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The Evolution of Returns to Education in Italy, 1978-1992
Changing Institutions or Changing Supply and Demand?

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ABSTRACT

In this paper I use SHIW micro data between 1978 and 1992 to study changes in returns to education in Italy. I show that between 1977 and 1985 the average return to one extra year of education decreased by approximately 0.4 percentage points and it increased by approximately 0.6 percentage points in the following seven years. I analyze the role played by the Scala Mobile, a wage indexation mechanism reducing wage dispersion as prices rose. Since the Scala Mobile was curbed over time, this candidates as a potential explanation for the observed trend. In order to separately identify the effect of this institution from any other macroeconomic force, I assume that in the absence of the Scala Mobile the gender earnings gap would have varied along a linear trend. Based on this assumption I show that the Scala Mobile was substantially responsible for the compression in returns to education between the late 1970s and the mid 1980s. If the Scala Mobile had not been curbed, the return to one extra year of education would have decreased by approximately 0.4 percentage points in 14 years, as opposed to an actual increase of 0.2 percentage points. Controlling explicitly for changes in the demand and supply of different educational labor inputs does not affect my basic conclusion.

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Introduction

In this paper I study the effect of a specific institution – the Scala Mobile - on changes in returns to education in Italy between the late 1970s and the early 1990s, using SHIW micro data.

A feature that makes this institutional arrangement almost unique is that it affected – although with a different degree on intensity - the whole distribution of wages. Broadly speaking, the Scala Mobile was an indexation mechanism granting the same nominal increase in wages to all employees as prices rose. In principle, by awarding the same wage increase to both low- and high-wage workers the Scala Mobile had a potential to compress wage differentials.

Over time, the equalizing effect of this indexation mechanism gradually declined and by the end of the period of observation this was virtually zero. This provides a unique experiment to test whether this institution had any effect on the structure of wages. One can do so by looking at changes in returns to education over time. If this institution had any effect, one might expect these changes to increase as this institution was curbed. Indeed, the data show that between 1978 and 1992 returns to education first decreased and then increased suggesting that in the absence of this institution returns to education would have increased all over the period of observation.

A difficulty with this conclusion is that one might argue that this institution had no effect on the structure of earnings and, in the absence of it, wage differentials would have evolved as they in fact did. This would be the case if the latent structure of returns to education happened to move as predicted by the Scala Mobile, and the latter just 'predated' the former. One way to address to this criticism is to identify a source of exogenous variation in the Scala mobile that is arguably exogenous to changes in the latent structure of wages. The Scala Mobile, however, affected all employees and in this sense it was intrinsically a 'macro-economic' institution. So, one does not have a natural control group to evaluate a counterfactual distribution of wages. To identify the effect of institution and distinguish it from any other macroeconomic factor, I assume – and later I provide some corroborating evidence – that, had the indexation mechanism not been at work, the gender earnings gap would have changed at a constant rate over the whole period of observation. This is equivalent to attributing any deviation around this linear trend to the Scala Mobile. Since the Scala Mobile potentially compressed the gender earnings gap, for this to be true one would expect this gap not to change uniformly across periods but to compress more as the Scala Mobile was stronger. That is precisely what I find in the data and I exploit this to uncover the effect of the Scala Mobile and separately identify its effect from other sources of wage changes. Based on this assumption, I show that if the Scala Mobile had not been curbed, returns to education would have decreased throughout the period of observation.

This basic conclusion mimics the results of my previous paper (Manacorda, 2000) where I look at changes at each percentile of the unconditional distribution of earnings, separately for men and women. However, this framework has a double advantage and is a natural complement to my previous analysis. First, it examines changes in the wage structure 'between' groups. It is known that changes in the wage structure between and within groups in the US are somewhat distinct economic phenomena (Juhn *et al.*, 1993). Broadly speaking, the former shows a downward trend in the 1970s and an upward trend in the 1980s, while the latter appears to have risen monotonically over both decades. One would like to know whether the same happened in Italy and – if this is not the case – how one can explain the different trends. Erickson and Ichino (1995) compare the evolution of wage differentials between education and age groups in Italy and the US and they conclude that the trends in the two countries differ because a combination of market forces, institutions and changes in inflation. However one does not know how much weight to attach to these different explanations and this paper is an attempt to answer this question.

Secondly, this framework provides an explicit way to contrast the hypothesis that the Scala Mobile shaped the evolution of returns to education in Italy with the alternative hypothesis that changes in the structure of labor supply and labor demand are to explain this evolution. By using data on the evolution of labor force by education, I can test whether the trend in the Scala Mobile obscured market responses to changes in supply and demand of skills. This hypothesis has some success in explaining changes in the returns to education in the US in the last three decades (see among others Katz and Murphy, 1992 and Card and Lemieux, 2000). One might suspect that the compression in returns to education in the first years of observation was only due to the circumstance the supply of educated labor outpaced demand, and the opposite happened when the trend in the wage structure reverted. I find that supply did play a role but this does not alter my basic conclusion, namely that changes in the structure of returns to education were affected by changes in the degree of 'toughness' of the Scala Mobile.

The plan of the paper is as follows. Section I provides evidence on the evolution of returns to education and other dimensions of changes in the structure of wages over the period of observation. In Section II I show how the Scala Mobile potentially affected the wage structure, by compressing it from the bottom, and how this potential declined over time. In section III I correlate changes in the wage structure to changes in the indexation mechanism and finally in Section IV I test for the robustness of my results to the inclusion of labor supply changes in the wage equation. Section V summarizes and concludes.

I. Changes in the Wage Structure: 1978-1992

A. The Data

The data I use are the individual records of the Bank of Italy SHIW (Survey of Households'Income and Wealth), for the period 1977-1993. The survey has been run on a yearly basis until 1987 (with the exception of 1985) and then every other year since then. Since I do not have repeated observations over the same individuals (the survey comes in the form of repeated cross sections) I look at wage changes by cells defined over 4 categories of education (5^{th} grade or below, 8^{th} grade, 13^{th} grade and College or above), 4 age groups (21-30, 31-40, 41-50, 51-65) and gender. Since some of the cells tend to be relatively small, and the associated estimates rather imprecise, I take average log wages for each cell over three-year intervals centered around the following years: 1978, 1981, 1985, 1988 and 1992.[1] In the following I will refer for brevity to the year 1978 to mean the average value between 1977 and 1979 and similarly for the other years. My basic observations are then the 160 cells defined by the interaction of education (4), sex (2) age (4) and time (5).

Yearly labor income, which is the earnings variable used in this study, is defined net of taxes and social security contributions and inclusive of thirteenth wages, bonuses and overtime payments. I will refer to this indifferently as 'earnings' or 'wage' but one has to bear in mind that this is really annual take home pay. Data are weighted by the sampling weights. Sampling weights for each cell are given by the sum of the weights for the individuals in each cell.

I restrict to full-year employees, both men and women, aged 21-65. Overall, I have 40,507 observations. [2] The sample size increases from 4,442 in 1978 to 10,824 in 1992 and the average cell size increases from 138 in 1978 to 338 in 1992. College workers constitute a relatively small share of the sample. Their average cell size within each age-gender group increases from 36 in 1978 to 137 in 1992 and their relative weight from 7% to 10%. Workers in the intermediate two groups account for almost 60% of the total observations. As expected there is a trend towards increased educational attainment, with those with 13th grade accounting for 25% of the total sample in 1978 and 39% 14 years later, and those with 5th grade reducing their relative weight from 39% to 17%.

B. Descriptive Evidence

In Table 1 I report log wages relative to the mean by education, gender and age, and interactions of these at each point in time. These data are obtained aggregating over the 160 cell averages with a fixed weighting scheme, where the weights are given by the average relative proportion of each cell over the whole period of observation. In this way one purges variations the structure of wages from any effect due to compositional changes. Alongside I also report annualized log changes over each period.

(Table 1 approximately here)

Unconditional returns to education, which are plotted in Figure 1, show some variation over time. One can see that, while the distribution of wages is compressing from the bottom, there is also some decompression going on at the top. Returns to College (College – 13^{th} grade) increase almost monotonically (from 5% in 1978 to 13% in 1992) while returns to 13^{th} grade (13^{th}- 8^{th}) stay basically constant (at around 10%) with some increase in the late 1980s. Returns to 8^{th} grade (8^{th}-5^{th}) reduce from 9% in 1978 to 3% in 1992.

(Figure 1 approximately here)

Table 1 illustrates that while men at the top of the distribution gain substantially, with the college premium increasing by about 9 percentage points over the whole period, those at the bottom do not seem to experience substantial changes in their relative wages. Returns to education change pretty dramatically for women who start from a relatively more dispersed wage distribution and lower wages at any level of education. The wage differential between the two bottom groups (8^{th}-5^{th}) reduces by 14 percentage points between 1978 and 1988 from 19% to 5%, but the college premium increases over the same period by 4 percentage points.

The unconditional male-female earnings gap decreases sensibly until the late 1970s and the late 1980s with a reduction of 6 percentage points (from 23% to 17%) but by the early 1990s it opens up again with an increase of 2 percentage points.

As the age structure is concerned, differentials stay basically unchanged until the late 1980s when they show some tendency to decompress. For example, the difference in wages between those in their 30s and those in their 20s reduces from 14% to 10% between 1978 to 1988 then to increase by 5 percentage points in the last four years.

A look at the rest of the table shows that it is mainly young college graduates to gain all over the period of observation (with an increases of 11 percentage points in the college premium from 1977 to 1992 for those in their 20s and a rise of 9 percentage points for those in their 30s) while it is older, poorly educated workers who mostly benefit from the compression in the in 1970s and 1980s, and who lose afterwards. The differential between 8th grade and 5th grade workers in their 50s reduces by approximately 9 percentage points in the first ten years to increase again in the last years by about 3 percentage points.

Overall, whatever dimension one looks at, it appears that the distribution compresses from the bottom favoring in particular women and less educated workers. Incidentally, note that the compression seems to be stronger for those groups who start with a more dispersed initial distribution of wages: these are again women (compared to men) and older workers (compared to younger workers). At the top some decompression is going on. Interestingly, while the compression from the bottom seems to come to a halt in the late 1980s, the trend at the top seems to be unaltered. If anything one would suspect that something changed for low skilled workers. I will argue below that all these three features (higher increases for those in the bottom tail of the wage distribution, faster compression within groups with more dispersed wages and timing of the change) are consistent with the effect of the Scala Mobile on the cross sectional distribution of wage changes and with changes in its 'toughness' over time. As changes at the top are concerned, I show in the next section that the Scala Mobile had a relatively weak effect there. A way to interpret the data then is that, if the compression at the bottom came from the indexation, in the absence of indexation wages would have decompressed at the bottom too.

The pattern I have described is reflected in the overall evolution of wage inequality. In Table 2 I decompose changes in wage inequality, as measured by the variance of the logarithm of wages, into a component between groups defined by the interaction of age and education and a component due to variations within these groups. To do so I have regressed the logarithm of wages in each year on a linear term in years of completed education and a quadratic term in age. The table tells a simple story: whatever dimension one looks at (total, within or between), wage inequality first decreases and then increases with a turning point in the late 1980s. Age and education (and gender) explain between one fourth to one fifth of the total variability of wages and, consistently with Table 1, inequality compresses dramatically for women and much less for men. In 1988 the two distributions display remarkably similar levels of dispersion. Interestingly, changes in between and within inequality show a similar trend suggesting that these are potentially driven by similar forces.

(Table 2 approximately here)

In order to summarize the salient features of changes in the wage distribution, I postulate that wage changes by cell can be expressed as linear function of years of completed education, a quadratic term in age, an intercept for female workers, plus a common macroeconomic term. I also assume that there is an additive error term which picks up measurement error as well as any other idiosyncrasy in wages. Finally, I assume that the marginal distribution of wage changes is characterized by changing returns to education, age and gender:

$$\Delta w_{ct}=\gamma_{0t}+\gamma_{1t}\text{education}+\gamma_{2t}\,\text{age}+\gamma_{3t}\text{age}^2+\gamma_{4t}\,\text{sex}+u_{ct} \qquad (1)$$

where w is log wages and the subscript 'c' refers to cell means, where the cells are defined by the interaction of age, sex and gender.[3]

In column (1) of Table 3 I report the estimation results for the marginal distribution of wage changes (equation (1)). Education is a linear term which represents the minimum numbers of years necessary to achieve any formal level of education while age is given by the midpoint in each interval.[4] For brevity I only report the coefficients on education and sex.

(Table 3 approximately here)

The dependent variable is given by the annualized wage change over each time interval (1978-1981, 1981-1985, 1985-1988, 1988-1992), expressed in percentage points. Estimation is performed on the 128 cell differences using GLS with weights given by the inverse sampling variance of the dependent variable. Although the estimates show some convexity over time in changes to returns to education, these estimates are pretty imprecise. To achieve more precision, I impose some parametric restrictions on the evolution of changes in returns to education, by restricting to a quadratic trend in column (2) (which takes the value 0 in the first period, 1 in the second, etc.). In column (3) I restrict to a linear trend and in column (4) I impose no variation in changes in returns to education over the different periods. For any of these specifications, I report a goodness-of-fit test which gives an indication as to whether the model fits the data as well as the unrestricted specification of column (1). As it can be seen from the table, specifications (2) and (3) do as well as the model in column (1). But as we restrict changes in returns to education to be constant, we have a significant loss of fit. If one takes the most parsimonious model of column (3), one can conclude that changes in returns to education show some positive trend, which is to say that returns to education (in log levels) accelerate over time. While in the first period of observation, differentials reduce by approximately 0.25 percentage points (-0.087 x 3), their decline tends gradually to slow down. Between 1981 and 1985 they reduce by around 0.1 percentage points ((-0.087+0.062) x 4) and they start then to increase, with a rise of 0.1 percentage points in the second half of the 1980s ((-0.087+0.062 x 2) x 3) and an increase of almost 0.5 percentage points in the last period ((-0.087+0.062 x 3) x 4). To get an idea of the magnitude of the changes, my estimates suggest that the (conditional) differential between 13th grade and 8th grade reduces by approximately 2 percentage points between 1978 and 1985 and subsequently rises by 3 percentage points. To visualize the trend, in Figure 2 I have depicted the evolution of the return one extra year of education obtained by cumulating the changes in returns to education as predicted from specification (3) in Table 3. The series is standardized to the level in 1977, as estimated in a separate cross-sectional regression.

(Figure 2 approximately here)

Interestingly, the male-female earnings gap also reduces during the period of analysis. Most of the decline takes place between 1978 and 1981, with a fall of more than 5 percentage points in three years (1.419 x 3). The gender gap reduces, although at a slower pace, in the subsequent periods, and in the last period of observations it reverts to its trend as it increases by almost 2 percentage points in four years ((1.419-1.838) x 4). In the rest of the paper I attribute the differential evolution of the gender gap over different time intervals to the effect of the Scala Mobile. In the next section I show how the Scala mobile was potentially able to produce this pattern and I provide some evidence that indeed it was the Scala Mobile – and not other forces – to shape variations around this trend.

II. The Effect of the Scala Mobile on the Wage Structure

A Institutional Features

The Scala Mobile (SM hereafter) was an indexation mechanism meant to ensure a partial automatic coverage of wages in face of past inflation.[5] Similarly to many North-American COLA agreements (see Card, 1983), in its original formulation the escalator implied the same quarterly flat increase in nominal wages (SM point) for all employees for any point increase in the consumer price index. If by W we denote nominal wages, by α the Scala Mobile point, by P the level of prices, by 0 some base period for computing price changes, the contingent increase in wages from time t-1 to time t for individual i, denoted by ΔSM_{it}, is:

$$\Delta SM_{it} = \alpha_t \,(\Delta P_t / P_0) \qquad (2)$$

If by lower case letters we denote logarithms, the proportional change in wages due to the SM is:

$$\Delta sm_{it} = \Delta SM_{it} / W_{it-1} \approx (\alpha_t P_{t-1} / P_0)(1/W_{it-1})\, \Delta p_t \qquad (3)$$

Note that while absolute contingent increases (2) do not depend on individual variables (indexed by i), proportional changes (3) do, since they are inversely related to the individual's initial wage.

The proportional increase in wages for individual i is directly related to the inflation rate (Δp) and to the SM point (α) relative to the real starting wage (W/P). The relative wage of two individuals i and j ($W_i > W_j$) then changes with the SM as follows:

$$\Delta sm_{it} - \Delta sm_{jt} \approx (P_{t-1}\alpha_t/P_0)/(1/W_{it-1} - 1/W_{jt-1})\ \Delta p_t < 0 \qquad (4)$$

So, for each couple of wages, the potential equalizing effect of the SM varies directly with inflation and the value of the SM point, and with some measure of distance between these two wages.

One might wonder how differentials would have evolved if inflation had been unchanged but only the SM point (α) varied over time. That is equivalent to computing equation (4) where the Δp_t is fixed at some reference period, say period 1. In formulas, this is:

$$\Delta sm_{it} - \Delta sm_{jt|\Delta p} = (P_{t-1}\alpha_t/P_0)/(1/W_{it-1} - 1/W_{jt-1})\ \Delta p_1 \qquad (5)$$

Analogously, one can experiment with a counterfactual obtained by varying only the inflation rate but letting the SM point be constant

$$\Delta sm_{it} - \Delta sm_{jt|\alpha} = \alpha_1(1/W_{it-1} - 1/W_{jt-1})\ \Delta p_t \qquad (6)$$

To get a better idea of how the SM worked, in Table 4 I report an illustration based on data for the first quarter of 1978. I take two individuals, one with a high wage and one with a low wage (corresponding approximately to the top and bottom deciles of the distribution of wages in January of that year).

Their wage in 1,000 lit is respectively 461 (W_{it-1}) and 192 (W_{jt-1}) and the relative wage is 2.4 (W_{it-1}/W_{jt-1}). The price index (P_t/P_0) with base (t=0) January 1977=100 is 162. In three months this rises by 5 points to 167 ($\Delta P_t/P_0$). This triggers a wage increase of 12 for both workers (ΔSM_{it}), obtained as the product of the SM point (α=2.4) and the price rise. The wage differential then reduces to 2.32 and the proportional reduction in the wage differential due to the SM is approximately 3% (2.32/2.40-1). A similar number can be obtained by using directly equation (4) (2.4 x 162/100 x (1/461-1/192) x 3).

(Table 4 approximately here)

B. The evolution of the SM: Econometric Evidence

In this section I integrate data on earnings with information on contingent payments based on the institutional parameters of the model (the SM point and the series of changes in prices) as published in ISTAT, *Annuario Statistico Italiano* (various issues). I estimate contingent wage increases for each individual in the sample and then I average across individuals in each cell by pooling observation across contiguous years, like in section I.[6]

In Figure 3 I report the annualized inflation rate: this declines from approximately 14% in the late 1970s-early 1980s, to around 6% in the late 1980s-early 1990s. That itself contributed to the decline in the potential equalizing effect of the SM (see equation (4)).

(Figure 3 approximately here)

In order to document changes in the toughness of the SM, I abstract from changes in inflation and compute variations over time in contingent wage changes due to variations in the SM point. This is equivalent to computing the expression in (5). That is what I do in Figure 4 where on the horizontal axis I report the average level of wages by cell at the beginning of each period (1978-81, 1981-1985, 1985-1988 and 1988-1992) and on the vertical axis the proportional contingent increase as implied by the SM, at fixed inflation rate. Changes are expressed in deviation with respect to the changes at the mean log wage.

(Figure 4 approximately here)

As the curve becomes flatter, the potential equalizing effect of the SM declines. This is because for any given difference with respect to the average wage, the proportional reduction in the relative wage tends to be smaller. While between 1978 and 1981 the SM implies a reduction of 1.1 percentage points a year in the differential between two wages initially 10% apart, by the end of the period this reduces to less than 0.4 percentage points.

Two reasons contributed to the decline. First, under the pressure of rank and file workers and the association of entrepreneurs, in 1983 the Government reduced the value of the SM point by approximately 15% relative to its 1977 level. Later, in 1986, the system was made semi-proportional (approximately by granting a 100% coverage of a given minimum wage, plus a 25% coverage of the difference between the actual wage and the minimum wage). This further dampened the equalizing effect of the SM. One might notice that the graph shows some slight convexity: for any proportional difference in relative wages, the potential equalizing effect of the SM declines as we move to the top of the wage distribution (see equation (4)). That is to say that, for any given difference in wages, one would expect the SM to have a relatively stronger effect at the bottom of the distribution, namely among women and low educated workers, which is substantially what we found in the data in Section I. Also, and most important, the SM is likely to have a stronger effect on inequality within those groups where initial inequality is higher, i.e., again, for women relative to men and for older workers relative to younger ones.

In order to assess the potential effect of the SM on returns on education, I assume that Δsm_{ct}, the average proportional contingent change in wages for cell c between time t-1 and time t, can be represented as an additive function of years of completed education, a quadratic term in age and a gender dummy. Again, I assume that returns to each of these observable characteristics vary over time and I allow for a common macroeconomic shock.

$$\Delta sm_{ct}=\theta_{0t}+\theta_{1t}education+\theta_{2t}\,age+\theta_{3t}age^2+\theta_{4t}\,sex+e_{ct} \qquad (7)$$

In Table 5 I estimate model (7) using GLS. I reproduce the same structure as in Table 3 where I allow for the changes to returns to one extra-year of education to vary unrestricted from period to period and then I impose some parametric restrictions and test for them. Specification (2) makes a relatively good job in accounting for the evolution of differentials by education conditional on age and sex. Contingent payments tend to compress the distribution of wages by education and gender. Over time its equalizing effect reduces although at a declining rate. The implied change in wages associated to one extra-year of education due to the SM is almost 1 percentage point between 1978 and 1981 (-0.317 x 3) and it declines to around 0.1 percentage points between 1988 and 1992 ((-0.317 + 0.205 x 3 - 0.037 x 3^2) x 4). As anticipated in the previous section, the SM implied a stronger equalizing effect on the male-female wage gap. While at the beginning of the period of observation the SM implies a reduction in the gap of approximately 9 percentage points (2.900 x 3), in the last four years this reduces to 1 percentage point ((2.900-2.620) x 4). This is broadly consistent with the observed evolution of the gender earnings gap, which, as we have seen in Table 3, first decreased and then increased. A way to interpret the data, then, is to assume that the gender gap was growing (or possibly being constant) over time but that this trend was counteracted by the SM. As the SM declined, the gender gap did increase as it would have done all over the period in the absence of the SM. This is substantially the identifying assumption I use in the next section, where I assume that the 'latent' gender earnings gap was increasing along some linear trend and I attribute any deviation around this trend to the SM.[7]

(*Table 5 approximately here)*

C. The Effect of the SM on Wages: Econometric Specification and Identification

To ultimately estimate the impact of the SM on the wage structure, I assume that total wage changes are related to contingent wage changes through some linear function:

$$\Delta w_{ct}=\gamma_{0t}+\eta\Delta sm_{ct}+\gamma_{1t}education+\gamma_{2t}\ age+\gamma_{3t}age^2+\ \gamma_4 sex+d_{ct} \qquad (8)$$

The model postulates a simple relationship between contingent and non contingent wage changes: conditional on some function of age, education, sex and time, the SM shifts the entire wage distribution by assigning to each individual a proportional growth in wages which is inversely related to the level of initial wages. However, not the whole amount of contingent wage changes translates into total ones but only a portion η, which is my parameter of interest. If η=0, the SM does not have any effect . For η=1 contingent wage changes translates one-to-one into total wage changes. For values between 0 and 1 the SM is partly undone by other sources of wage increase so it tends to compress the distribution of wages although not as much as one might have expected from the simply descriptive evidence presented above.

Note that in this equation I positively rule out that, once I condition for the SM, changes in the gender earnings gap can vary over time. As said, this is equivalent to assuming that I allow this gap to follow some trend but I attribute any deviation around this trend to the effect of the SM. This hypothesis is ultimately untestable with my data, the reason being that one does not have a control group of otherwise similar individuals to check how this gap would have changed in the absence of the SM. One way to gauge some indirect evidence on this, however, is to recall that the SM had a potentially smaller effect at the top of the wage distribution and a smaller effect the lower the dispersion of wages within groups. For my identifying assumption to be true, one would then expect that for highly educated (and therefore high wage) workers the gender gap follows some linear trend. Also, one would expect that the higher is the initial dispersion within a group, the higher is the compression.

Figure 5 reports the gender earnings gap for the four education groups in which we have classified the individuals in the sample. One can easily see that most of the compression in the gap comes from the bottom on the distribution, i.e. those with 5th grade. As we move up the distribution, the gap stays basically constant over time, with possibly some increase at the end. Also, one might notice that low educated workers start from a relatively higher gap (around 40%) and over time this is brought in line with the gap of the other groups (around 20%). Both these hypothesis speak in favor of my identifying assumption and suggest, if anything, that in the absence of the SM women would not have fared much better in the late 1980s than in the late 1970s.

(Figure 5 approximately here)

D. Estimation Results

In Table 6 I report the result of my estimation. I regress annualized changes in wages by cell on annualized contingent wage increases, a linear term in education, a quadratic term in age, all interacted with year dummies. The model includes also a gender dummy, but no interaction between sex and year dummies. It is interesting to see that once I condition on latent changes in the wage structure as picked up by the restrictive specification in equation (8), the Scala Mobile shows a strong effect of the distribution of wages changes. It turns out that about 80% of wage changes translate into total ones. The point estimate is not very precise and suggests that one cannot reject a value of $\eta=1$. In the remaining columns of Table 6 I report more restrictive specifications for the evolution of changes in returns to education. As in the previous table, a specification with a quadratic term in the linear trend is not rejected while more restrictive specifications do not to fit the model as well as in column (1). Column (2) tells a simple story: conditional on contingent wage increases, wage differentials by education grow allover the period of observation, although at a declining rate. By the end of the period, returns accelerate again. The return to one extra year of education increases by around 0.7 percentage points between 1977 and 1981 (0.224*3), 0.3 percentage points between 1981 and 1985 ((0.224-0.209+0.061)*4), 0.15 percentage points between 1985 and 1988 ((0.224-0.209*2+0.061*2^2)*3) and finally by 0.6 percentage points in the last period ((0.224-0.209*3+0.061*3^2)*4). By cumulating these changes, this gives a rise in latent returns to education of 1.7 percentage points over 14 years. This implies, to get an idea, that returns to 8th grade relative to 5th grade would have increased over the period of observation by about 5 percentage points. Analogously, returns to 13th grade relative to 8th grade would have increased by about 8.5 percentage points in 14 years.

(*Table 6 approximately here)*

It is also interesting to notice that once I condition for the SM, the change in the gender gap is negative, albeit only marginally significant, suggesting that the reduction in the wage gap between men and women was exclusively the product of the SM. If anything the gender gap would have increased (women would have lost) by about 0.5 percentage points a year.

One of the problems with these estimates is that one might be spuriously attributing to the SM some effect which instead is due to 'market forces'. In other terms, as long as some latent compression (decompression) of wage differentials was going on for reasons other than the SM (and over and above the one picked up by my parametric specification for latent wage changes), and to the extent that latent wage changes are correlated with contingent payments, estimation of equation (8) with GLS will lead to biased estimates for the effect of the SM.

A way to get round this is simply to use instrumental variables. Under my maintained assumption that deviations around a linear trend in the gender earnings gap only depend on the SM, one can use the interaction of the gender dummy and the year dummies in equation (8) as an instrument for the SM. That is what I do in Table 7, where, for brevity, in column (1) only report the results for the same specification as in column (2) of Table 6, i.e. the one with a quadratic trend interacted with a linear term in education. It turns out that the point estimate declines from 0.808 in Table 6 to 0.599, suggesting some positive correlation between the omitted components of latent wage changes and contingent wage changes. Yet, estimates are pretty imprecise and one cannot distinguish statistically between the two. This is confirmed by the value of the exogeneity test at the bottom of the table. This suggests that one cannot reject equality of OLS and 2SLS estimates.

(*Table 7 approximately here)*

Based on these results, I am in a position to estimate a counterfactual series of changes in returns to education. To do so, I simulate a series of wage changes that is obtained by attributing to each cell a contingent wage growth as the one implied by the SM. Since part of the observed decline in the equalizing effect of the SM is due to changes in the inflation rate across periods, in constructing this counterfactual distribution I fix the SM point at its value in the first period (equation (6)). Also, because we know that not all of the contingent wage changes translated into total ones, I use the estimated value for η from column (1), Table 7 (η=0.599) to compute this counterfactual wage distribution.

By cumulating changes over time, I reconstruct the overall evolution of returns to education. That is what I do in Figure 6 where I report the actual distribution of returns to education, as plotted in Figure 2, alongside their evolution had the SM being as 'strong' as in the first period of observation (i.e. if the SM point had not changed in real terms). The picture makes it very clear that had the SM not been curbed, the return to one extra year of education would have <u>decreased</u> by approximately 0.4 percentage point over 14 years, while on average this, if anything, increased. The difference between these two series is then the 'genuine' effect of the decline in the SM toughness.

(*Figure 6 approximately here)*

Note that by the end of the period returns to education would have started to increase, even at fixed SM toughness. This happened because latent returns to education (the term in education and its interactions with time in equation (8)) increase over time. I estimate that if latent inequality had not increased and the SM had not been curbed, returns to education would have decreased by approximately 2 percentage points between 1978 and 1992, almost five times as much as my estimates in Figure 6.

IV. Changes in Supply and Demand

One of the hypotheses which has encountered some success in explaining changes in the wage structure in the US in the last 30 years is one which postulates that these changes can be explained simply by a trend in demand for skilled workers (maybe due to skill-biased technological change) coupled with some (assumed exogenous) variation in labor supply around this trend. For example, Card and Lemieux (2000) show that the variations in the college premium in US the 1970s (when it decreased) and 1980s (when it increased) can be completely explained by changes in the relative labor supply of college workers, (i.e. their acceleration in the 1970s and their deceleration in the 1980s) relative to a steadily growing demand. Implicitly, they have in mind a very simple model of the labor market, where the interplay of demand and supply affects equilibrium prices. In this paper I follow a similar approach, and I assume that in the face of some trend in demand for highly educated labor relative to poorly educated one, relative supply changes will imply some variation in wages. The interest of this exercise is to check whether the trend in the SM obscures wage reactions to changing supply and demand conditions. Sine I do not have direct have information on the level of educational attainment for both employed and unemployed workers in the SHIW,[8] I use for this purpose published data for each of the cells as provided in ISTAT, *Forze di Lavoro* (various issues). My measure of labor supply is simply the number of individuals in the labor force in each cell. In Table 8 I present the basic data.

One can see that, over the whole period, the proportion of highly educated workers increases but there is no clear break in the trend to explain the reversion in returns during the 1980s. If the u-shaped trend in returns to education in Figure 2 were to be due to changes in labor supply, one would expect to see some deceleration in the supply of highly educated individuals in the second half of the 1980s (assuming again a steady growth in the demand for skills). The evidence in Table 8 lends little support to this.

A comparison of the growth rates in labor supply across different education groups shows however that changes in labor supply might explain the compression in the wage distribution from the bottom. To see this, in Figure 7 I have plotted the log difference between the number of individuals (men and women) in the labor force between contiguous education levels. One can see that while the differences between the supply of college graduates and high school graduates (18-13) and high school graduates and those with 8th grade (13-8) stay essentially constant, the difference between those with 8th grade and those with 5th grade (8-5) more than doubles over the period of observation. A simple comparison with Figure 1 shows that changes in labor supply have a potential to explain some of the variation in relative wages if, as standard theory predicts, a rise in labor supply depresses wages, everything else being equal. One could conclude that the relative wage gains for the very poorly educated during the 1980s were due to a pronounced decline in their labor supply.

In order to look more formally at the issue and evaluate the relative explanatory power of these two (non-necessary competing) explanations (SM versus market forces), I re-estimate equation (8) by adding as an extra regressor a measure of labor supply:

$$(9) \qquad \Delta w_{ct}=\gamma_{0t}'+\eta'\Delta sm_{ct}+\pi\Delta lf_{et}+\gamma_{1t}'education+\gamma_{2t}'\ age+\gamma_{3t}'age^2+\gamma_4'sex+d_{ct}' \qquad (c\in e)$$

where Δlf_{et} is the rate of growth of the labor force share of each educational group within each gender group and irrespective of age. In the Technical Appendix I show how one can derive a wage equation of this kind as an equilibrium condition for a system of demand and supply curves for each input c. The assumption that wages of each age group within each education group only depend on the aggregate supply of that educational input is equivalent to assuming, as it is common practice in applied labor economics (see for example Katz and Murphy, 1992), that within each education group the different age inputs are perfect substitutes. Analogously, along the labor supply schedule, one can assume that workers' wage claims depend only on the aggregate supply of those groups with the same level of education. The second underlying assumption in this model is that supply and demand shifts for each educational input vary uniformly across gender and age groups (the additive terms in education).

In Table 7 I report the result of this estimation exercise, again using specification (2) in Table 6. For comparison, in column (2) I set $\eta'=0$, i.e. I restrict the SM to have no effect on the wage distribution. If one ignored the effect of the SM, one would conclude that increases in labor supply depressed wages at fixed demand. The point estimate is approximately -0.08 and statistically different form zero at standard significance levels, suggesting that wages are weakly but significantly responsive to changes in labor supply. In column (3) I explicitly control for changes in the SM. The estimate ($\eta'=0.724$) leaves the result of the previous section unchanged, namely that contingent payments translated into total wage changes without being completely undone by market forces. The coefficient of the labor supply term, on the other hand, is in the order of -0.04 and statistically not different from zero. In column (4) I report the 2SLS estimates using the same instrument as in column (1).[9] The coefficient on the SM is 0.599, which is remarkably similar to the value in column (1), while the coefficient on the labor supply term remains essentially unchanged and statistically insignificant. The implied estimate for the growth in latent returns to education is also similar to the one implied by specification (2) in Table 6 (1.7 percentage points in 14 years). Overall, these results show that the conclusions of section II are essentially robust to the inclusion of explicit controls for changes in the structure of labor supply. As argued in the Technical Appendix, implicitly these results suggest - as often argued- that the equilibrium in the Italian labor market is determined along a flat (portion of the) labor supply curve corresponding to some exogenous level of wages. Changes in labor demand, therefore, mainly affect unemployment.

V. Conclusions

In this paper I have examined changes in returns to education in Italy from the late 1970s to the early 1990s. I have shown that Scala Mobile did compress the structure wages and, as it was curbed in the 1980s, wage differentials started to become more unequal. This happened because, at the same time, there was an underlying tendency for returns to education to increase.

The conclusion of this paper is line with some recent research on the evolution of earnings inequality in the US, where some consensus is forming around the idea that (at least part of) the rise in inequality in the 1980s was due to the decline in institutions and in particular to the erosion in the real value of the minimum wage (DiNardo *et al.*, 1996; Lee, 1999).

One aside finding of this paper is that much of the compression of the gender earnings gap which occurred in the late 1970s and early 1980s can also be traced down to the effect of the indexation mechanism. My most conservative estimates show that, in the absence of this mechanism, women would have not fared much better in the early 1990s than in late the 1970s.

At the end of the paper I also look explicitly at the role of supply and demand. Freeman and Katz (1995) suggest a supply-demand-institution explanation for the different trends in wage differentials on the two sides of the Atlantic during the 1980s, and one would like to know what is the relative contribution of these different explanations to the trend in returns to education in Italy. I find that, even after controlling explicitly for the effect of changes in labor supply, my conclusions on the effect of the SM are substantially unchanged. My estimates suggest that despite the fact that the supply of highly educated labor increased relative to poorly educated labor, its effect on changes in returns to education was essentially negligible. It appears that changes in demand for educated labor potentially explain why latent returns to education tended to grow, while the SM counteracted this trend by acting in the opposite direction.

Technical Appendix

Consider a representative firm producing an output Y combining E labor inputs with education e according to a CES production function with elasticity of substitution σ, where $\sigma=1/(1-\rho)$:

$$Y = \left(\sum_{e=1}^{E} \alpha_e N_e^{\rho} \right)^{\frac{1}{\rho}}$$

and N is employment.

Assume that each input e is a combination of A perfectly substitutable labor inputs with age a (a=1,..,A):

$$N_e = \left(\sum_{a=1}^{A} \alpha_a N_{ae} \right)$$

Assuming that markets are perfectly competitive, the wage rate for input ae is:

$$\text{(A1)} \quad \begin{aligned} W_{ae} &= \frac{\partial Y}{\partial N_e} \frac{\partial N_e}{\partial N_{ae}} = \alpha_e N_e^{\rho-1} Y^{1-\rho} \alpha_a = \\ &= \alpha_e \alpha_a \left(\frac{N_e}{N} \right)^{-\frac{1}{\sigma}} \left(\frac{N}{Y} \right)^{-\frac{1}{\sigma}} \end{aligned}$$

On the supply side assume that:

$$\text{(A2)} \quad W_{ae} = \theta_{ae} \left[\frac{N_e}{N} \Big/ \frac{L_e}{L} \right]^{\lambda}$$

where θ_{ae} is a wage pressure term that in principle can also account for the effect of contingent wage increases and λ is a measure of wage elasticity along the labor supply curve. If we further assume that (possibly but for the SM) the wage pressure term is additive in age and education:

$$\ln\theta_{ae} = \ln\theta_a + \ln\theta_e$$

and we combine equation (A1) and (A2), it follows:

$$\text{(A3)}\quad w_{ae} = (\sigma\lambda+1)^{-1}\left[\left(\sigma\lambda\ln\alpha_e + \ln\theta_e\right)+\left(\sigma\lambda\ln\alpha_a + \ln\theta_e\right) - \lambda\ln\frac{L_e}{L} + \lambda\ln\frac{N}{Y}\right]$$

so log wages by age and education are a linear function of the share in the labor force of each education group (L_e/L), an additive term in e which picks up both changes in education-specific demand (α_e) and wage pressure (θ_e), an additive term in a which picks both changes in age-specific demand (α_a) and wage pressure (θ_a) and finally a common macro-economic effect.

The coefficient on the log labor force share is a combination of real wage flexibility and the elasticity of substitution. It can be shown that a sufficient condition for the coefficient to be in line with the empirical results ($\approx$0.04), is either that the elasticity of wages w.r.t. to the labor force share along the labor supply λ is remarkably low ($\approx$0.025) or that the elasticity of substitution across education groups is remarkably high (>10), or both. Since the existing evidence on the degree of substitutability between labor inputs with different levels of education points to a value of σ relatively low ($\approx$2, see for example Katz and Murphy, 1992), the estimates in Table 7 suggest that wages must be relatively unresponsive to changes in relative employment rates.

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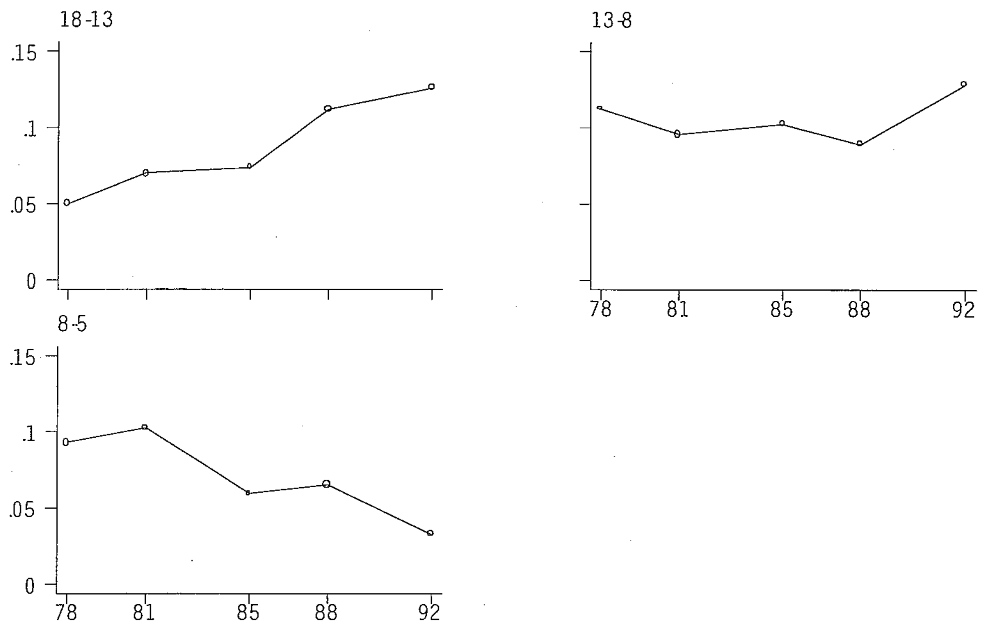

Figure 1
Changes in the Structure of Wages: Wage Differentials by Education[1]

[1] The picture reports unconditional log wage differentials by years of formal education for men and women together. The top left-hand panel reports the differential between college graduates (18) and those with 13th grade (13). Analogously, the other two panels report the differential between those with 13th grade and those with 8th grade, and between those with 8th grade and those with 5th grade. All series are obtained at fixed composition of observable characteristics. See notes to Table 1 for details. Source: SHIW individual records.

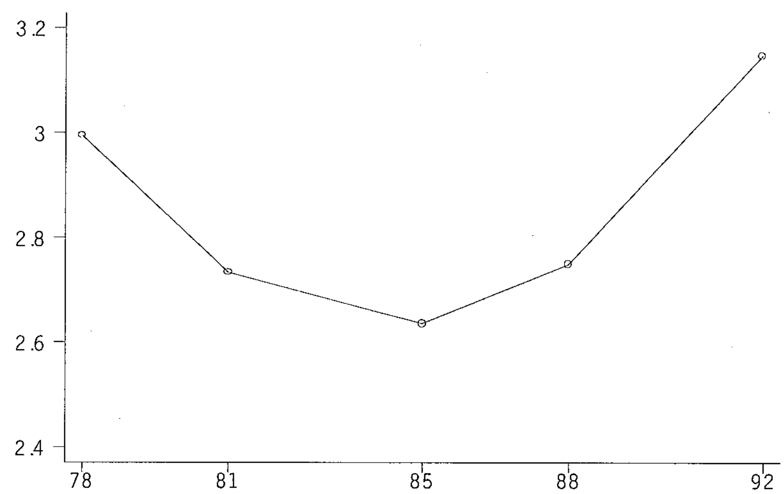

Figure 2
Changes in the Average Return to One Extra-Year of Education[2]

[2] The figure reports the estimated return to one extra-year of education, conditional on gender, age and a common macroeconomic effect. The values are expressed in percentage points. The series is obtained based on the results of specification (3) in Table 4. See text for details. Source: SHIW individual records.

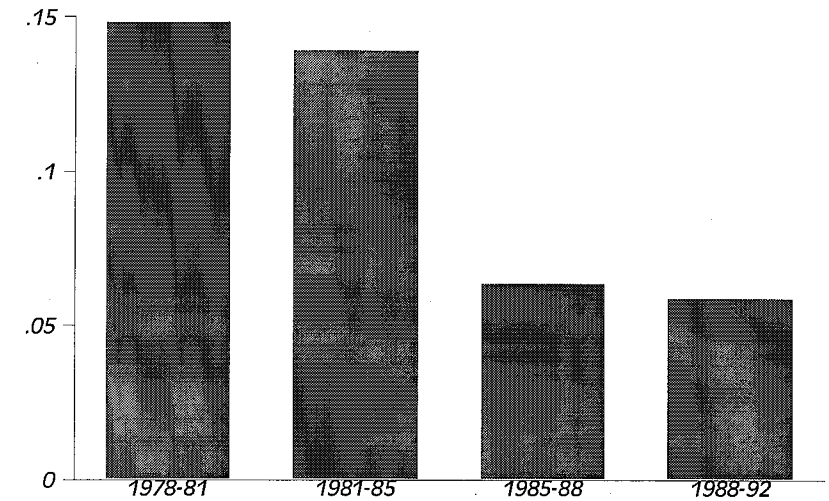

Figure 3

The Inflation Rate[3]

[3] The picture reports the annualized inflation rate in consumer prices over four periods: 1978-1981, 1981-1985, 1985-1988, 1988-1992. Source: ISTAT *Annuario Statistico Italiano* (various issues).

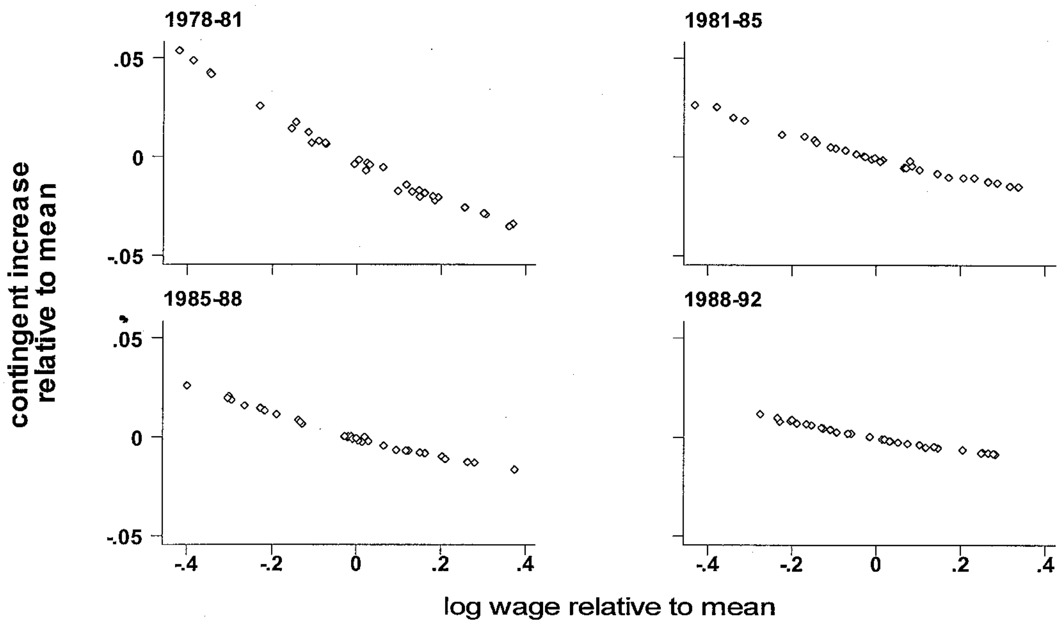

Figure 4
The Decline in the Scala Mobile Toughness[4]

[4] The figure reports on the horizontal axis the average level of initial wages and on the vertical axis the average annualized contingent wage changes as implied by the Scala Mobile in each period for the 32 cells defined by age, sex and education. Data are obtained at fixed inflation rate (see text for details). Source: SHIW individual records and ISTAT, *Annuario Statistico Italiano* (various issues).

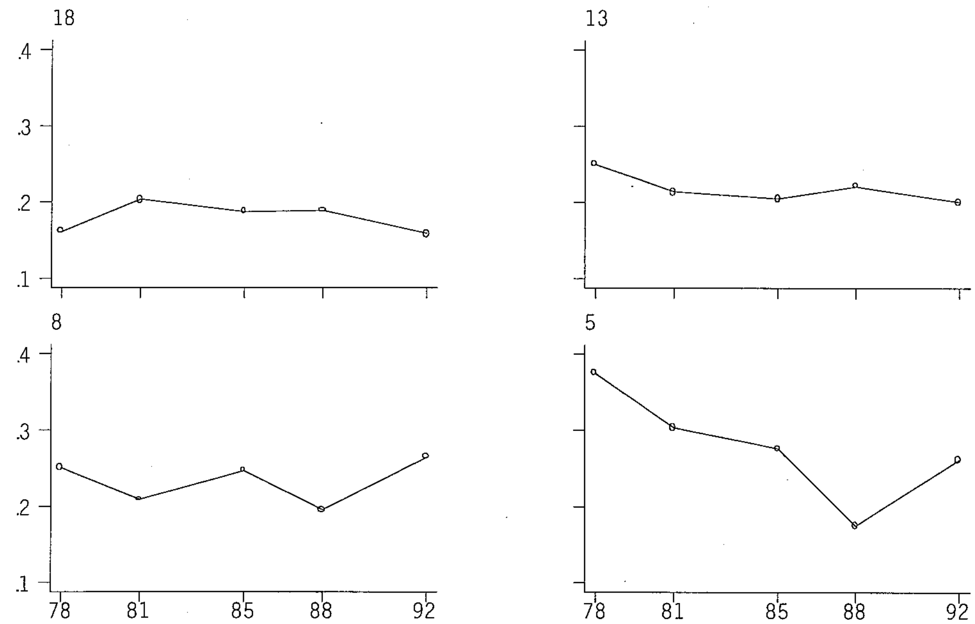

Figure 5
Changes in the Gender Earnings Gap by Education[5]

[5] The picture reports the male-female log wage differential by education. The top left-hand panel reports the differential between male and female college graduates (18). Analogously, the other panels report the differential between those with 13th grade, 8th grade, and 5th grade, respectively. All series are obtained at fixed composition of observable characteristics. See notes to Table 1 for details. Source: SHIW individual records.

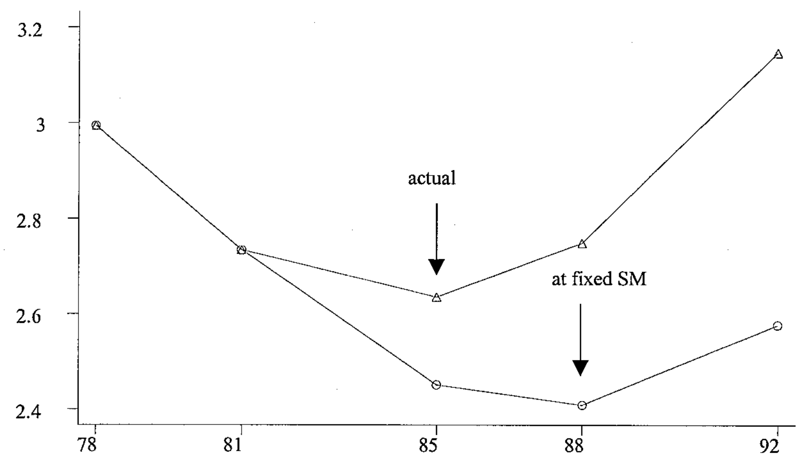

Figure 6
The Effect of the Decline in the Scala Mobile Point
on the Average Return to One Extra-Year of Education[6]

[6] The figure reports the estimated returns to one extra-year of education, conditional on gender, age and a common macroeconomic effect (same as in Figure 2) and the estimated counterfactual distribution obtained by setting the Scala Mobile point to its value between 1978 and 1981. The series is estimated based on the estimates in column (1), Table 7. Source: SHIW individual records and ISTAT *Annuario Statistico Italiano* (various issues).

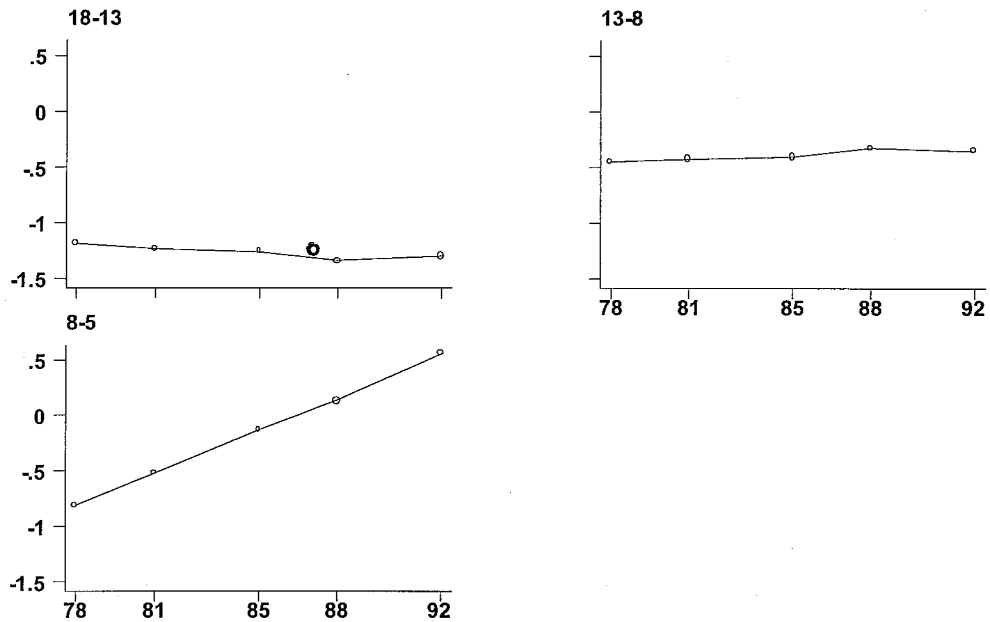

Figure 7
Changes in the Structure of Supply: Relative Labor Force by Education [7]

[7] The picture reports the difference in log labor force between consecutive levels of education. See also notes to Figure 1. Source: ISTAT, *Forze di Lavoro* (various issues).

Table 1

Changes in the Structure of Wages: Relative Log Wages by Cell[8]

	Log levels					Annualized log changes (x 100)			
	1978	1981	1985	1988	1992	1978-81	1981-85	1985-88	1988-92
I. Education									
College	0.13	0.14	0.14	0.17	0.20	0.38	-0.11	0.96	0.68
13th grade	0.08	0.07	0.07	0.06	0.07	-0.29	-0.19	-0.32	0.32
8th grade	-0.03	-0.02	-0.04	-0.03	-0.06	0.25	-0.35	0.12	-0.66
5th grade	-0.12	-0.12	-0.09	-0.10	-0.09	-0.06	0.73	-0.08	0.16
II. Gender									
Men	0.08	0.07	0.07	0.06	0.07	-0.41	0.03	-0.36	0.21
Women	-0.15	-0.12	-0.13	-0.11	-0.12	0.76	-0.07	0.67	-0.39
III. Age									
21-30	-0.11	-0.11	-0.12	-0.09	-0.13	0.07	-0.18	0.85	-1.08
31-40	0.03	0.03	0.03	0.01	0.02	-0.02	-0.08	-0.59	0.16
41-50	0.06	0.05	0.06	0.05	0.08	-0.19	0.05	-0.19	0.69
51-56	0.03	0.04	0.05	0.05	0.06	0.21	0.34	-0.01	0.33
IV. Education and gender									
Men									
College	0.21	0.24	0.23	0.26	0.27	1.07	-0.31	0.99	0.31
13th grade	0.19	0.17	0.16	0.15	0.16	-0.80	-0.28	-0.10	0.11
8th grade	0.05	0.04	0.04	0.03	0.02	-0.17	-0.07	-0.38	-0.15
5th grade	-0.03	-0.05	-0.03	-0.05	-0.03	-0.65	0.56	-0.92	0.70
Women									
College	0.05	0.04	0.04	0.07	0.11	-0.35	0.11	0.93	1.06
13th grade	-0.06	-0.05	-0.05	-0.07	-0.04	0.37	-0.07	-0.60	0.61
8th grade	-0.21	-0.17	-0.21	-0.17	-0.24	1.25	-1.01	1.32	-1.87
5th grade	-0.40	-0.35	-0.30	-0.23	-0.29	1.72	1.24	2.45	-1.46
V. Education and age									
Age: 21-30									
College	-0.01	0.04	0.09	0.13	0.07	1.87	1.10	1.43	-1.49
13th grade	-0.05	-0.07	-0.06	-0.06	-0.08	-0.61	0.06	-0.01	-0.33
8th grade	-0.17	-0.15	-0.17	-0.13	-0.21	0.72	-0.57	1.15	-1.98
5th grade	-0.23	-0.25	-0.27	-0.17	-0.18	-0.66	-0.50	3.39	-0.39
Age: 31-40									
College	0.11	0.11	0.12	0.15	0.17	0.06	0.18	1.12	0.42
13th grade	0.11	0.11	0.09	0.06	0.08	0.05	-0.48	-0.94	0.35
8th grade	0.00	0.00	-0.01	-0.03	-0.04	0.16	-0.37	-0.42	-0.46
5th grade	-0.12	-0.14	-0.10	-0.14	-0.11	-0.53	1.06	-1.42	0.73
Age: 41-50									
College	0.11	0.11	0.12	0.15	0.17	-0.40	-1.14	1.07	1.70
13th grade	0.11	0.11	0.09	0.06	0.08	-0.47	-0.10	-0.35	0.73
8th grade	0.00	0.00	-0.01	-0.03	-0.04	-0.10	-0.26	-1.17	0.82
5th grade	-0.12	-0.14	-0.10	-0.14	-0.11	0.00	0.75	0.41	0.28
Age: 51-65									
College	0.22	0.21	0.16	0.19	0.26	1.09	-0.44	-0.40	2.26
13th grade	0.20	0.19	0.18	0.17	0.20	0.02	-0.32	0.50	1.52
8th grade	0.08	0.08	0.07	0.03	0.07	-0.17	0.15	1.15	-0.35
5th grade	-0.11	-0.11	-0.08	-0.07	-0.06	0.36	0.86	-0.76	-0.19

[8] The table reports the average log wages by cell at five points in time: 1978, 1981, 1985, 1988 and 1992, and the annualized proportional change (x 100) over each time interval. Wages are standardized relative to the average wage at each point in time. Aggregation across elementary cells is performed using a fixed weighting scheme, with weights given by the average proportion of each cell over time. Source: SHIW individual records.

Table 2

Variance Decomposition[9]

	Variance log wages					Annualized changes in variance log wages (x 100)			
	1978	1981	1985	1988	1992	1978-81	1981-85	1985-88	1988-92
I. Men and Women									
Total	0.115	0.097	0.088	0.077	0.097	-0.60	-0.23	-0.37	0.50
Between	0.013	0.014	0.012	0.011	0.017	0.03	-0.05	-0.03	0.15
	(0.115)	(0.149)	(0.139)	(0.138)	(0.180)				
Within	0.102	0.082	0.075	0.066	0.08	-0.67	-0.18	-0.30	0.35
	(0.885)	(0.851)	(0.861)	(0.862)	(0.820)				
II. Men									
Total	0.091	0.082	0.073	0.072	0.084	-0.30	-0.23	-0.03	0.30
Between	0.013	0.015	0.014	0.014	0.019	0.07	-0.03	0.00	0.13
	(0.145)	(0.185)	(0.185)	(0.196)	(0.226)				
Within	0.078	0.067	0.06	0.058	0.065	-0.37	-0.18	-0.07	0.18
	(0.855)	(0.815)	(0.815)	(0.804)	(0.774)				
III. Women									
Total	0.127	0.101	0.090	0.071	0.102	-0.87	-0.28	-0.63	0.78
Between	0.022	0.017	0.016	0.01	0.023	-0.17	-0.03	-0.20	0.33
	(0.174)	(0.172)	(0.178)	(0.146)	(0.225)				
Within	0.105	0.084	0.074	0.061	0.079	-0.70	-0.25	-0.43	0.45
	(0.826)	(0.828)	(0.822)	(0.854)	(0.775)				

[9] The table reports the decomposition of the total variance of log wages into the portion explained by a linear term in education and a quadratic term in age (between) and the residual part (within), for men and women together and separately. In brackets I report the proportion relative to total. Source: SHIW individual records.

Table 3

Changes in the Structure of Wages[10]

Dependent Variable: Annualized Proportional Changes in Wages by Cell (x 100)

	Specification 1		2		3		4	
years of education	-0.008	(0.079)	-0.018	(0.074)	-0.087	(0.052)	0.037	(0.024)
*81-85	-0.047	(0.092)						
*85-88	0.020	(0.093)						
*88-92	0.123	(0.087)						
*trend			-0.063	(0.097)	0.062	(0.023)		
*trend^2			0.036	(0.027)				
Female	1.335	(0.674)	1.345	(0.670)	1.419	(0.670)	1.286	(0.687)
*81-85	-1.342	(0.783)	-1.364	(0.777)	-1.460	(0.776)	-1.396	(0.797)
*85-88	-0.409	(0.791)	-0.404	(0.787)	-0.529	(0.784)	-0.395	(0.804)
*88-92	-1.776	(0.734)	-1.789	(0.730)	-1.838	(0.732)	-1.614	(0.747)
Adj. R2	0.944		0.944		0.944		0.941	
Chi2			0.29	(0.59)	4.51	(0.10)	22.00	(0.00)
D.f.			1		2		3	

[10] Notes. The table reports the results of a regression of annualized proportional wage changes by cell defined by sex, 4 age groups (21-30, 31-45, 41-50, 51-65) , 4 education groups (5th grade, 8th grade, 13th grade, 18th grade) and 4 time intervals (1978-81, 1981-85, 1985-1988, 1988-92) on a linear term in education (years of completed education), 4 period dummies, a quadratic term in age and a sex dummy. All specifications include the interaction between age and time dummies. 'Trend' is a linear trend equal to 0 in the first period, 1 in the second period etc. "Female" is a dummy variable for female workers. Control group: Men, 21-30, 5th grade, in 1978-81. Number of observations: 128. Estimates obtained with GLS with weights given by the inverse sampling variance of the dependent variable. Standard errors in parenthesis. Chi-2 is a test for the goodness of fit relative to the model in column (1). Under the null that the two models fit equally well the data, the statistic is distributed as a Chi2, whose number of degrees of freedom is reported in the last row. The P-value is reported in parenthesis. Source: SHIW individual records and ISTAT, *Annuario Statistico Italiano* (various issues).

Table 4
The Scala Mobile at Work: an Illustration[11]

	Initial earnings	Price index	Change in prices	SM point	Contingent increase	Final earnings
	(a)	(b)	(c) = Δ(b)	(d)	(e)=(c)*(d)	(f) =(a)+(e)
High wage	461	162				
		167	5	2.4	12	473
Low wage	192	162				
		167	5	2.4	12	204
High / low	2.40					2.32

[11] The table shows the salient feature of the Scala Mobile. Data refer to the first quarter 1978 and wages are expressed in (,000) lit. In the first column I report the level of wages at the end of 1977 for two individuals respectively in the top and bottom decile of the wage distribution. Their relative wage in 3. Columns (b) and (c) report respectively the value of the price index (January 1977=100) in January 1978 and 3 months later, and the associated increase. Column (e) reports the nominal increase in wages accruing to each individual obtained as the product of the price increase (c) and the value of the SM point (d) which at the time was set equal to 2.389. In column (f) I report the value of wages in April 1978 under the assumption that there is no other source of wage increase. This is simply the sum of the initial wage (a) and the escalated wage increase (e). Because of the SM, the relative wage reduces from 2.40 to 2.34. Source: SHIW individual records and ISTAT, *Annuario Statistico Italiano* (various issues).

Table 5

Changes in the Scala Mobile[12]

Dependent Variable: Annualized Proportional Contingent Changes in Wages by Cell (x 100)

	Specification							
	1		2		3		4	
years of education	-0.332	(0.027)	-0.317	(0.024)	-0.213	(0.017)	-0.057	(0.006)
*81-85	0.196	(0.031)						
*85-88	0.271	(0.028)						
*88-92	0.296	(0.027)						
*trend			0.205	(0.026)	0.061	(0.006)		
*trend^2			-0.037	(0.007)				
Female	2.915	(0.226)	2.900	(0.227)	2.793	(0.255)	2.630	(0.343)
*81-85	-1.827	(0.261)	-1.797	(0.260)	-1.687	(0.293)	-1.627	(0.394)
*85-88	-2.369	(0.239)	-2.360	(0.239)	-2.210	(0.269)	-2.089	(0.361)
*88-92	-2.636	(0.230)	-2.620	(0.231)	-2.523	(0.260)	-2.322	(0.348)
Adj. R2	0.984		0.984		0.980		0.962	
Chi2			1.33	(0.25)	29.47	(0.00)	132.76	(0.00)
D.f.			1		2		3	

12 See notes to Table 3.

Table 6

The Effect of Scala Mobile on the Structure of Wages[13]

Dependent Variable: Annualized Proportional Wage Changes by Cell (x 100)

	Specification							
	1		2		3		4	
Scala mobile	0.818	(0.203)	0.808	(0.203)	0.686	(0.199)	0.727	(0.173)
years of education	0.252	(0.097)	0.224	(0.092)	0.079	(0.067)	0.105	(0.028)
*81-85	-0.203	(0.095)						
*85-88	-0.172	(0.101)						
*88-92	-0.112	(0.098)						
*trend			-0.209	(0.101)				
*trend^2			0.061	(0.027)	0.011	(0.026)		
Female	-0.490	(0.243)	-0.482	(0.243)	-0.390	(0.244)	-0.419	(0.233)
Adj. R2	0.947		0.947		0.945		0.946	
Chi2			2.09	(0.15)	13.63	(0.00)	14.06	(0.00)
D.f.			1		2		3	

[13] The table reports the results of a regression of annualized proportional wage changes by cell over annualized proportional contingent wage changes. See also notes to Table 3.

Table 7

The Effect of Scala Mobile on the Structure of Wages : Further Analysis[14]

	Specification							
	1		2		3		4	
	2SLS		OLS		OLS		2SLS	
			Labor supply		Labor supply		Labor supply	
Scala mobile	0.599	(0.261)			0.724	(0.209)	0.599	(0.259)
Labor supply			-0.077	(0.030)	-0.047	(0.031)	-0.045	(0.031)
years of education	0.164	(0.103)	0.038	(0.075)	0.233	(0.092)	0.197	(0.102)
*trend	-0.175	(0.105)	-0.059	(0.095)	-0.191	(0.101)	-0.171	(0.105)
*trend^2	0.055	(0.027)	0.033	(0.027)	0.056	(0.027)	0.053	(0.028)
Female	-0.320	(0.274)	1.323	(0.654)	-0.448	(0.243)	-0.350	(0.271)
Adj. R2	0.948		0.947		0.948		0.948	
Chi2	2.42	(0.12)	0.46	(0.50)	2.27	(0.13)	2.47	(0.12)
D.f.	1				1		1	
Exogeneity test	0.493	(0.389)					0.334	(0.411)

[14] The table reports the results of a regression as the one in column (2), Table 6. 2SLS are obtained using the interaction of a sex dummy with time dummies as an instrument for the 'Scala mobile'. 'Labor supply' is the log of the relative labor force share of each educational group within cells defined by sex and time. 'Exogeneity test' is a test for the exogeneity of contingent wage changes. Under the null hypothesis that contingent wage changes are exogenous, the statistic is distributed as a t-student. P values in brackets. See also notes to Table 6.

Table 8

Changes in the Structure of Labor Supply[15]

	Levels					Annualized log changes (x 100)			
	1978	1981	1985	1988	1992	1978-81	1981-85	1985-88	1988-92
I. Education									
College	4.79	5.37	6.31	6.81	7.81	3.81	4.02	2.54	3.43
13th grade	15.67	18.54	22.28	25.98	28.56	5.60	4.60	5.13	2.36
8th grade	24.47	28.38	33.33	35.91	40.44	4.93	4.02	2.48	2.97
5th grade	55.06	47.71	38.08	31.30	23.19	-4.78	-5.64	-6.53	-7.50
II. Gender									
Men	68.75	67.07	65.42	63.83	62.77	-0.83	-0.62	-0.82	-0.42
Women	31.25	32.93	34.58	36.17	37.23	1.75	1.22	1.50	0.72
III. Age									
21-30	25.65	25.88	26.64	27.75	29.23	0.30	0.72	1.36	1.30
31-40	27.53	27.13	28.20	27.71	27.13	-0.49	0.97	-0.58	-0.53
41-50	25.23	25.13	24.01	24.02	24.01	-0.13	-1.14	0.02	-0.02
51-56	21.59	21.86	21.15	20.51	19.63	0.41	-0.82	-1.02	-1.10
IV. Education and gender									
Men									
College	3.12	3.42	3.93	4.08	4.57	3.06	3.53	1.20	2.85
13th grade	9.68	11.08	12.95	14.62	15.92	4.51	3.90	4.05	2.14
8th grade	17.26	19.51	22.44	23.80	26.57	4.08	3.50	1.96	2.75
5th grade	38.70	33.06	26.10	21.33	15.70	-5.24	-5.92	-6.73	-7.65
Women									
College	1.68	1.96	2.38	2.73	3.24	5.15	4.87	4.64	4.26
13th grade	6.00	7.46	9.33	11.37	12.64	7.28	5.59	6.57	2.65
8th grade	7.21	8.87	10.89	12.10	13.87	6.89	5.13	3.53	3.40
5th grade	16.37	14.65	11.98	9.97	7.49	-3.70	-5.02	-6.12	-7.17
V. Education and age									
Age: 21-30									
College	1.07	1.05	0.95	0.87	1.06	-0.74	-2.59	-2.79	4.94
13th grade	6.79	8.01	9.21	10.42	11.13	5.50	3.50	4.13	1.64
8th grade	10.27	11.78	13.37	14.12	15.47	4.57	3.16	1.84	2.27
5th grade	7.52	5.05	3.12	2.33	1.57	-13.29	-12.05	-9.69	-9.80
Age: 31-40									
College	1.69	2.06	2.69	2.88	2.90	6.73	6.67	2.28	.14
13th grade	4.54	5.43	7.09	8.38	8.99	6.02	6.66	5.57	1.75
8th grade	7.27	8.45	10.29	10.79	12.14	4.99	4.94	1.57	2.95
5th grade	14.03	11.18	8.12	5.66	3.10	-7.57	-7.99	-12.06	-15.03
Age: 41-50									
College	1.01	1.15	1.44	1.76	2.38	4.18	5.61	6.84	7.49
13th grade	2.47	2.97	3.70	4.54	5.51	6.11	5.50	6.89	4.83
8th grade	4.31	5.11	6.24	7.04	8.29	5.71	5.00	3.99	4.10
5th grade	17.44	15.90	12.63	10.67	7.82	-3.06	-5.76	-5.61	-7.78
Age: 51-65									
College	1.02	1.11	1.23	1.29	1.47	2.85	2.62	1.50	3.20
13th grade	1.88	2.13	2.28	2.63	2.93	4.19	1.71	4.75	2.65
8th grade	2.62	3.04	3.43	3.96	4.54	4.93	3.02	4.76	3.46
5th grade	16.07	15.58	14.21	12.64	10.69	-1.04	-2.30	-3.90	-4.17

[15] The table reports the share of each cell in the labor force. Source: ISTAT, *Forze di Lavoro* (various issues).

[1] I only take data for the first and last year of each time interval to calculate averages (so, respectively: 1977 and 1979; 1980 and 1983; 1984 and 1986; 1987 and 1989; 1991 and 1993). To calculate average values by cell I regress individual wages over a full set of cell dummies and a set of year dummies within each period. The coefficient on each cell dummy is the estimated average log wage by cell.

[2] I start with 50,908 observations from ten repeated cross sections. Of these, I drop 6,638 observations for workers who have worked only part of the year, 1,729 observations for workers aged less than 20 years or more than 65, 109 observations for workers with missing education and 2 observations for workers with no reported sex. I drop top executives (1,186 individuals) for which I do not have direct information on the parameters of the indexation mechanism and finally 737 observations for those with wages below the first percentile or above the top one.

[3] Note that equation (1) allows for group fixed effects in the specification for levels.

[4] Education is transformed as follows: 5 years for '5th grade or below', 8 years for '8th grade', 13 years for '13th grade', 18 years for 'College or above'. The age variable takes the following values: 25, 35, 45, 57.5.

[5] In this section I describe the salient features of the Scala Mobile. The interested reader can refer to Erickson and Ichino (1995) and Manacorda (2000) (and references therein) for more details on this institution.

[6] See Manacorda (2000) for the exact procedure used in this paper to impute SM payments to individuals in the SHIW sample.

[7] This is different from the assumption used in Manacorda (2000). There the identifying assumption is that within each time period, the gender earnings gap would have reduced at the same rate across the skills distribution, if not for the Scala Mobile.

[8] Data on the educational attainment are only available for income recipients until 1987, which in Italy, where there are no benefits for first-job seekers, excludes most unemployed persons.

[9] In order for the interaction of sex and year dummies to be a valid instruments, it is necessary to assume that gender differentials in labor supply growth do not affect the structure of wages. A look at Table 8, however, shows that the relative labor supply growth of women if anything decreases in the late 1980s implying a rise in the female-male earnings gap, which is the opposite of what we observe.