inequality is, in fact, due to the increased dispersion in the right tail where the 90-50 wage gap passed from 0.567 to 0.587) that has been in part compensated by a compression of wages in the left tail (the 50-10 wage gap has decreased from 0.346 to 0.338).

The columns 3 and 4 of the table reports the statistics for two counterfactual distributions: the distribution of wages that would have been in 2002 had the workers characteristics been paid according to the price vector of 1995, and the distribution of wages of 2002 had also the workforce composition been stable at the 1995 level. These can be used to calculate the effect of price and composition both for different measures of inequality and for the between and within groups inequality. A look at the overall variance shows that the price of observable characteristics are not responsible for the increase in inequality: in fact the contribution of prices changes has been a negative one, suggesting that, overall, there has been a compression of the skill and socio-demographic prices. In the next paragraph I will explore more closely along which dimensions and categories this compression has occurred. In contrast, the change in the composition of the workforce and, to a lesser extent, changes due to unexplained factors can be addressed as the forces that have driven the rise in inequality. The behaviour of the residual inequality closely tracks that of the total inequality, with a large percentage of the changes that can be imputed to changes in the workforce composition. Accordingly, changes in composition plays a relevant role on the other measures of dispersion. Jointly with the analysis of the section 5, where it has been shown that inequality is an increasing function of the level of education and experience, and with the fact that the workforce composition has shifted toward more educated and partially toward experienced employees, this measurement supports the view that the residual wage (within groups) inequality is mostly accounted for by changes in the composition of the workforce. The role of unobservable price changes hypothesis is hence greatly reduced in this analysis.

A visual look up at the changes in the distribution helps to better appreciate the description based on the table. Figure 5.*a* compares the kernel density estimates[11] of the wage distributions for 1995 and 2002. Two features are worth noting: first, the right tail of the distribution for the 2002 is longer than the one for 1995; second, the distribution of 2002 gets more concentrated at the mode with a reduction in the density at the middle-high wages. The following panels of the figure show the effects of prices, composition and unexplained comparing actual and counterfactual distributions. Prices and compositions seem to have counterbalancing effects. While the former shifts the distribution of real wages on the left, the latter move it back to the right. From the figure is difficult to appreciate the effect on the variance. Figure 6 plots the change in the real wage along the quantiles of the distribution, hence providing a visual tool, alternative to that of figure 5, to understand the changes along the distribution[12]. Panel *a* shows clearly that while for most of the quantiles there has been a reduction in the real wage, the reverse is true for the higher wages that seems to have gained much in the reference period. Moreover, the decrease of the wages for most of the quantiles is decreasing with the wage level with an accentuated fall from the 65$^{th}$ to the 85$^{th}$ percentile. Panel *b* and *c* makes evident that the price effect has been decreasing over the wage distribution while the composition effect has been increasing. This is the visual counterpart of the result on the table that prices did compress the variance while composition did enlarge it. Intuitively the price for skills of workers that have a higher wage have decreased more than the prices of skills of workers who earn a lower wage. The evolution of wage counterbalance that of composition that have shifted towards groups of worker placed a higher wage levels. Panel *d*, reporting the unexplained effect, makes clear that neither price nor composition changes can account for the throat observed in the middle-right zone of the quantile sequence and the steep rise for the highest income. In order to see if the results are sensible to the order of decomposition, figure 7 and 8 show the inverted decomposition[13] by calculating first the difference due to composition and then the difference due to prices. The results are not significantly different from the previous analysis.

[11] They are obtained with an optimal chosen bandwidth according to the Silverman Rule of Thumb.
[12] The quantiles shown on the figure are from the 5th to the 95th. It must be remarked that the overall analysis has been performed on the total samples without trimming any observation. Sensitivity analysis aimed to see if the results were somewhat influenced by the extreme values have however shown that the results are robust to the trimming of 1% of data at the two extreme of the distribution.
[13] The reference distribution is still the one for 1995.

## 8. Between groups changes

In order to complete the analysis of the wage structure evolution, I now pass to measure the between groups changes. The methodology is a straightforward derivation of the one used for calculating the changes in the wage distribution. First, average wages of the various detailed socio-demographic groups for each year are those obtained by the former regression. In fact the coefficients of the former regressions define the wages for our sex-education-experience arrays of cells. Second, to obtain the wage for more aggregate groups (e.g. educational groups) I weight the detailed wage figures with the sum of hours over each cell for each year. The change calculated with this current weighting procedure encompass both price effects and composition effects (continuing the example, the composition of each educational group in terms of gender and experience). To remove the compositional effect I average the vector of prices of 1995 using the weights for 2002. In this way I obtain the average wages for 2002 had the price remained constant at 1995 level[14]. Table 6 resumes the results of this procedure. The first two columns shows the level of average wages for 1995 and 2002, while the third column shows the counterfactual wages for 2002 with price at 1995 level. A look at the $4^{th}$ and at $6^{th}$ column shows that compositional effects play a significant role in the measurement of these averages. Column 5 is what really we are looking for as it measures the changes due to prices and thus possibly explained by market forces and institutions. Analysing the results is apparent that the women have improved their relative position in the labour market: in fact their average wage is decreased of 2% compared to the loss of 6% of the male workers. Moving to education, the only group that has not suffered a loss in purchasing power is the group of university graduates who registered an increase of 3% over the 7 years. Relatively to high school graduates they gained about 9%. Quite surprisingly, the second group in the graduation of relative wages is the group with the poorest education who gained relatively to the high school graduates. Splitting up the analysis by gender reveals similar pattern with an important exception: while for male, the group of high school workers was the one who suffered the highest loss (-9%) the female high school graduates lost relatively little.

[14] Alternatively, to purge the composition effects I could have averaged the wages of 2002 with the new weights obtained from the propensity score reweighting procedure. The average wages could also be defined as the average wages that would have been obtained had the composition between socio demographic groups not changed since 1995.

To finish, a somewhat clear pattern emerges from the analysis of price changes related to experience: the older workers are those who experienced the higher loss and thus have seen their wage relatively to young people decreasing. The analysis of this paragraph qualifies the compressing effect of prices on inequality, emerged from the previous paragraph, showing that the relative price attached to low wage groups (e.g women and people with low potential experience) increased. The rising relative price of university education is one notable exception. However, due to the low share of workforce of university graduates, this effect does not weigh much in the overall price effect.

## 9. What drives the changes in the between groups wage differentials?

As seen in the previous section one of the most striking fact that emerges from the analysis is the change in the wage structure by educational levels. When controlling for composition effects in terms of experience and gender the change in the wages differentials between universities graduates and lower educational groups increases. In particular, the highest growth is measured with respect to workers with high school degree. This finding holds also true when we look at two genders separately but it is especially evident for men. The aim of this section is to discover in which measure the university premium is accounted for by changes in related covariates or can be traced back to a rise in relative demand for high education workers.

*Industrial compositions changes and inter-industry wage differentials*

One possible explanation for these changes has to do with changes of the industry structure. As is common for most developed countries in recent years the employment distribution has kept shifting away from manufacture and industry toward services. If the employment shift had occurred toward sectors that employs higher quota of universities graduates and also pays higher salaries this would help explain the increase of the universities/high school wage gap. The persistent existence of inter-industry wage differentials, even after controlling for personal and firm characteristics, is a well known phenomenon in labour economics. Most authors agree that one factor that is behind these differentials is the existence of industry rents that helps keep the wage of workers in some sectors to be above the productivity level. To be able to see if industrial composition and inter-industry wage differentials have an impact on the recorded increase of the high skill-low skill wage gap I use two

techniques: a within-between decomposition of the change of the labour input and a comparative regression analysis to see if the price of education changes when controlling for industrial effects. The within–between decomposition is performed through a traditional tool: the fixed input requirements index due to Freeman (see for instance Freeman 1980).

The original index by Freeman can be built, following Airola and Juhn (2005), in the following way. Let's define in employment of the group *j* by $\Delta E_{jt}$. This change can be decomposed as:

$$\Delta E_{j_t} = \sum_i \lambda_{ij} \Delta E_{it} + \sum_i \left(\Delta \lambda_{ij}\right) E_i \qquad [13]$$

Where $\lambda_{ij}$ represents the share of employment of the group *j* in industry *i*, $\Delta E_{it}$ is the change in employment of the industry *i*.

However, being interested in the change of relative input, following Katz, Loveman and Blanchflower (1995) I obtain a simple variant of the previous formula defining:

$$e_{jt} = E_{jt} / E_t \text{ and } e_{it} = E_{it} / E_t \qquad [14]$$

In this way the [13] can be written as:

$$\Delta e_{jt} = \sum_i \lambda_{ij} \Delta e_{it} + \sum_i \left(\Delta \lambda_{ij}\right) e_i \qquad [15]$$

The first term of [15] represents the (relative) change in group *j* due to the growth (or decline) of each industry had the input shares of group *j* in each industry been constant, and the second term is the change due to the change in the input shares for fixed employment at industry level. In other words, the first term measures the between industry shift that would have been observed if the production technique in each industry would have not been changed, while the second term measures the within industry shift due to the change in these techniques. I apply this technique to 28 sectors that are either divisions of the NACE rev 1.1 or aggregation of divisions. The level of aggregation is clearly a fundamental point. Ideally one would have a very detailed industry breakdown, since performing the analysis at more aggregated level is likely to bring about an over estimate of the within effect and a under estimate of between effect. The number of sectors utilized here is a fair compromise between the necessity of the analysis and data quality. The skill groups are the 4 educational categories examined before. The analysis is performed for three variable, the number of employees, the number of hours worked and the wage bill. The use of wage bill alongside the more usual measures of labour input is justified by the fact that in presence of relative

price movements the movement of quantities can be a biased measure of the demand shifts. See Berman, Bound and Griliches (1994). However measured, the analysis, illustrated in table 7, shows that in the period considered there has been an increase in the share of workers with high school and university degree and that this increase is due in large part to within industry shifts. For instance the analysis of the wage bill shows that the share of high school graduates is increased by 97% and that of universities graduates by 47%. The 97% (0.94/0.97) of the shift of high school workforce and the 94% (0.44/0.047) of the shift of university graduates are attributable to within shifts.

The second method consists in comparing the wage differentials between educational categories that results from a regression that does not control for industries and one that control for it. The basic specification is that of the previous section, while the alternative specification adds a number of dummy variables that span the 28 industries. The results, in table 8, of the price effect, calculated as in the previous section, report that there is no much difference between the estimates of the two regression analysis.

Even if it is possible that the level of aggregation somewhat affects the extent of the results, the two methods strongly points out toward an explanation of wage changes that does not give much weights to shift between industries. In other terms the increase in the wage premium of university graduates is not affected by changes in industry composition. To take this conclusion a step further one can argue that if the relative price increase is due to a relative demand increase of high educated workers, this shift in relative demand has been pervasive across industries.

*The increase in the share of non-standard workers*

Another important structural change that has affected the Italian economy is the increase in the share of non-standard workers here defined as those workers who work under an arrangement that is either non permanent or non full time. According to the SES the share of non standard workers on the total employment has increased in the observed period from 9.7% to 14.6% accounting for most of the growth of the total employment. As it has been observed above, other things being equal, for most of the new contracts the hourly wage should not differ from the standard arrangement. However this argument does not exclude that the non-standard jobs are filled by workers with a different degree of (unobserved) ability from the standard jobs and thus pay a different wage. A

second possibility is that the opportunity of opening non-standard job vacancies with lower firing costs has lowered the cost of jobs that otherwise would have not been created. Table 9 shows the estimated coefficient of a dummy variable for standard workers vs non standard workers in two different models of a wage equation [15]. All the coefficients, significant at least at 1%, are positive indicating that there is a premium associated to standard jobs. Thus, if, for instance, non standard jobs are mainly filled by workers with a low level of education this would qualify the increase in the university - high school wage gap. To check for this possibility I run the following analysis. First, a regression of log wage on educational dummies[16] is run for each year and 4 possible group of workers according to their work arrangement: permanent-full-time, permanent part-time, temporary full-time, temporary part-time.

The coefficient of the dummy for university workers (against the reference category of high school workers) is retained as a measure of the return to university education. Let's denote it by $r_{it}$, *with* $i=1,2,3,4$ and $t=1995,2002$.

Second, the share of number of hours over the total number of hours for each of the four groups is calculated in each year: let's define those weights as $w_{it}$ .

The change in the average return to university can thus be expressed as:

$$\bar{r}_{02} - \bar{r}_{95} = \sum_{i\_1} r_{i02} w_{i02} - \sum_{i\_1} r_{i95} w_{i95} \qquad 16$$

Adding and subtracting $\sum_{i\_1} r_{i02} w_{i95}$ from the 1:

$$\bar{r}_{02} - \bar{r}_{95} = \left[ \sum_{i\_1} r_{i02} w_{i02} - \sum_{i\_1} r_{i02} w_{i95} \right] + \left[ \sum_{i\_1} r_{i02} w_{i95} - \sum_{i\_1} r_{i95} w_{i95} \right] \qquad 17$$

The term in the first square brackets measures the change due to the structure of employment and the second term the change due to the return to education.

Table 10 shows that only a tiny fraction of the overall change is due to change in the composition across contracts and again the results point toward a change happened within the groups.

*Shifts in the relative demand of skilled workers*

[15]Model 1 control only for sex, education and potential experience, while model 2 add to the previous regressors 28 dummies for economic activity sectors and a quadratic in tenure.

[16] The model also contain dummies for experience and a dummy for gender.

The evidence presented so far indicate that the increase in the university premium is not accounted for by composition effects of industries or labour arrangements.

The common explanation to justify increases in the skill related wage gap is an increase in the relative demand for skilled workers that over compensate the increase in the relative labour supply, due, for instance, to the speed up in the pace of skill biased technological change. As pointed out by Gottschalk and Joice (1998) if the change of relative prices is due to movements in the labour market forces it's likely that quantities as well as prices should be affected. To add to this argument, the common view is that in European labour markets, characterised by a higher level of wage rigidity compared to the American labour market, relative changes in the demand and supply for skills should have more effects on the unemployment rates than on wage prices. Following Prasad (2004) I examine the changes in the unemployment rates and employment to population ratios of the 4 educational groups as measured by the Labour force survey of 1995 and 2002. The figures reported in table 11 are composition adjusted so that the changes are not affected by changes in the age structure of the population. Although the unemployment rate of elementary school workers has worsened and that of middle school workers decreased much less than that of more educated workers, the unemployment rate of universities workers and high school workers moved exactly by the same quantity thus leaving their relative unemployment rate unchanged. The picture remains substantially unchanged when split by gender. A similar result is conveyed by the analysis of the employment to population ratios where the two most educated groups experienced similar changes changes.

This finding constitutes clearly a puzzle for an explanation based on the progress of (Skill Biased) technological change, because it's unlikely that if such force was in motion it had effect only on the relative wages and not on the relative unemployment rate or relative employment to population ratio.

## 10. Conclusions

This work has accounted for the changes in the wage structure occurred in Italy between 1995 and 2002 according to the Structure of Earning Survey. The analysis has documented a number of characteristics of the change in wage distribution. First, it has shown that a slight, but not neglectable, increase in inequality, measured as either the variance of log wages or the 90-10 wage

gap, has occurred in the reference period. Hence this study confirms the slow pace inequality drift that has characterized the Italian labour market since the mid 80's (see Borgarello and Devicienti 2002). Second, this rise has been driven by a change in the residual inequality while the between groups inequality has instead narrowed. However, the increase in the residual inequality is due mainly to composition effect due to the increase in the share of the groups with a higher within group inequality (mainly more educated workers). Third, the analysis has shown that the major changes have happened in the right tail of the distribution, with a sharp increase in the wage of most paid workers and more generally a rise of the 90-50 wage gap. In contrast, a wage compression has occurred in the left tail with the workers who get a pay below the median that have suffered lower losses.

Fourth, the role played by the prices of observable skills has been to reduce the inequality, mainly through the flattening of the wage experience profile. The compression of skill prices has been partly compensated by the notable increase in the premium associated with university education. This last element is not explainable by a shift in the industrial composition nor in the composition by work arrangement (standard vs. non standard). Moreover, the data on labour force shows no significant change in the relative unemployment rate of the labour force with a university degree relative to the labour force with high school degree, suggesting that no significant demand shift against low skilled workers has occurred. The source of the rise in the university premium thus remain to be explained and is therefore one of the most interesting point left to future research. A second point to be investigated is to account for the unexplained movement in the wage distribution such as the seemingly increase in the polarization of wages.

**References**

Airola, Jim and Chinhui, Juhn. 2005. Wage Inequality in Post-Reform Mexico. *IZA Discussion Paper* n. 1525

Autor, David H., Katz, Lawrence F. and Melissa S. Kearney, 2005a. "Trends in U.S. Wage Inequality: Re-Assessing the Revisionists," *NBER Working Papers* 11627, National Bureau of Economic Research, Inc.

Autor, David H., Katz, Lawrence F. and Melissa S. Kearney, 2005b. "Rising Wage Inequality: The Role of Composition and Prices," *NBER Working Papers* 11628, National Bureau of Economic Research, Inc.

Autor, David H., Katz, Lawrence F. and Melissa S. Kearney, 2006. "The Polarization of the U.S. Labor Market" *NBER Working Papers* 11986, National Bureau of Economic Research, Inc.

Autor, David H., Levy Frank and Richard J. Murnane, 2003. "The Skill Content Of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics*, MIT Press, vol. 118(4), pages 1279-1333.

Berman, Eli, Bound, John and Zvi Griliches, 1994. "Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufactures," *The Quarterly Journal of Economics*, MIT Press, vol. 109(2), pages 367-97

Blinder, Alan S. "Wage Discrimination: Reduced Form and Structural Estimates". *Journal of Human Resources*, 8, 4 (1973): 436-455.

Borgarello, Andrea and Francesco Devicienti, 2002. What Accounts For the Rise in Wage Inequality in Italy? Evidence from Administrative Matched Employer-Employee Data, 1985-1996. *LABORatorio Revelli Working Paper* N.18 October 2002.

Budría, Santiago and Pedro Telhado Pereira, 2005. "Educational Qualifications and Wage Inequality: Evidence for Europe," *IZA Discussion Papers* n. 1763.

Card, David and John E. DiNardo, 2002. "Skill-Biased Technological Change and Rising Wage Inequality:Some Problems and Puzzles." *Journal of Labor Economics* 20 (October): 733-83.

Casadio, P., 2003. "Wage Formation in the Italian private sector after the 1992-93 Income Policy Agreements", in Fagan, G., Mongelli, P. e Morgan, J. (eds, 2003) *Institutions and Wage Formation in the New Europe*, Edward Elgar, Northampton.

DiNardo, John E., 2002. "Propensity Score Reweighting and Changes in Wage Distributions", *Unpublished paper*, University of Michigan, Department of Economics.

DiNardo John, Fortin, Nicole M. and Thomas Lemieux 1996. "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach," *Econometrica*, Econometric Society, vol. 64(5), pages 1001-44.

Freeman, Richard B.,1980. An Empirical Analysis of the Fixed Coefficient Manpower Requirements Model, 1960-1970, *Journal of Human Resources* XV:2, p 176-199, Spring 1980.

Goos, Maarten and Alan Manning. 2003. "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain." *Mimeo*, London School of Economics, September 2003.

Gottschalk, Peter and Mary Joyce, 1998. "Cross-National Differences In The Rise In Earnings Inequality: Market And Institutional Factors," *The Review of Economics and Statistics*, MIT Press, vol. 80(4), pages 489-502.

Juhn, Chinhui, Murphy, Kevin M. and Brooks Pierce, 1993. "Wage Inequality and the Rise in Returns to Skill," *Journal of Political Economy*, University of Chicago Press, vol. 101(3), pages 410-42.

Katz, Lawrence F., Gary W. Loveman and David G. Blanchflower. 1995. A Comparison of Changes in the Structure of Wages in Four OECD Countries. In *Differences and Changes in Wage Structures*, edited by Richard B. Freeman and Lawrence F. Katz, Chicago: University of Chicago Press.

Lemieux, Thomas 2002. "Decomposing changes in wage distributions: a unified approach," *Canadian Journal of Economics*, Canadian Economics Association, vol. 35(4), pages 646-688.

Lemieux, Thomas, 2006a "Increasing Residual Wage Inequality: Composition Effects, Noisy Data, or Rising Demand for Skill?", forthcoming in American Economic Review.

Lemieux, Thomas, 2006b. "The Mincer Equation Thirty Years after Schooling, Experience, and Earnings," forthcoming in S. Grossbard-Shechtman (ed.) Jacob Mincer, A Pioneer of Modern Labor Economics, Springer Verlag,

Lemieux, Thomas, 2006c. "Post - secondary education and increasing wage inequality", *NBER working paper n.12077*. NBER March 2006.

Oaxaca, Ronald. "Male-Female Wage Differentials in Urban Labor Markets". *International Economic Review*, 14, 3 (1973): 693-709.

Pereira, Pedro Telhado & Martins, Pedro Silva, 2004. Does education reduce wage inequality? Quantile regression evidence from 16 countries. *Labour Economics*, Volume 11, Issue 3, June 2004, Pages 355-371

Prasad Eswar S., 2004. "The Unbearable Stability of the German Wage Structure: Evidence and Interpretation," *IMF Staff Papers*, International Monetary Fund, vol. 51(2), pages 7.

**Appendix A1.** The reweighting of the SES survey

The original sampling weights that come with the SES data can misrepresent the workforce composition. Since one of the scope of this paper is to account for changes in composition the preliminary treatment of the data has included a step of reweighting. Since the infra census survey deputed to measure the change in the labour force composition is the Labour Force Survey (LFS) it was a natural choice to rely on that.

The dimensions along which the reweighting procedure has occurred are gender, education, age, geographical area and two types of work arrangement In simple words, the reweighted data mirrors the composition of the LFS in each of the two years along the previous dimensions.

The procedure has implied the following steps for each year.

1. Calculation of the number of employees estimated from the LFS in each of the cell defined by the intersection of 2 gender, 5 age classes, 4 education groups, 3 geographical areas, two work arrangement related to the working time (full time/part time) and two work arrangement related to the duration of the contract (permanent /temporary) in each of two macro sectors of economic activity: Industry and Services[17].
2. In each of the two sectors the share of employment of each basic cell on the total has been calculated.
3. The shares thus calculated have been multiplied by the estimate of the employment of Industry and Service coming from the SES. This total for each basic cell is the population total to which the original weights of the survey have been calibrated to.
4. The calibration procedure has been run in each of this basic cell.
5. The calibration procedure ensure that the sum of weights in each cell is equal to the total defined in 3 and the distance between original weights and final weights is minimum according to a determined distance function.

In this way the new weights:

A) Ensure that the employment estimate for Industry and Services is equal to the original estimate of the SES. This is a good quality since this estimate, arising from the system of business surveys and register, is very reliable.

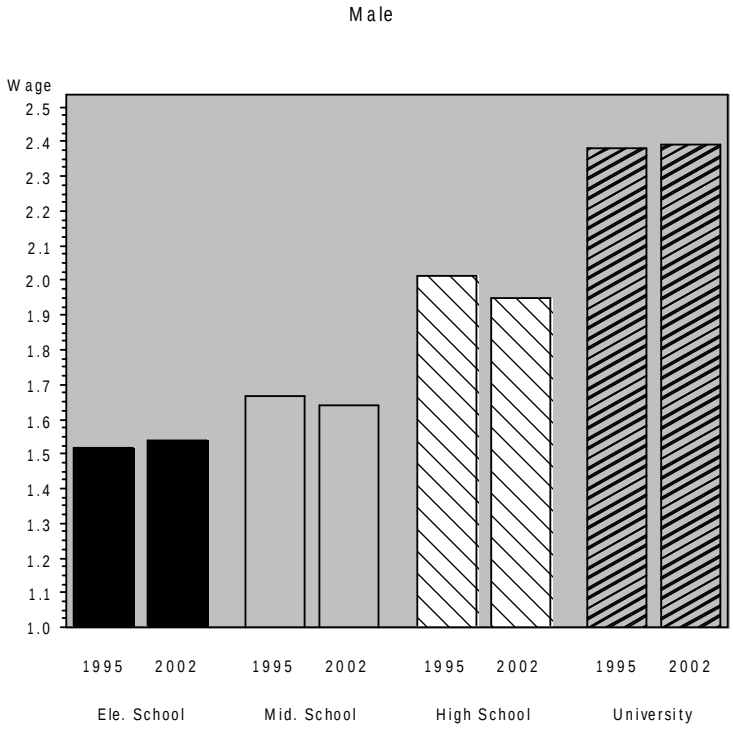
[17] Some of these basic cells had to be aggregated to ensure the presence a minimum number of sampling observation.

B) The estimate of the employment in each sub sector of economic activity is very close to the original estimate. The same consideration applies as in A.

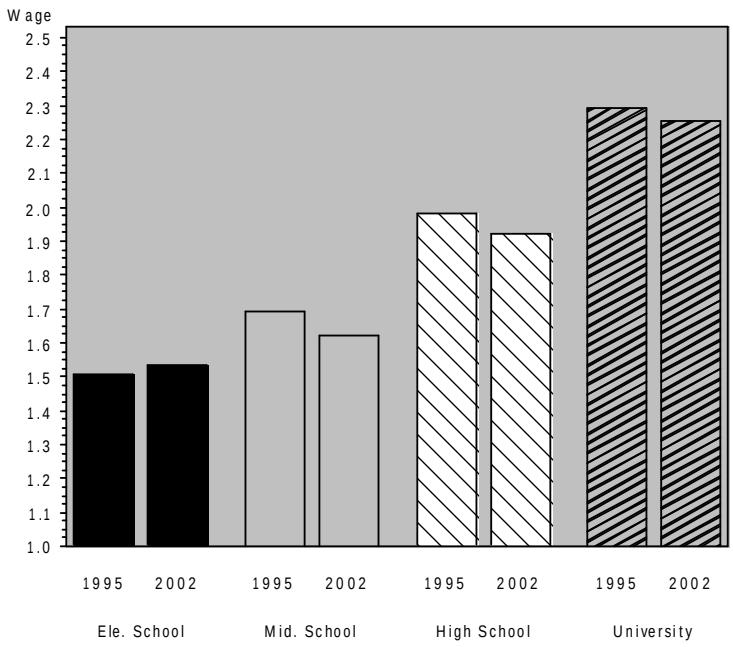
C) The estimate of the structure of employment, along the 6 dimensions, in each macro sector is equal to the one coming from the Labour Force Survey.

D) One by-product of this procedure is that it adjust the structure of employment for possible misclassification of workers deriving for instance from the different classifications of education or from the different sampling units and thus different geographical localization.

# Figure 1. Median effect of education by sex

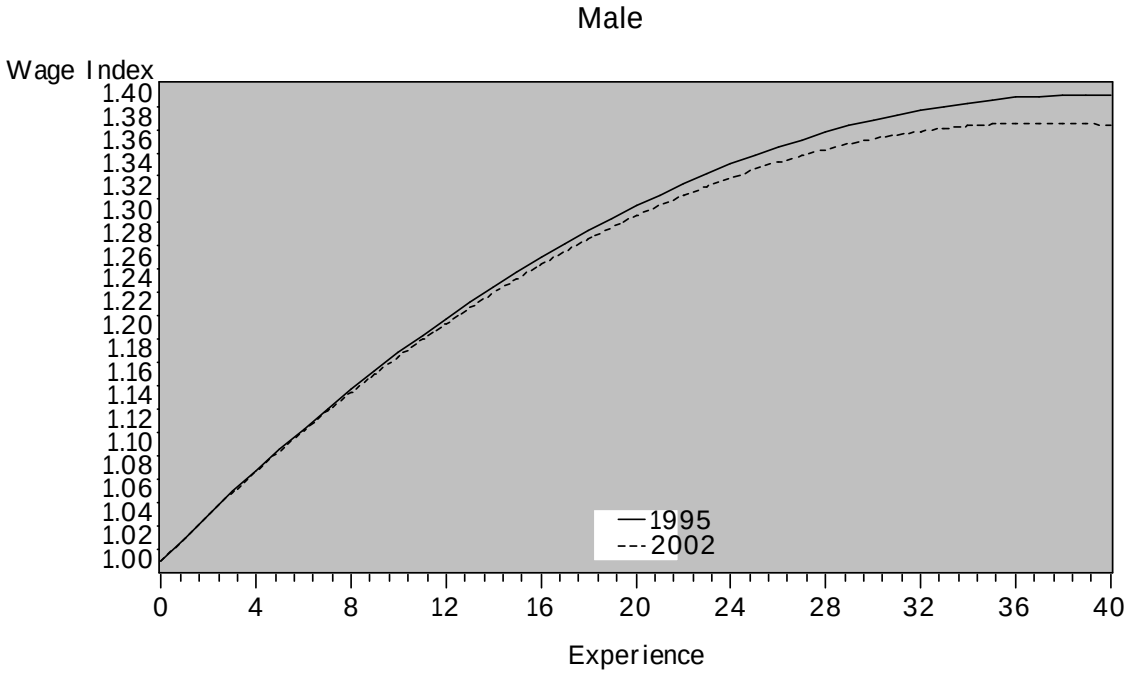



a

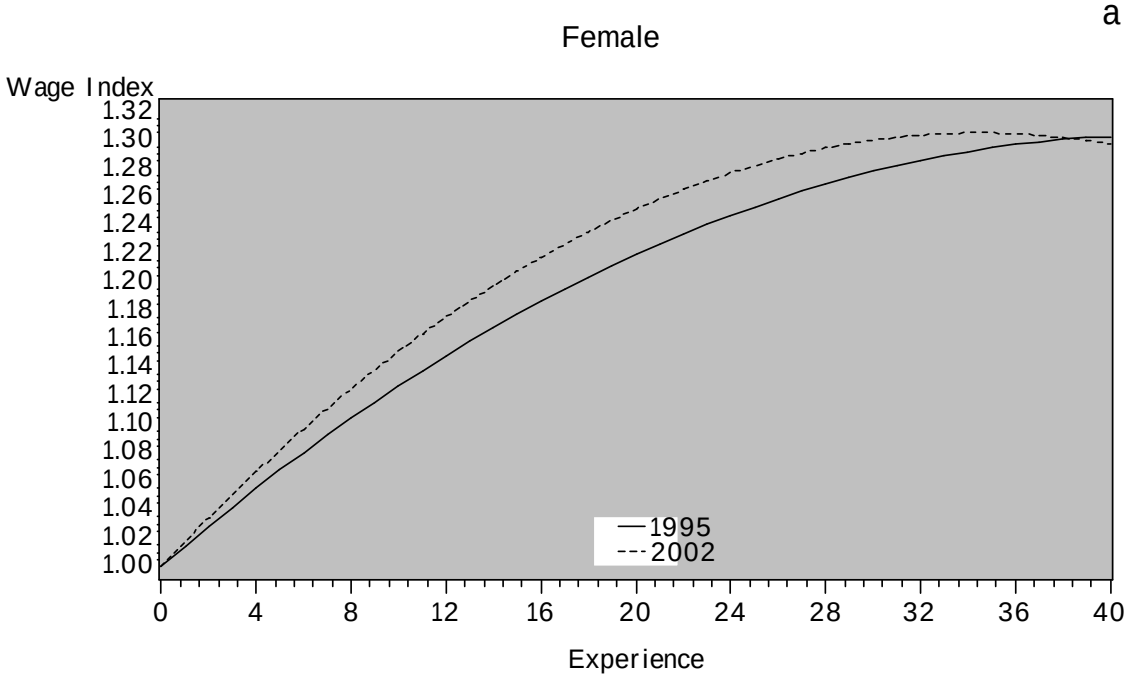



b

# Figure 2. Median effect of experience by sex

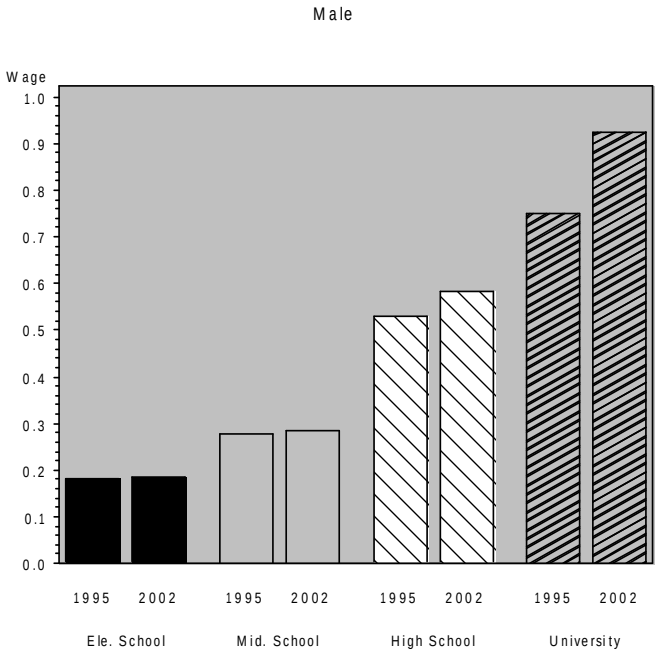



a

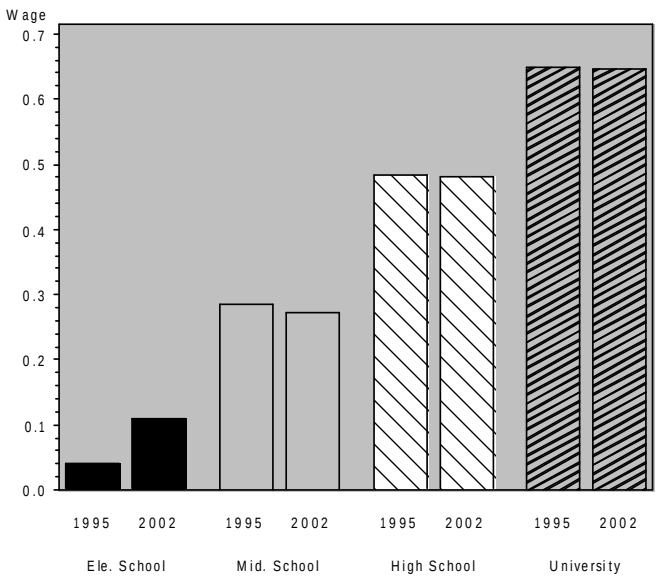



b

Figure 3.90-10 effect of education by sex

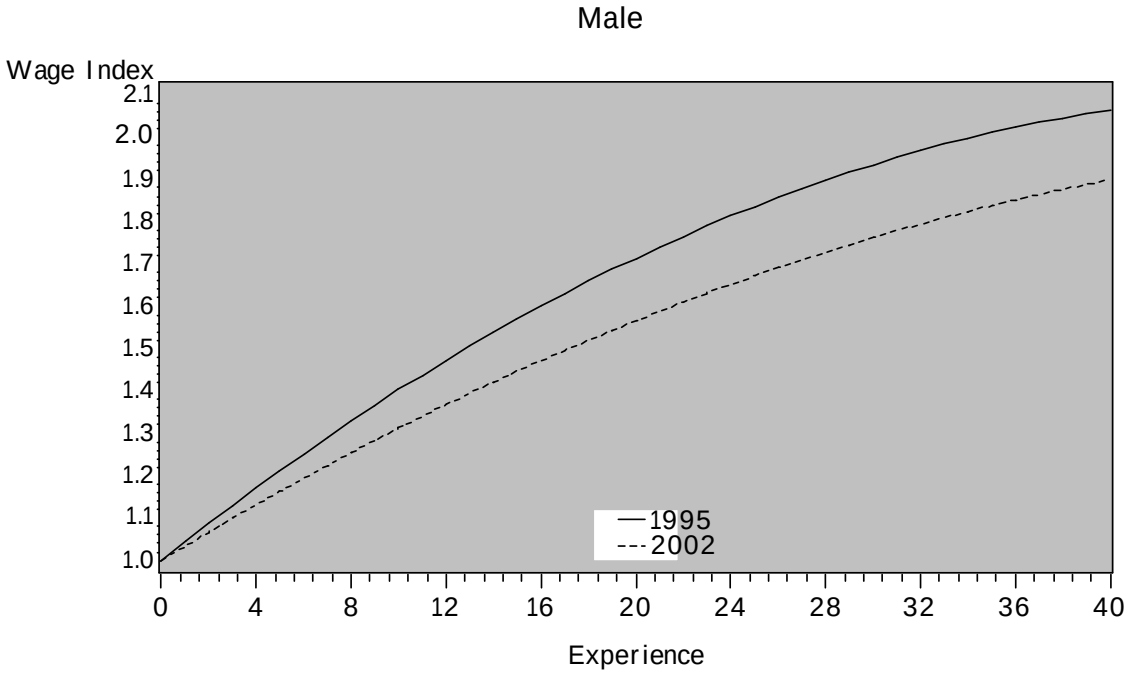



a

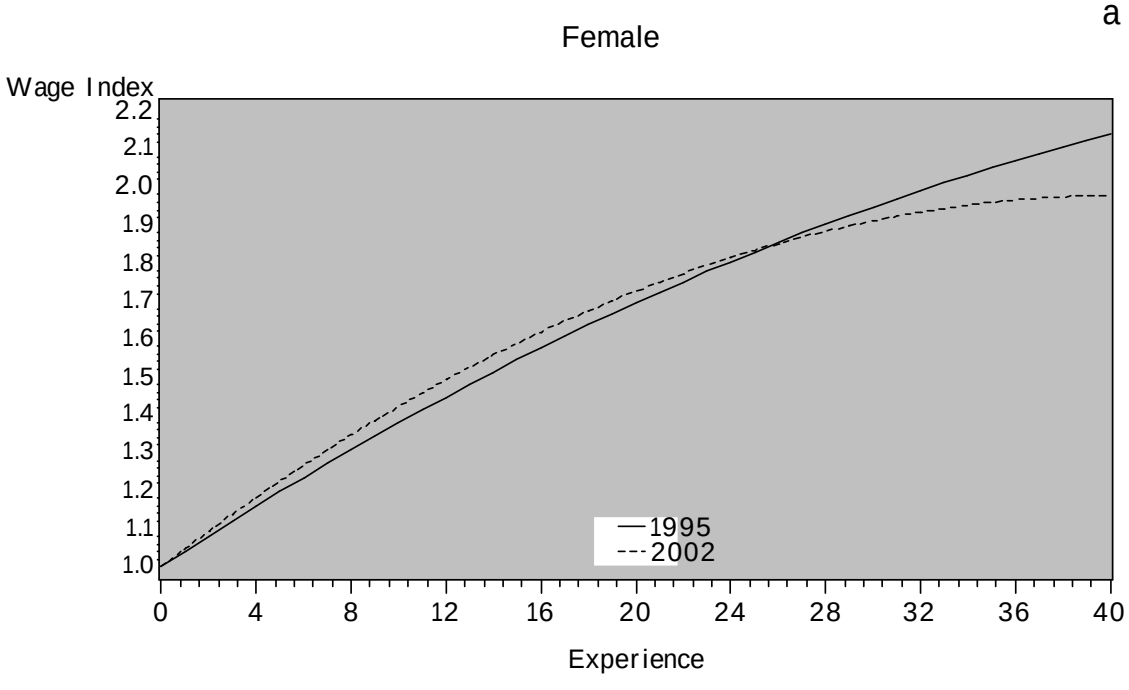



b

# Figure 4. 90-10 effect of experience by sex




a




b

Figure 5. Raw and Counterfactual densities

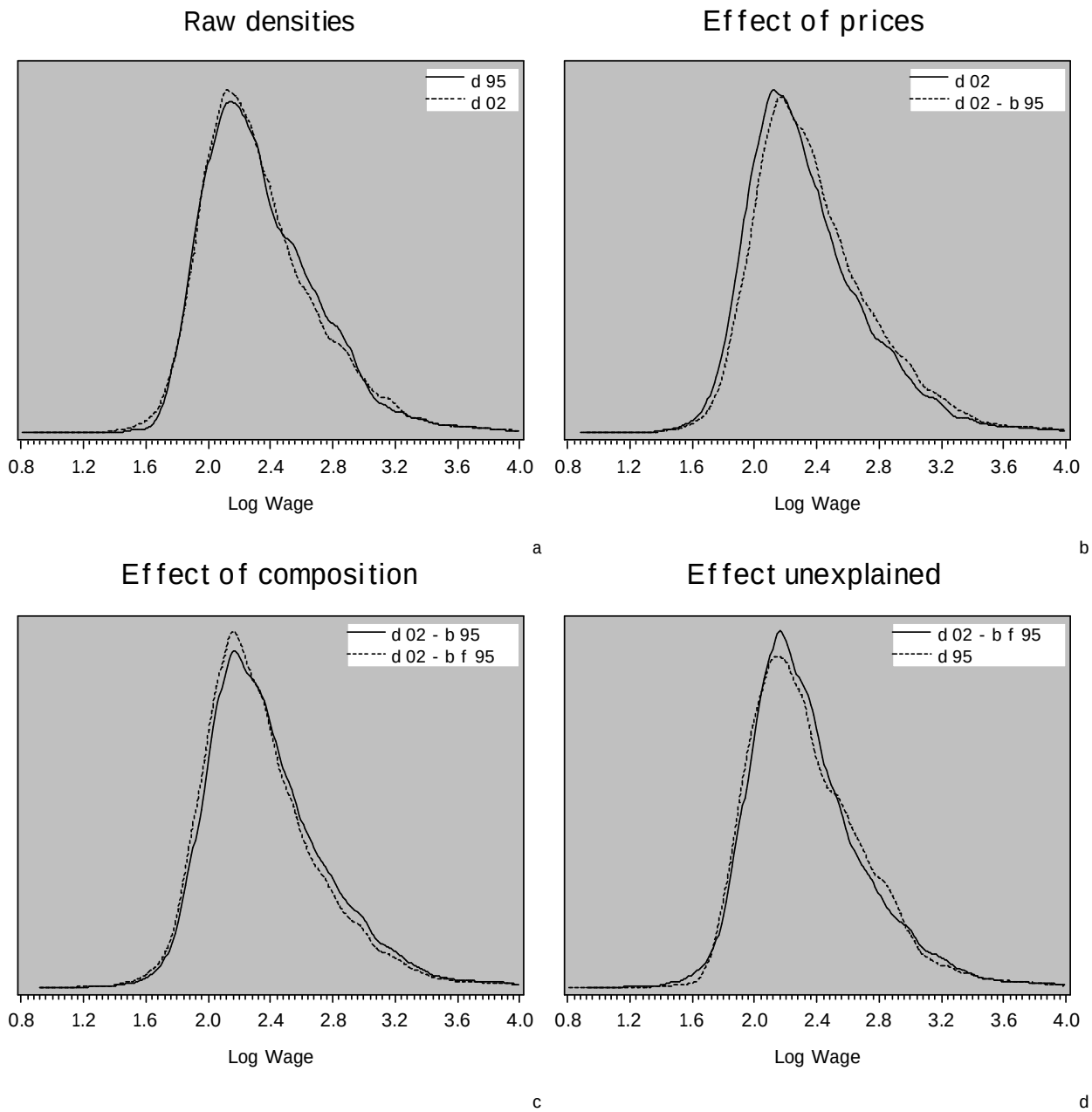


Figure 6. Wage growth by quantiles

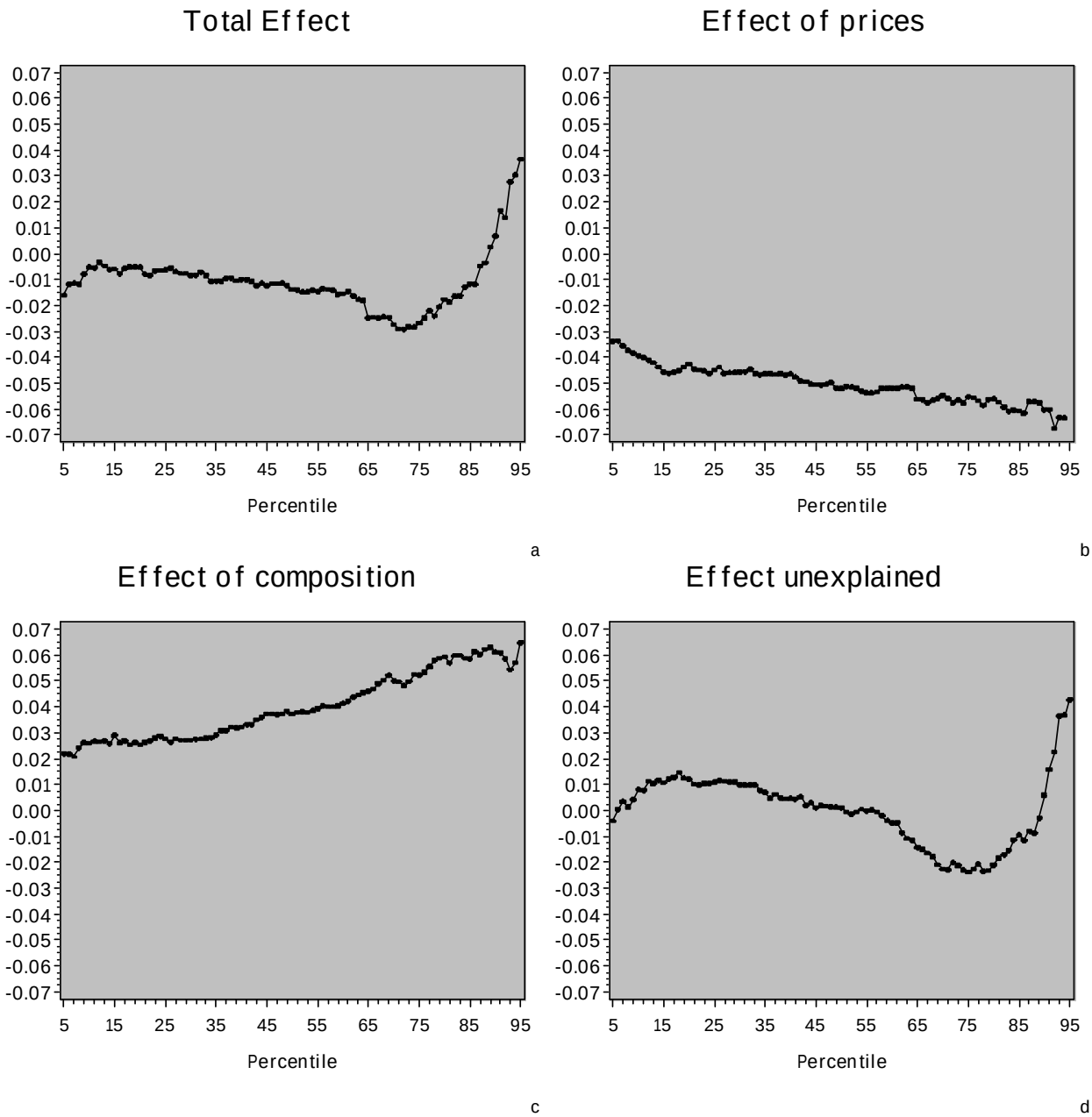


Figure 7. Raw and Counterfactual densities - Inverted decomposition

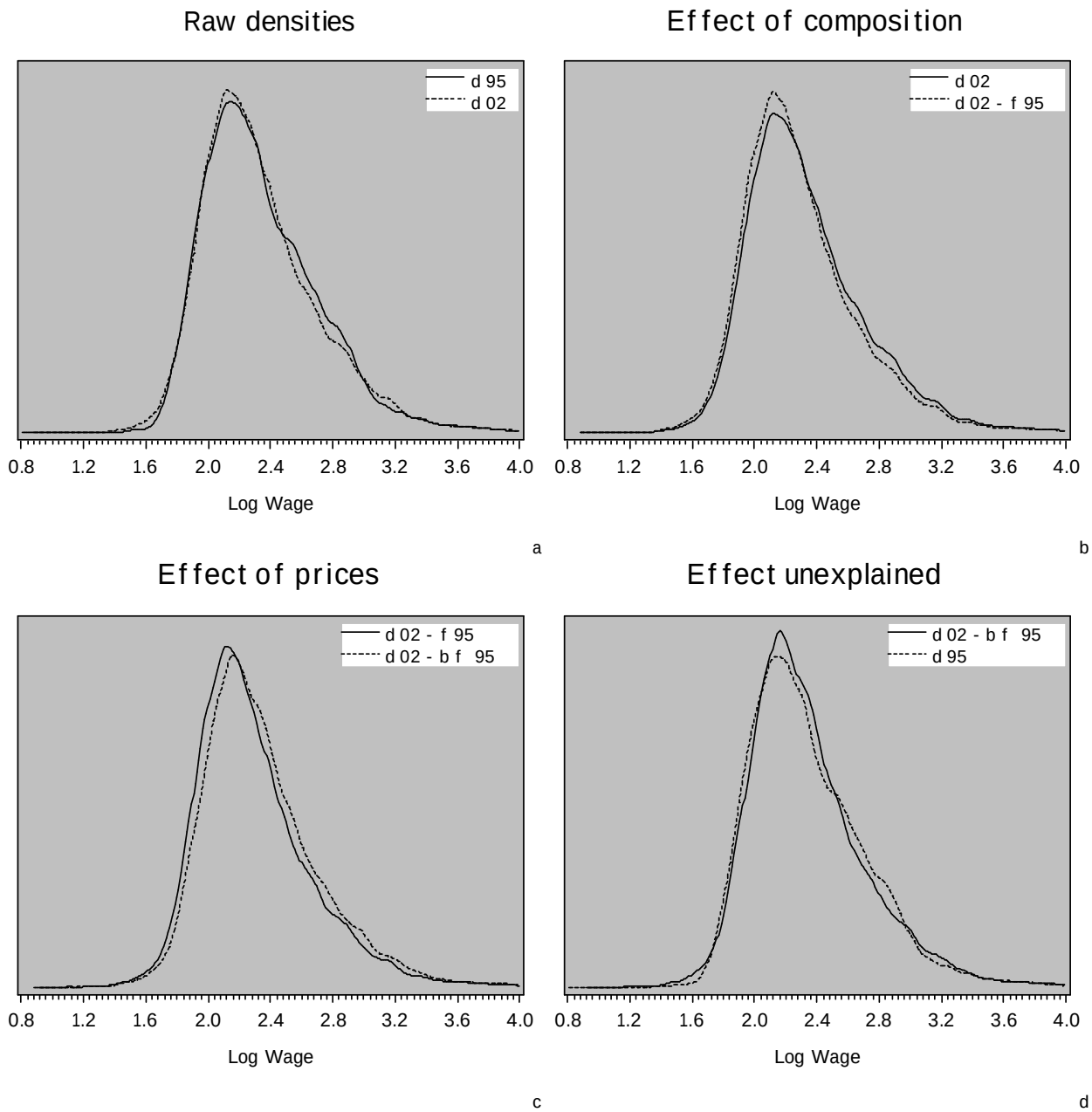


Figure 8. Wage growth by quantiles - Inverted decomposition

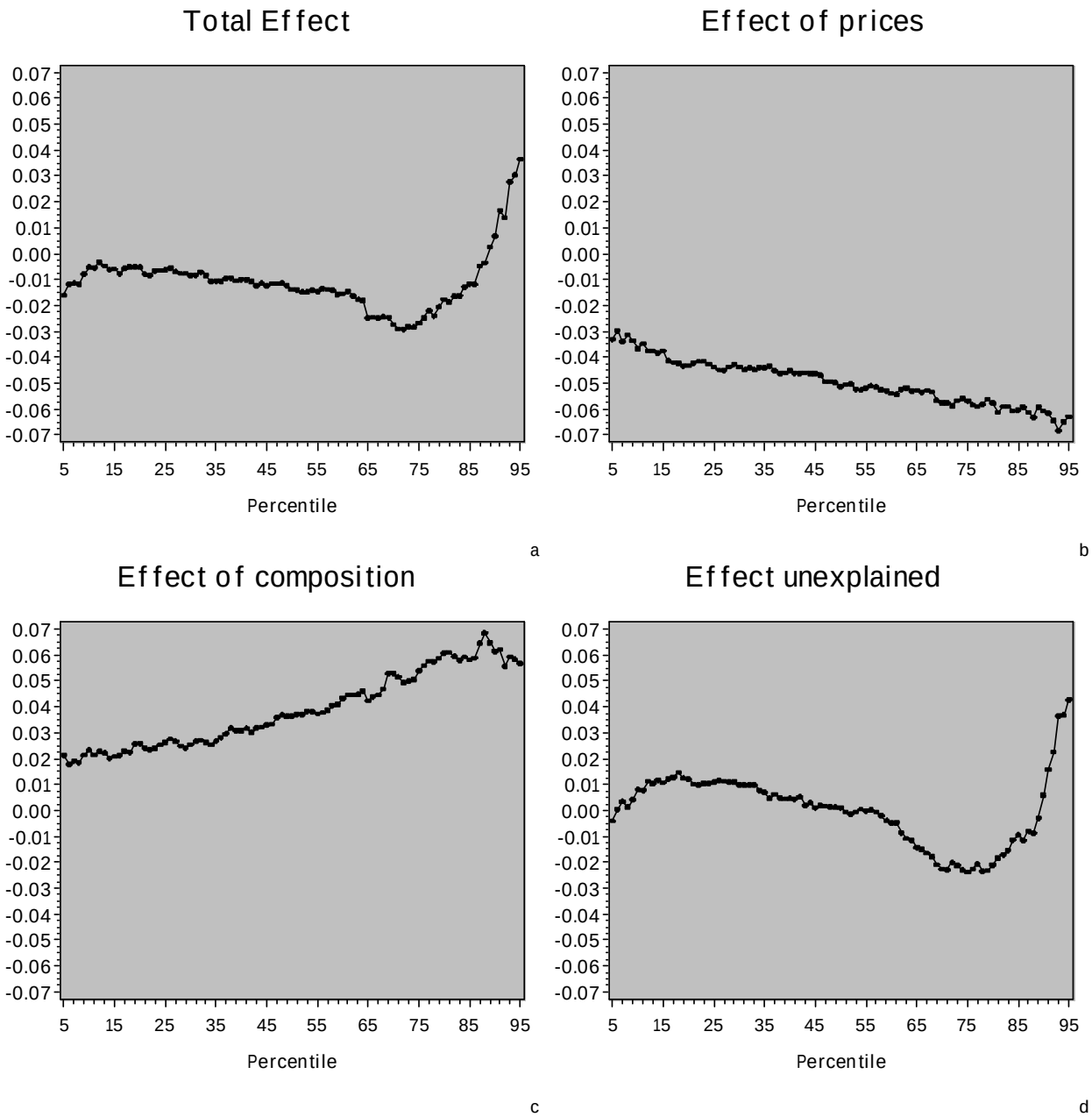


***Table 1. Descriptive analysis Relative Wages level and changes***

| | | *Mean* | | *Median* | | *Changes* | |
|---|---|---|---|---|---|---|---|
| *Group* | | *1995 (1)* | *2002 (2)* | *1995 (3)* | *2002 (4)* | *Mean (2-1)* | *Median (4-3)* |
| All | | 2.345 | 2.334 | 2.276 | 2.263 | -0.01 | -0.014 |
| Gender | Men | 2.397 | 2.372 | 2.325 | 2.294 | -0.025 | -0.031 |
| | Women | 2.214 | 2.253 | 2.154 | 2.193 | 0.039 | 0.039 |
| Education | Elem. School | 2.255 | 2.215 | 2.219 | 2.186 | -0.04 | -0.033 |
| | Middle School | 2.241 | 2.211 | 2.198 | 2.182 | -0.03 | -0.016 |
| | High School | 2.458 | 2.411 | 2.408 | 2.35 | -0.047 | -0.059 |
| | University | 2.788 | 2.741 | 2.769 | 2.672 | -0.048 | -0.097 |
| Gender and education | Men - E.S. | 2.303 | 2.254 | 2.264 | 2.221 | -0.049 | -0.043 |
| | Men - M.S. | 2.281 | 2.245 | 2.237 | 2.214 | -0.035 | -0.024 |
| | Men - H.S. | 2.539 | 2.467 | 2.519 | 2.409 | -0.072 | -0.109 |
| | Men - Unive. | 2.886 | 2.846 | 2.856 | 2.782 | -0.039 | -0.074 |
| | Women - E.S. | 2.088 | 2.096 | 2.061 | 2.07 | 0.008 | 0.009 |
| | Women - M.S. | 2.129 | 2.115 | 2.078 | 2.08 | -0.014 | 0.002 |
| | Women - H.S. | 2.304 | 2.319 | 2.257 | 2.263 | 0.014 | 0.006 |
| | Women - Unive. | 2.504 | 2.556 | 2.529 | 2.489 | 0.052 | -0.04 |
| Experience (years) | < 5 | 2.122 | 2.139 | 2.083 | 2.102 | 0.017 | 0.019 |
| | 5 =<10 | 2.182 | 2.209 | 2.134 | 2.158 | 0.028 | 0.024 |
| | 10=<15 | 2.255 | 2.259 | 2.201 | 2.196 | 0.003 | -0.006 |
| | 15=<20 | 2.332 | 2.339 | 2.27 | 2.267 | 0.007 | -0.003 |
| | 20=<25 | 2.395 | 2.368 | 2.327 | 2.295 | -0.027 | -0.032 |
| | 25=<30 | 2.473 | 2.431 | 2.405 | 2.351 | -0.042 | -0.054 |
| | 30=<35 | 2.495 | 2.464 | 2.44 | 2.392 | -0.032 | -0.048 |
| | 35=<40 | 2.452 | 2.435 | 2.379 | 2.367 | -0.017 | -0.012 |
| | 40=< | 2.365 | 2.312 | 2.295 | 2.255 | -0.053 | -0.04 |

***Note. The wages are expressed in logs***

***Table 2. Descriptive analysis Measures of inequality***

| | | *Variance* | | *90-10* | | *Changes* | |
|---|---|---|---|---|---|---|---|
| *Group* | | *1995 (1)* | *2002 (2)* | *1995 (3)* | *2002 (4)* | *Variance (2-1)* | *90-10 (4-3)* |
| All | | 0.141 | 0.149 | 0.913 | 0.925 | 0.007 | 0.012 |
| Gender | Men | 0.147 | 0.156 | 0.923 | 0.936 | 0.009 | 0.013 |
| | Women | 0.101 | 0.122 | 0.79 | 0.857 | 0.021 | 0.067 |
| Education | Elem. School | 0.078 | 0.081 | 0.71 | 0.68 | 0.003 | -0.03 |
| | Middle School | 0.093 | 0.08 | 0.768 | 0.694 | -0.013 | -0.074 |
| | High School | 0.16 | 0.16 | 0.969 | 0.992 | 0 | 0.023 |
| | University | 0.257 | 0.259 | 1.334 | 1.288 | 0.001 | -0.046 |
| Gender and education | Men - E.S. | 0.076 | 0.082 | 0.715 | 0.69 | 0.006 | -0.025 |
| | Men - M.S. | 0.091 | 0.078 | 0.754 | 0.682 | -0.014 | -0.072 |
| | Men - H.S. | 0.171 | 0.175 | 1.011 | 1.037 | 0.004 | 0.026 |
| | Men - Unive. | 0.255 | 0.286 | 1.366 | 1.434 | 0.031 | 0.068 |
| | Women - E.S. | 0.047 | 0.06 | 0.513 | 0.561 | 0.013 | 0.047 |
| | Women - M.S. | 0.081 | 0.074 | 0.705 | 0.645 | -0.006 | -0.06 |
| | Women - H.S. | 0.104 | 0.122 | 0.783 | 0.874 | 0.018 | 0.091 |
| | Women - Unive. | 0.157 | 0.157 | 0.992 | 0.968 | 0 | -0.024 |
| Experience (years) | < 5 | 0.062 | 0.095 | 0.666 | 0.773 | 0.033 | 0.107 |
| | 5 =<10 | 0.084 | 0.098 | 0.74 | 0.745 | 0.014 | 0.006 |
| | 10=<15 | 0.101 | 0.123 | 0.779 | 0.847 | 0.022 | 0.068 |
| | 15=<20 | 0.13 | 0.141 | 0.881 | 0.898 | 0.011 | 0.017 |
| | 20=<25 | 0.138 | 0.149 | 0.901 | 0.938 | 0.011 | 0.038 |
| | 25=<30 | 0.176 | 0.166 | 1.008 | 0.987 | -0.011 | -0.021 |
| | 30=<35 | 0.168 | 0.185 | 0.992 | 1.036 | 0.016 | 0.044 |
| | 35=<40 | 0.161 | 0.173 | 0.929 | 0.995 | 0.012 | 0.066 |
| | 40=< | 0.125 | 0.122 | 0.862 | 0.819 | -0.003 | -0.043 |

**Table 3 Quantile regression of log wages. A) Men**

| | | *Quantile* | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *0.1* | | *0.25* | | *0.5* | | *0.75* | | *0.9* | |
| | | *Estimate* | *Std Err* | *Estimate* | *Std Err* | *Estimate* | *Std Err* | *Estimate* | *Std Err* | *Estimate* | *Std Err* |
| *1995* | *Elem. School* | 1.52349 | 0.0199 | 1.51156 | 0.01504 | 1.51703 | 0.01741 | 1.61522 | 0.01814 | 1.70666 | 0.02466 |
| | *Middle School* | 1.6068 | 0.0178 | 1.62107 | 0.01248 | 1.66764 | 0.01494 | 1.79444 | 0.01527 | 1.88573 | 0.01853 |
| | *High School* | 1.79843 | 0.01806 | 1.8867 | 0.01361 | 2.01506 | 0.01552 | 2.17877 | 0.01582 | 2.32795 | 0.02013 |
| | University | 2.04676 | 0.03845 | 2.23674 | 0.01642 | 2.38047 | 0.01955 | 2.61361 | 0.01916 | 2.79519 | 0.02975 |
| | *Experience* | 0.0248 | 0.00152 | 0.03274 | 0.00113 | 0.0412 | 0.00131 | 0.04407 | 0.00134 | 0.04854 | 0.00173 |
| | *Experience Sq.* | -0.0003 | 0.00003 | -0.00041 | 0.00002 | -0.00053 | 0.00003 | -0.00054 | 0.00003 | -0.00055 | 0.00004 |
| *2002* | *Elem. School* | 1.52094 | 0.01699 | 1.51561 | 0.01719 | 1.53812 | 0.01529 | 1.60972 | 0.02172 | 1.7043 | 0.03054 |
| | *Middle School* | 1.57398 | 0.01374 | 1.58868 | 0.0146 | 1.63967 | 0.01341 | 1.73565 | 0.01931 | 1.85688 | 0.02782 |
| | *High School* | 1.74404 | 0.01447 | 1.80448 | 0.01577 | 1.94666 | 0.01542 | 2.13852 | 0.02007 | 2.32683 | 0.02999 |
| | University | 2.0089 | 0.02101 | 2.19172 | 0.01719 | 2.39188 | 0.01645 | 2.6338 | 0.02453 | 2.93439 | 0.03123 |
| | *Experience* | 0.02555 | 0.00117 | 0.03286 | 0.00126 | 0.03938 | 0.00119 | 0.04319 | 0.00167 | 0.04547 | 0.00236 |
| | *Experience Sq.* | -0.00036 | 0.00002 | -0.00045 | 0.00003 | -0.00053 | 0.00002 | -0.00054 | 0.00003 | -0.00053 | 0.00005 |

***Note. All the coefficients are significant at 1 percent***

**Table 3 Quantile regression of log wages. B) Women**

| | | *Quantile* | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *0.1* | | *0.25* | | *0.5* | | *0.75* | | *0.9* | |
| | | *Estimate* | *Std Err* | *Estimate* | *Std Err* | *Estimate* | *Std Err* | *Estimate* | *Std Err* | *Estimate* | *Std Err* |
| *1995* | *Elem. School* | 1.55315 | 0.02268 | 1.54149 | 0.01936 | 1.50496 | 0.02059 | 1.49395 | 0.03225 | 1.5931 | 0.04136 |
| | *Middle School* | 1.62202 | 0.02172 | 1.66607 | 0.01526 | 1.69242 | 0.01891 | 1.77119 | 0.0288 | 1.90668 | 0.03511 |
| | *High School* | 1.80213 | 0.01993 | 1.89009 | 0.01177 | 1.97959 | 0.0146 | 2.12153 | 0.02596 | 2.28599 | 0.02873 |
| | University | 1.92761 | 0.04439 | 2.0536 | 0.04046 | 2.29021 | 0.02756 | 2.45758 | 0.03541 | 2.57601 | 0.03181 |
| | *Experience* | 0.01753 | 0.002 | 0.02023 | 0.00138 | 0.02851 | 0.00174 | 0.03449 | 0.00257 | 0.03738 | 0.00316 |
| | *Experience Sq.* | -0.00024 | 0.00004 | -0.00023 | 0.00003 | -0.00034 | 0.00004 | -0.00039 | 0.00005 | -0.00039 | 0.00007 |
| *2002* | *Elem. School* | 1.46516 | 0.02206 | 1.51475 | 0.0172 | 1.5362 | 0.02078 | 1.53114 | 0.01938 | 1.57386 | 0.04749 |
| | *Middle School* | 1.49503 | 0.0182 | 1.57391 | 0.01488 | 1.61979 | 0.01482 | 1.68272 | 0.01547 | 1.76809 | 0.03392 |
| | *High School* | 1.72095 | 0.01551 | 1.83213 | 0.01299 | 1.92263 | 0.01207 | 2.04857 | 0.01335 | 2.20267 | 0.03074 |
| | University | 1.97021 | 0.02181 | 2.11068 | 0.01325 | 2.2546 | 0.01902 | 2.43132 | 0.0227 | 2.61757 | 0.0339 |
| | *Experience* | 0.02349 | 0.00153 | 0.02616 | 0.00126 | 0.03404 | 0.00132 | 0.04044 | 0.0014 | 0.04668 | 0.00305 |
| | *Experience Sq.* | -0.00034 | 0.00003 | -0.00038 | 0.00003 | -0.00049 | 0.00003 | -0.00055 | 0.00003 | -0.00063 | 0.00007 |

***Note. All the coefficients are significant at 1 percent***

**Table 4. Composition of the workforce, %Share**

| | | *Employees* | | *Hours* | |
|---|---|---|---|---|---|
| *Group* | | *1995 (1)* | *2002 (2)* | *1995 (3)* | *2002 (4)* |
| | | | Total | | |
| Gender | Men | 70.07 | 66.1 | 71.49 | 68.36 |
| | Women | 29.93 | 33.9 | 28.51 | 31.64 |
| Education | Elem. School | 16.76 | 9.31 | 16.77 | 9.35 |
| | Middle School | 43.51 | 40.81 | 43.39 | 40.8 |
| | High School | 35.29 | 42.91 | 35.34 | 42.91 |
| | University | 4.45 | 6.97 | 4.5 | 6.94 |
| Experience | < 10 | 17.18 | 17.73 | 16.71 | 17.28 |
| (years) | 10 =<20 | 33.48 | 31.94 | 33.35 | 31.87 |
| | 20=<30 | 22.68 | 26.48 | 22.86 | 26.65 |
| | 30=<40 | 18.89 | 17.42 | 19.2 | 17.62 |
| | 40< | 7.77 | 6.43 | 7.87 | 6.57 |
| | | | Men | | |
| Education | Elem. School | 18.29 | 10.36 | 18.26 | 10.35 |
| | Middle School | 44.79 | 44.05 | 44.71 | 44.08 |
| | High School | 32.27 | 39.06 | 32.35 | 39.11 |
| | University | 4.65 | 6.53 | 4.69 | 6.46 |
| Experience | < 10 | 13.75 | 14.85 | 13.28 | 14.36 |
| (years) | 10 =<20 | 32.57 | 30.56 | 32.46 | 30.46 |
| | 20=<30 | 24.05 | 27.85 | 24.24 | 28.18 |
| | 30=<40 | 20.51 | 19.3 | 20.82 | 19.45 |
| | 40< | 9.12 | 7.43 | 9.19 | 7.54 |
| | | | Women | | |
| Education | Elem. School | 13.17 | 7.27 | 13.05 | 7.21 |
| | Middle School | 40.51 | 34.49 | 40.08 | 33.69 |
| | High School | 42.35 | 50.42 | 42.84 | 51.11 |
| | University | 3.97 | 7.83 | 4.03 | 7.99 |
| Experience | < 10 | 25.21 | 23.35 | 25.31 | 23.6 |
| (years) | 10 =<20 | 35.61 | 34.63 | 35.58 | 34.92 |
| | 20=<30 | 19.47 | 23.81 | 19.43 | 23.33 |
| | 30=<40 | 15.11 | 13.74 | 15.12 | 13.68 |
| | 40< | 4.6 | 4.47 | 4.56 | 4.48 |

***Table 5 Lemieux decomposition of the changes in the wage distribution between 1995 and 2002***

| | *1995* | *2002* | | | *diff. 1995-2002* | | | |
|---|---|---|---|---|---|---|---|---|
| *Statistic* | *Simple (1)* | *Simple (2)* | *b 1995 (3)* | *b,f 1995 (4)* | *Simple (2)-(1)* | *Due to b (2)-(3)* | *Due to f (3)-(4)* | *Unexplained (4)-(1)* |
| mean | 2.345 | 2.334 | 2.385 | 2.344 | -0.01 | -0.05 | 0.04 | 0 |
| var | 0.141 | 0.149 | 0.154 | 0.145 | 0.007 | -0.005 | 0.009 | 0.004 |
| var(xb) | 0.057 | 0.053 | 0.058 | 0.057 | -0.004 | -0.005 | 0.002 | 0 |
| var(res) | 0.084 | 0.095 | 0.095 | 0.088 | 0.011 | 0 | 0.007 | 0.004 |
| cv | 16.018 | 16.51 | 16.441 | 16.244 | 0.492 | 0.069 | 0.196 | 0.226 |
| p90 | 2.844 | 2.85 | 2.91 | 2.849 | 0.007 | -0.06 | 0.061 | 0.006 |
| p50 | 2.276 | 2.263 | 2.315 | 2.278 | -0.014 | -0.052 | 0.037 | 0.001 |
| p10 | 1.93 | 1.925 | 1.964 | 1.938 | -0.005 | -0.039 | 0.026 | 0.008 |
| p9010 | 0.913 | 0.925 | 0.946 | 0.911 | 0.012 | -0.021 | 0.035 | -0.002 |
| p9050 | 0.567 | 0.587 | 0.596 | 0.572 | 0.02 | -0.008 | 0.024 | 0.005 |
| p5010 | 0.346 | 0.338 | 0.351 | 0.339 | -0.009 | -0.013 | 0.011 | -0.007 |
| nobs | 95090 | 86191 | 86191 | 86191 | . | . | . | . |

***Table 6. Between group Relative Wages level and changes. Prices and composition***

| | | *Levels* | | | *Changes* | | |
|---|---|---|---|---|---|---|---|
| *Group* | | *1995 (1)* | *2002 (2)* | *2002 b 1995 (3)* | *Total (4=2-1)* | *due to b (5=2-3)* | *due to f (6=3-1)* |
| All | | 2.34 | 2.33 | 2.38 | -0.01 | -0.05 | 0.04 |
| Gender | Men | 2.4 | 2.37 | 2.44 | -0.02 | -0.06 | 0.04 |
| | Women | 2.21 | 2.25 | 2.28 | 0.04 | -0.02 | 0.06 |
| Education | Elem. School | 2.26 | 2.22 | 2.25 | -0.04 | -0.03 | -0.01 |
| | Middle School | 2.24 | 2.21 | 2.27 | -0.03 | -0.06 | 0.03 |
| | High School | 2.46 | 2.41 | 2.47 | -0.05 | -0.06 | 0.01 |
| | University | 2.79 | 2.74 | 2.72 | -0.05 | 0.03 | -0.07 |
| Gender and education | Men - E.S. | 2.3 | 2.25 | 2.3 | -0.05 | -0.04 | -0.01 |
| | Men - M.S. | 2.28 | 2.25 | 2.31 | -0.04 | -0.07 | 0.03 |
| | Men - H.S. | 2.54 | 2.47 | 2.55 | -0.07 | -0.08 | 0.01 |
| | Men - Unive. | 2.89 | 2.85 | 2.83 | -0.04 | 0.02 | -0.06 |
| | Women - E.S. | 2.09 | 2.1 | 2.09 | 0.01 | 0.01 | 0 |
| | Women - M.S. | 2.13 | 2.12 | 2.16 | -0.01 | -0.05 | 0.04 |
| | Women - H.S. | 2.3 | 2.32 | 2.34 | 0.01 | -0.02 | 0.03 |
| | Women - Unive. | 2.5 | 2.56 | 2.52 | 0.05 | 0.04 | 0.02 |
| Experience (years) | < 5 | 2.12 | 2.14 | 2.14 | 0.02 | 0 | 0.01 |
| | 5 =<10 | 2.18 | 2.21 | 2.24 | 0.03 | -0.03 | 0.06 |
| | 10=<15 | 2.26 | 2.26 | 2.31 | 0 | -0.05 | 0.05 |
| | 15=<20 | 2.33 | 2.34 | 2.36 | 0.01 | -0.02 | 0.03 |
| | 20=<25 | 2.39 | 2.37 | 2.4 | -0.03 | -0.04 | 0.01 |
| | 25=<30 | 2.47 | 2.43 | 2.49 | -0.04 | -0.06 | 0.02 |
| | 30=<35 | 2.5 | 2.46 | 2.57 | -0.03 | -0.1 | 0.07 |
| | 35=<40 | 2.45 | 2.43 | 2.53 | -0.02 | -0.1 | 0.08 |
| | 40=< | 2.37 | 2.31 | 2.39 | -0.05 | -0.07 | 0.02 |

**Table 7. Between Wthin decomposition of the change of share od educational groups**

| *education* | *total* | *between* | *within* | *total* | *between* | *within* | *total* | *between* | *within* |
|---|---|---|---|---|---|---|---|---|---|
| | Employment | | | Hours worked | | | Wage Bill | | |
| El School | -1.08 | -0.03 | -1.05 | -1.08 | -0.03 | -1.05 | -0.99 | -0.05 | -0.95 |
| M. School | -0.38 | -0.05 | -0.32 | -0.38 | -0.05 | -0.33 | -0.45 | -0.02 | -0.43 |
| High School | 1.12 | 0.07 | 1.06 | 1.12 | 0.06 | 1.06 | 0.97 | 0.04 | 0.94 |
| University | 0.34 | 0.02 | 0.32 | 0.33 | 0.01 | 0.32 | 0.47 | 0.03 | 0.44 |

**Table 8. Price Effects of industry control on the return to education**

| Education | Before controlling | After controlling |
|---|---|---|
| Total | | |
| El. School | -0.03 | -0.01 |
| M. School | -0.06 | -0.03 |
| High School | -0.06 | 0 |
| University | 0.03 | 0.07 |
| Relative to High school | | |
| El. School | 0.03 | - 0.01 |
| M. School | 0 | - 0.03 |
| University | 0.09 | 0.07 |

***Table 9. Effect of dummy for standard workers in a wage equation***

| | *year* | | | |
|---|---|---|---|---|
| | *1995* | | *2002* | |
| | *Estimate* | *Std. Err.* | *Estimate* | *Std. Err.* |
| *MODEL 1* | 0.07616 | 0.00388 | 0.06741 | 0.0036 |
| *MODEL 2* | 0.03924 | 0.00357 | 0.04551 | 0.00335 |

***Note 1. All the coefficients are significant at 1 percent***

***Note 2. See text for the specification of models***

***Table 10. Effect of composition (by work arrangement) and prices on the return to education***

| *average return 2002 (1)* | *average return 1995 (2)* | *average return 2002 weights 1995 (3)* | *Change in average return (2-1)* | *Change due to weights (1-3)* | *Change not due to weights (3-2)* |
|---|---|---|---|---|---|
| 0.408 | 0.349 | 0.409 | 0.059 | -0.001 | 0.060 |

***Note: See explanation in the text***

**Table 11. Change in other labour markets quantities**

| | *Level* | | *Change* | *Level* | | *Change* |
|---|---|---|---|---|---|---|
| | *1995* | *2002* | *95-02* | *1995* | *2002* | *95-02* |
| | Unemployment rate | | | Employment to population ratio | | |
| Elementary School | 9.65 | 10.45 | 0.79 | 35.04 | 34.63 | -0.42 |
| Middle school | 10.17 | 9.51 | -0.65 | 60.84 | 62.81 | 1.97 |
| High School | 11.85 | 9.18 | -2.67 | 59.92 | 63.68 | 3.76 |
| Univerisity | 8.07 | 5.4 | -2.67 | 78.81 | 81.89 | 3.08 |
| Men - E.S. | 8.27 | 8.57 | 0.3 | 56.94 | 54.62 | -2.32 |
| Men - M.S. | 7.71 | 7.25 | -0.46 | 78.52 | 78.95 | 0.43 |
| Men - H.S. | 8.8 | 6.85 | -1.95 | 69.88 | 72.7 | 2.81 |
| Men - Unive. | 5.63 | 3.73 | -1.9 | 85.81 | 87.29 | 1.48 |
| Women - E.S. | 12.51 | 14.32 | 1.81 | 18.75 | 19.75 | 1 |
| Women - M.S. | 14.75 | 13.73 | -1.01 | 41.31 | 44.97 | 3.66 |
| Women - H.S. | 15.94 | 12.3 | -3.64 | 49.41 | 54.18 | 4.77 |
| Women - Unive. | 11.01 | 7.42 | -3.59 | 71.28 | 76.08 | 4.8 |

**Note: All the figures are adjusted for composition changes**