

The Evolution of Earnings Inequality in Italy and the Escalator Clause

Marco Manacorda  
April, 1999

Center for Labor Economics, UC Berkeley  
Dept. of Economics, University College London

**Abstract:** This paper investigates the effect of changes in the ‘toughness’ of the Scala Mobile, a wage indexation mechanism linking wage growth to price inflation, over the distribution of wages in Italy from 1977 to 1993. By granting a flat universal increase in wages for each percentage point rise in the consumer price index, the Scala Mobile had a potential to compress wage differentials. Yet, this potential was reduced over time. Based on SHIW data, I show that latent wage inequality in Italy has been constantly rising over the 80s but the indexation mechanism counteracted the decompression of earnings. As the Scala Mobile was curbed, observed wage inequality increased appreciably.

**Keywords:** *Scala Mobile*, wage inequality, kernel density estimates.

**JEL classification:** J31, J51.

I am indebted to my supervisors Steve Machin and Costas Meghir for dedicated guidance throughout the writing of this paper and to David Card and Alan Manning for very useful suggestions and comments. My thanks to the Research Division of the Bank of Italy for providing data. Financial support from the Italian *Consiglio Nazionale delle Ricerche* in the form of a NATO Advanced Fellowship is gratefully acknowledged.



It is well known that the US and the UK experienced a dramatic increase in the dispersion of wages in the last two decades while wage inequality “failed” to increase in most of continental Europe (for all, see OECD, 1996).

Some consensus is forming around the idea that labor market deregulation and in particular the decline in the real value of the minimum wage is responsible for most of this trend. Lee’s (1998) estimates for the US suggest that the reduction in the real value of the minimum wages is by itself able to explain all of the rise in wage inequality during the 80s. DiNardo *et al*, (1996) look separately at male and female workers and find a significant effect of changes in the value of the minimum wage on wage dispersion. Machin and Manning (1994) for the UK find that the abolition of wage councils implied an appreciable rise in wage inequality in the affected industries.

This view is often contrasted with the hypothesis that wage differentials have been driven by skill biased change: a rise in the demand for skills not matched by an equal rise in the supply (Katz and Murphy, 1992). This view is supported by the observation that part of the rise in wage inequality is explained by changes in wages between groups with different levels of skills. Among those who have supported this view, some have stressed the role played by the introduction of new technologies (Juhn *et al*., 1993) while others have emphasized the role played by international trade (Feenstra and Hanson, 1996)

A natural question which arises is why continental European countries have apparently been spared by this trend in wage inequality. Comparison across countries can shed some light over the plausibility of the different explanations which have been put forward. In this spirit, Blau and Khan (1996) try and explain different *levels* of wage inequality across countries in terms of market forces as opposed to institutions.

In this paper I document the evolution of the inequality of earnings in Italy from 1977 to 1993 and assess the role played by the evolution of the *Scala Mobile*, a wage indexation mechanism, in shaping this trend. By granting an universal flat increase in nominal wages for each percentage point rise in a special consumer price index, the indexation mechanism had a potential to reduce wage differentials. Based on SHIW data, I find that wage inequality compressed appreciably until the late 80s. Inequality then reverted its trend and by 1993 it was at a level comparable to 1977. By looking at the cross sectional distribution of wage changes over subsequent sub-periods, based on the knowledge of

the institutional features of the system and armed with some parametric assumptions about the evolution of wage inequality in the absence of the indexation mechanism, I am able to separately identify the effect of the escalator from changes in latent wage inequality. I find that the compressionary effect of the *Scala Mobile* was only partly undone by non-contingent wage changes. Since the compressionary potential of the escalator was gradually reduced over the period of observation, this candidate as an explanation for the observed rise in wage inequality. Based on my estimates of the effect of contingent wage increases net of the counteracting effect of non-contingent ones, I am able to reconstruct a counterfactual wage distribution, i.e. the one which would have been observed in the absence of indexation. I show that latent wage inequality has tended to increase monotonically over the 80s and early 90s. The *Scala Mobile* partly counteracted the tendency of wages to decompress. As the *Scala Mobile* was gradually curbed, observed wage inequality increase, resembling the pattern of latent wage inequality.

A related issue which I deal with in this paper is that the observed evolution of the wage distribution might mask some compositional effects. An argument which is often heard (Krugman, 1994) is that a rise in latent wage inequality coupled with some rigidity in wages could be blamed for the rise in unemployment in Europe. The argument goes as follows: at fixed wages, any shift in demand for skilled workers would translate into employment changes. One would then expect to see a rise in the unemployment of the unskilled and a rise in the overall rate of unemployment. An important corollary to this assertion is that any employment loss at the bottom of the distribution would further compress the observed distribution of wages. In this sense the circumstance that the wage distribution “failed” to decompress in continental Europe could be ascribed to the circumstance that the observed trend in inequality masked pronounced compositional changes in the distribution of employment. To deal with this issue, I use the re-weighting procedure suggested by DiNardo *et al.* (1996). I show how one can extend this procedure to incorporate endogenous changes in the composition of employment as the distribution of wages changes over time.

The plan of the paper is as follows. In section 1, I describe the institutional features of the indexation mechanism. In section 2 I illustrate the SHIW data used in the rest of the analysis while in section 3 I present some stylized evidence on the evolution of wage

inequality and the toughness of the Scala Mobile over the period of observation. Section 4 describes the basic idea of the paper: non-escalated wage increases might partly undo the compressionary effect of the escalator. I show how one can gauge evidence on this from the actual contingent and non-contingent wage changes and decompose total wage growth into two orthogonal components. Section 5 discusses the estimation procedure, which is somehow in the spirit of DiNardo *et al.* (1996). To implement my estimation procedure I use kernelized wage densities and estimate changes at each percentile of the wage distribution. Section 6 presents the estimates of the effect of the *Scala mobile* on wage inequality. In section 7 I extend the analysis by allowing for changes in the distribution of employment as wage differentials change. Section 8 concludes and states the main findings.

### **1. The institutional setting: wage determination and income policy**

Wages of Italian workers are set through a strongly centralized system whose mainstay is the national agreement between the confederations of trade unions and the association of the entrepreneurs (*Confindustria*). The agreement sets minimum binding wages according to the different skill levels (*inquadramento*). Minimum wages extend to both unionized and non unionized workers.

Wage conditions more favorable to the worker can be bargained at the firm level or set unilaterally by the firm for single workers or groups of workers.

Until 1993, wages were integrated by *Scala Mobile*, literally *escalator*, meant to ensure a partial automatic coverage of wages in face of inflation.<sup>1</sup> Similarly to many North-American COLA agreements (Card, 1983), in its original formulation the escalator implied a flat increase in nominal wages (*Scala Mobile* point) for any point increase in a special quarterly consumer price index (*indice sindacale*). If by  $W$  we denote nominal wages, by  $a$  the *Scala Mobile* point, by  $P$  the level of prices, by 0 the base period for computing price changes, the contingent increase in wages from time  $t$  to time  $s$  ( $s > t$ ), denoted by  $SM$ , is:

$$\begin{aligned}
SM_s &= a_t I_{s,t}^0 \\
I_{s,t}^0 &= \left( \frac{P_s - P_t}{P_o} \right) * 100
\end{aligned} \tag{1}$$

If by lower case letters we denote logarithms, for moderate changes in prices and wages, one can decompose proportional changes in wages between time  $t$  and  $s$  into a contingent and a non-contingent component

$$w_s - w_t = \ln \frac{W_s}{W_t + SM_s} + \ln \frac{W_t + SM_s}{W_t} = (w_s - w_*) + (w_* - w_t) \tag{2}$$

where  $w_*$  is the logarithm of the of the initial wage plus the escalated wage increase. Also note that from equation (1), the proportional increase in wages due to the Scala Mobile (hereafter SM) is approximately equal to

$$w_* - w_t = \ln \frac{W_t + SM_s}{W_t} \approx e_t dp_s \tag{3}$$

where  $dp$  is the inflation rate and  $e$  is the SM coverage, i.e. the protection offered to nominal wages by the indexation mechanism in face of inflation, defined as

$$e_t = \frac{a_t P_t}{W_t P_0} * 100 \tag{4}$$

A value of  $e$  above (below) one implies that, everything else being equal, real wages grow (decrease) as prices grow.

It is clear from equation (4) that the proportional growth in wages due to the SM depends inversely on the level of initial wages. The SM bears therefore a potential for the reduction of wage differentials. Further, the speed of wage convergence varies directly with inflation and the value of the SM point.

## 2. The data

The basic data I use throughout the analysis are given by the individual records of the Bank of Italy SHIW (Survey of Household's 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. The sampling unit is the household but a number of questions refer to each of its members. Information on sex, age, education and region of residence are collected for each individual and variables such as occupation and industry of activity, although a quite a broad level of aggregation, are available for all employees. As far as the sample size is concerned, this varies over time: it was approximately 3,000 households until 1981, it was raised to about 4,000 in 1984 and then doubled in 1986.

Yearly labor income, which the earnings variable used in this study, is defined net of taxes and social security contributions and inclusive of thirteenth wage, bonus and overtime payments. Unfortunately, data on months worked are not available in the first years of the survey. I restrict to full-year employees, aged 18-65. Finally, I eliminate managers from my sample because the indexation system worked somehow differently for them and I do not have direct information on the parameters of the indexation mechanism. Overall, they account for about 3% of the male sample and only .5% of the females sample.

In Tables 1a and 1b I report some descriptive statistics for my data at five points in time (1977, 1980, 1984, 1989, 1993) and on average over these years. Analogously to the rest of the OECD countries, in the last two decades Italy witnessed a decline in the share of blue collars and those employed in manufacturing. The share of white collars among males increases from approximately 32% in the late 70s to 49% at the end of the period. The corresponding figures for females are 41% and 67%. Analogously, the share of male employees with post compulsory school qualification (thirteen years of education or more) increases from about 24% in the late 70s to around 39% in the early 90s while for females the proportion grows from 36% to 60%. Both for males and female workers we witness a reduction in the share of young workers. Along the same lines, the share of employment in manufacturing reduces from about 49% to 43% for males and from 36% to 26% for females. What is remarkable is that most of this decrease is absorbed by an

increase in the employment in the enlarged public sector, which grows from 21% to 36% for males and from 27% to 55% for females. This constitutes a notable difference with respect to the US and the UK, where the decline in manufacturing was absorbed by the rapid expansion of private services.

Despite some clear trends being detectable, there is a sign of the distribution of employment being sensitive to the state of the business cycle. In 1984, when the economy was booming, we can see a relatively high proportion of blue collars, those aged 31-40, workers in the South and those employed in the tertiary sector. This suggests, that the observed changes probably confound compositional effects of varying attributes of the labor force (say, because of a generalized increase in educational attainment) together with the increase in unemployment among the less skilled, the youngest workers and those in the South. On balance, Italy witnesses large and rapid changes in its labor market in the period of observation.

Real earnings grow both for men and for women, with an average reduction of the male-female wage gap of approximately 1% a year.

Data on individual earnings are integrated with data on escalated wage increases due to the SM which are presented in Tables A3-A5 and discussed in appendix A.

SHIW data are the only source of publicly accessible micro data for Italy covering this long span of time and they are unique in providing information on human capital characteristics of the individuals, alongside information on industry and occupation. Because of the sample design, the survey provides estimates of the population of employees. Yet, earnings are defined relative to the whole year while SM payments triggered every three or six months depending upon the period of observation. Second, earnings are net, while the parameters of the SM are defined relative to gross monthly income. To cope with this problem I use information on tax brackets at each decile of the wage distribution as obtained on 1989 SHIW data. Third, as I discuss in the appendix A, starting from 1986, SM payments were made dependant on contractual wages and this information is not directly available in my data. In order to estimate the impact of the SM on the distribution of wages I need therefore to make some assumptions. I discuss them in the appendix A, alongside the likely implications they have on my results. As a general



rule, I try to be as conservative as possible, i.e., if any, to underestimate the effect of the SM on the dispersion of wages.

### **3. Stylized evidence**

In this section I illustrate the basic evidence which motivates my study. The evidence presented here is only suggestive. The point I want to make here is that the decline of the Scala Mobile candidates as a plausible explanation for the evolution of wage inequality.

In the rest of the paper I develop an estimation strategy to assess the effect of the indexation mechanism over the wage distribution.

In Table 2, I report the level of nominal wages (in logarithms) at selected points in time separately for males and females. Data are computed on the kernelized wage densities (see sections 5 and 6 for details). It is easy to see that at each decile, the female distribution is always at the left of the male distribution. Yet, as I document below, the two distributions tend to converge.

In Tables 3a-3b I report different measures of dispersion of the wage distribution. Also, I report the annualized changes in inequality from one point in time to the other. Whatever measure we take, it appears that wage differentials compress dramatically in the first sub period (1977-1980) and they keep on compressing, although at a slower pace, in the first half of the 80s. The level of inequality is sensibly higher for females than for males at the beginning of the period. In 1977, the ratio of the extreme deciles is approximately 35% higher for females than for males. By the mid 80s, male and females workers show a similar level of inequality but inequality keeps on decreasing for females while it starts to increase for males. We have to wait until the late 80s to see the reversion in wage inequality for females. By 1993 the level of inequality both for males and females is comparable to 1977.

As far the SM is concerned, in Figure 2 I report the evolution of the coverage of the Scala Mobile over the four sub-periods (1977-1980, 1980-1984, 1984-1989, 1989-1993) at each percentile of the distribution of wages and with the exclusion of the five bottom and top percentiles. Recall that coverage is defined as the ratio between the proportional growth in wages due to the SM and the growth in prices. This can also be interpreted as

the ratio of any given level of wages to the wage fully covered (for which the coverage is one). Similarly to the Kaitz index used in the minimum wage literature (Machin and Manning, 1994, Card and Krueger, 1994), it is an easily interpretable measure of the “toughness” of the SM. It is easy to see that coverage declines almost monotonically as we move along the distribution of wages. Most important, it tends to decline over time at each percentile. This reflects both the fact that real wages increase over time, so that, everything else being equal, the protection offered by the indexation system declines, and the circumstance that the SM point, i.e. the nominal increase in wages triggered by a one percent rise in the consumer price index, reduces over time. Finally, starting in 1986, the length of wage adjustment increases and the system became semi-proportional. By switching from a flat nominal adjustment to a semi-proportional one the SM potential for compressing wage differential is further reduced. This is reflected in the flattening of the curve in the last periods, especially at the lowest percentiles. It is easy to see that at each percentile coverage is higher for females than for males, which is easily explained since the distribution of females earnings is on the left of the one for males at each given percentile.

#### 4. Decomposing changes in the wages: methodology

Suppose I want to measure changes in the dispersion of wages as measured by changes at each percentile of the distribution.

Before describing my procedure, I need to introduce some notation. Suppose each observation is represented by a point in the  $(w, z, t)$  space, with joint density  $f(w, z, t)$ , where  $w$  is the logarithm of wages ( $w = \log(W)$ ),  $z$  denotes a vector of observable characteristics and  $t$  time. Let us denote the distribution of wages at time  $t$  by  $f_t(w) \equiv f(w|t)$  and by  $F_t(\cdot)$

let us denote the corresponding cumulative distribution function  $F_t(\omega) = \int_{-\infty}^{\omega} f_t(w) dw$ .

Finally, denote by  $w_t^q = F_t^{-1}(q)$  the  $q$ -th quantile of distribution of wages at time  $t$ .

Suppose one wishes to measure the effect of the SM on the wage distribution and build a counterfactual wage distribution, i.e. the distribution which one would have expected to prevail had the indexation rule not been at work. In principle one could follow a

straightforward route, namely subtract the changes in wages implied by the indexation mechanism from the actual changes. One would then only be required to know the few parameters of the indexation rule and the inflation rate.

If I ignore for the moment changes in the distribution of the observables, this is equivalent to apply the decomposition (2) to each percentile of the wage distribution

$$w_s^q - w_t^q = (w_s^q - w_*^q) + (w_*^q - w_t^q) \quad (5)$$

The first term on the right hand side is the effect of non-escalated wage increases while the second is the effect of the indexation rule.

Yet, this does not seem a very promising route: there was a potential for other sources of wage changes to undo the effect of the SM, i.e. non-escalated wage changes might be endogenous to escalated ones. Let us refer to the second term on the right hand of equation (5) as the *ex-ante effect* of the SM, i.e. its effect in the absence of any correlation between contingent and non-contingent wage changes..

I show how one can estimate the “desired” wage distribution, i.e. the distribution of wages which would have prevailed in the absence of the indexation rule from knowledge of distribution of wages at two different times  $t$  and  $s$  and the escalated wage increases in this time interval. In turn, this allows to experiment with a number of counterfactuals obtained by varying the parameters of the wage indexation rule. Specifically, at the end of the paper, I will look at the evolution of the distribution of wages in the absence of indexation. This is what I will refer to as latent wage inequality.

Since it is known that most of the increase in unemployment in Italy was concentrated among those in the lower tail of the wage distribution (young, less educated workers and those in the South) the SM could candidate as the main source of this effect via increases in relative wages at the bottom of the distribution. In turn compositional changes induced by the SM could be partly responsible for the observed trend in inequality. I will show in section 7 how my model can accommodate compositional changes and I will provide a quantitative estimate of this employment effect based on different assumptions on labor demand.

To keep things simple, assume that actual wage changes at each percentile can be expressed as some linear combination of desired wage changes and contingent ones (in the empirical implementation below I will allow for some non linearity in the relationship between total and contingent wage changes)

$$E[w_s^q - w_t^q | \beta_{0s}^q, (w_*^q - w_t^q)] = \beta_{0s}^q + \beta_1 (w_*^q - w_t^q) \quad (6)$$

where expectations are taken once contingent wage changes have triggered (i.e. at time  $t=*$ ).  $\beta_0$  represents some desired wage change, i.e. the one which I would have expected to observe had the SM been set to zero.  $\beta_1$  is the degree at which contingent wage increases translate into actual ones. A value of one suggests that contingent wage changes fully translate into actual wage changes. A value of zero suggests that the non-contingent wage increases completely counteract the effect of the SM. Values between minus one and zero, suggest that to some degree institutions matter since the compressionary effect of the SM is only partly undone by other sources of wage increase.

The term  $(w_*^q - w_t^q) \beta_1$  can then be interpreted as the genuine wage change attributable to the SM, i.e. once one has parsed out the counteracting effect of non escalated wage changes. I will refer to this as the *ex-post* effect of the SM. Analogously, one can think of  $(w_s^q - w_*^q)$  as the *ex-ante* effect of non-escalated wage changes and  $\beta_{0s}$  as their *ex-post* effect.

To obtain an estimate of the parameters of interest, one can simply regress total wage changes on ex-ante contingent ones or, which is the same, use as dependent variable the ex-ante non-contingent wage changes obtained as a difference between total and ex-ante contingent wage changes

$$E[w_s^q - w_*^q | \beta_{0s}^q, (w_*^q - w_t^q)] = \beta_{0s}^q + (\beta_1 - 1) (w_*^q - w_t^q) \quad (7)$$

So, one can use the available information on contingent and non-contingent wage changes to estimate their corresponding ex-post effects.

Essentially, by orthogonalizing wage changes one can use the estimated parameters  $\beta$ 's to construct a number of counterfactuals, obtained by varying arbitrarily the effect of the SM.

Up to now, I have ignored the fact that in comparing two cross-sectional distributions of wages, some differences might arise because of differences in the distribution of individual characteristics.

Let us denote by  $f_{s,t}(w) \equiv f(w|t_w=s, t_z=t)$  the distribution of wages which one would have observed if individuals observed at time  $t$  had been paid according to the wage schedule at time  $s$ . By definition,  $f_{t,t}(w) \equiv f_t(w)$ . One can therefore add an extra element to the decomposition in (5) and write

$$w_s^q - w_t^q = (w_s^q - w_{*,s}^q) + (w_{*,s}^q - w_{*,t}^q) + (w_{*,t}^q - w_t^q) \quad (8)$$

where  $w_{*,t}^q$  is the  $q$ -th quantile of the distribution of wages which one would have observed at time  $s$  if individuals observed at time  $t$  had only been awarded contingent wage increase triggered between  $t$  and  $s$ . By the same token,  $w_{*,s}^q$  can be thought as the  $q$ -th quantile of the distribution of wages which one would have observed if individuals observed at time  $s$  had been deprived of any non-contingent wage increase awarded between  $t$  and  $s$ .

Equation (8) illustrates that changes at each percentile of the distribution of wages can be decomposed into (in the reverse order):

- a. a change due to the effect of the *Scala Mobile*, conditional on a set of attributes, set at their time- $t$  value;
- b. a change due to the effect of varying attributes;
- c. a change due to the non-contingent wage changes, conditional on a set of attributes evaluated at their time- $s$  value.

Equation (7) then rewrites

$$E[w_s^q - w_{*,s}^q | \beta_{0s}^q, (w_{*,t}^q - w_t^q)] = \beta_{0s}^q + (\beta_1 - 1)(w_{*,t}^q - w_t^q) \quad (9)$$

and the rest of the analysis is unchanged. From knowledge of the two components of wage changes in equation (8) one can estimate equation (9) and derive the ex-post effect of contingent and non-contingent wage changes.

## 5. Estimation strategy

Estimation of the empirical quantiles is obtained based on kernel density estimates of the wage distributions at selected points in time. This has a double advantage. On the one hand it allows to have a visual impact of changes in the variables of interest. On the other, since we have a relatively small samples, especially for women, by smoothing the distribution of wages, this is a way to control for measurement error.

A kernel density estimate of the wage distribution at time  $t$  (or  $s$ ) can be obtained straightforwardly as

$$\hat{f}_t(w) = \sum_{i \in S_t} \frac{\theta_i}{h} K\left(\frac{w - w_i}{h}\right) \quad (10)$$

where  $i$  denotes individual observations,  $S_t$  is the set of indexes for  $i$  at time  $t$ ,  $w_i$  are the individuals (log) wages used as a support for the kernel,  $h$  is the bandwidth and  $K(\cdot)$  is a kernel function which integrates to one.  $\theta$  are the SHIW sampling weights, standardized to sum to one.

In order to derive the distribution which would have prevailed in the absence of non-contingent sources of wage increases, let us define

$$w_{i^*} = \ln(w_{it} + SM_{is}) \quad (11)$$

where  $SM$  is the wage increase due to the SM between  $t$  and  $s$ .

An estimate of the distribution  $f_{*,t}(w) \equiv f(w|t_w=*, t_z=t)$  can be obtained by the following expression

$$\hat{f}(w|t_w = *, t_z = t) = \sum_{i \in S_t} \frac{\theta_i}{h} K\left(\frac{w - w_i^*}{h}\right) \quad (12)$$

Finally, in order to allow for changes in observables, I use the re-weighting procedure of DiNardo *et al.* (1996)

$$f(w|t_w = *, t_z = s) = \int f(w|t_w = *, t_z = s, z) dF(z|t_w = *, t_z = s) \quad (13)$$

Under the assumption that the density of wages does not depend on the distribution of attributes, this expression simplifies to

$$\begin{aligned} f(w|t_w = *, t_z = s) &= \int f(w|t_w = *, z) dF(z|t_z = s) = \\ &= \int f(w|t_w = *, z) \lambda(z) dF(z|t_z = t) \end{aligned} \quad (14)$$

where

$$\lambda(z) = \frac{dF(z|t_z = s)}{dF(z|t_z = t)} \quad (15)$$

Equation (14) is saying that one can recover the desired wage distribution by a simple re-weighting of the distribution at time  $t$ . Since by Bayes' rule the re-weighting function can be written as

$$\lambda(z) = \frac{\Pr(t_z = s | z) \Pr(t_z = t)}{\Pr(t_z = t | z) \Pr(t_z = s)} \quad (16)$$

one can easily obtain estimates of the weights by pooling observations at time  $t$  and  $s$  and estimating the probability of being observed at each time, in turn conditionally and

unconditionally on  $z$ . Conditional estimates can be recovered by non parametric means or, as I do in the following, by means of a simple binary choice model where the dependent variable (year at which one individual is observed) is regressed on a low order polynomial in  $z$ , using the appropriate sampling weights. Unconditional probabilities can be estimated as the weighted proportion of individuals at each time over the total number of individuals.

A kernel density estimate of distribution (14) is therefore

$$\hat{f}(w | t_w = *, t_z = s) = \sum_{i \in S_t} \frac{\theta_i}{h} \hat{\lambda}_i K\left(\frac{w - w_i^*}{h}\right) \quad (17)$$

With these estimates of the distribution of wages, one can estimate the percentiles of each of the distributions and decompose the overall change in wages at each percentile according to the decomposition in (8). Finally one can run a regression of ex-ante non-escalated wage changes on escalated ones and obtain an estimate of the corresponding ex-post effect. From this, it is straightforward to derive a counterfactual distribution at zero SM. This is simply the sum of the ex-post non-escalated wage changes (the desired wage changes) and the compositional effect.

## 6. Estimation results

Estimation of kernel densities is performed using a Gaussian smoother, with optimal bandwidth under the hypothesis that the underlying distribution is normal (Silverman, 1986). The kernel densities are estimated at five points in time: 1977, 1980, 1984, 1989, 1993. Observe that a window of at least three years guarantees that all workers had (at least) one contract renewal over each interval. This is important because I rule out the possibility that price surprises coupled with some nominal rigidity in contractual wages during the life of the contract induce some deviation between actual and desired wage changes in the short term (see Card, 1990).



In each of the panels in Figure 3 I report the estimated density at two consecutive times, standardized to the median and separately for males and females. This figure gives substantially the same information as the one presented in Figure 1 and in Table 3. The distribution of men's wages compresses in the late 70s, tends to be steady afterwards and then decompresses in the second half of the 80s. For females, the same story is true but the reversion in inequality takes place in the second half of the 80s.

Figure 4 compares the distribution of wages at some initial time  $t$  (say 1977), with the distribution of the artificial variable  $w_*$  which is obtained by attributing to each individual the ex-ante escalated wage increase between time  $t$  and time  $s$  (say 1980). The comparison is done at time- $t$  weights. Differences between these two distributions can be interpreted as the *genuine* effect of the SM only under the assumption that contingent and non-contingent wage increases are orthogonal.

One can see how the SM tended to compress wages dramatically in the first period of observation but its compressionary effect vanishes over time. This is true both for men and women, yet female workers experience somehow a bigger impact of the SM in turn due to their wages being on average lower than those for males.

Figure 5 shows the effect of ex-ante non-escalated wage changes. I compare the distribution of wages at time  $t$  (say 1970), augmented by escalated contingent wage increases between time  $t$  and  $s$  (say, 1980) with the distribution at time  $s$ . It is important to observe that the artificial distribution of wages which is used for comparison is weighted at time- $s$  weights. Probit estimates of the weights are obtained by pooling observations from time  $t$  and  $s$  and regressing a dummy equal to one if the individual is observed at time  $t$  ( $s$ ) on a set of additive dummies for education, age, industry, occupation and region and interactions of industry and occupation, industry and age and age and education. For definition of categories see Table 1. Also included is a category for missing values for each variable.

One can see, how the non-escalated wage changes tended to decompress the distribution of wages all over the period of observation, and this effect is particularly pronounced in the last period, when the SM was relatively ineffective. If any, this points out to a trend towards an increase in latent wage inequality.

In tables 4 and 5 I report respectively the contribution of each source of wage increase to proportional changes in nominal wages and to different measures of inequality, obtained as differences between order statistics of the distribution of the logarithm of wages.

The ratio of the extreme decile of the distribution of males wages compresses by about 2.4% a year between 1977 and 1980, well above the reduction implied by the SM alone, which would have, if any, triggered a reduction of almost 7% a year. For females, changes are even more dramatic: the ninth to first decile reduces by more than 10% a year of the first three years of observation . The Scala Mobile alone would have implied a reduction of more than 14% a year. Over time, we see that the effect of the SM reduces and its magnitude at each decile tends to be similar for males and females, this in turn being due to the partial process of wage convergence between males and females.

As far as changes in the distributions of the observables are concerned, it is interesting to note that these changes are sometimes sizeable and can have opposite effects on the distribution of males and female wages. In principle, an increase in the proportion of high skilled workers, as documented in Tables 1A and 1B, has an ambiguous effect on the distribution of wages, depending on the initial distribution of skills. In the first period of observation, since the proportion of skilled workers among females is relatively high, the generalized trend in skill attainment tends to compress further their distribution, while, by increasing the mass in the upper tail of the distribution of males workers, who are relatively unskilled, this trend tends to have the opposite sign. Note that between 1977 and 1980, compositional changes account for a decline of almost 2% in ratio of the 9<sup>th</sup> to the 1<sup>st</sup> decile for female workers, i.e. almost 20% of the total observed decline. The recovery of the mid 80s tends to increase the share of low wage workers (those employed in the tertiary sector, those working in the South, blue collars) and so the effect is towards some increase in wage inequality for both males and females. In the second half of the 80s, the same pattern as in the first period is observable, but in the early 90s, a strong recession tends to reduce the proportion of low-wage earners for both males and females and overall to compress both distributions.

In theory, changes in the employment composition can have sizeable effects on the distribution of wages. I will return to this issue in section 7, where I discuss the

employment effects of relative wage changes induced by the indexation mechanism on observed wage inequality.

Figure 6 finally shows the annualized changes attributable to each of the three components, at each percentile of the distribution of initial wages. All the measures are standardized to changes at median and I have trimmed the top and bottom five percentiles. One can see that there is a clear sign of the SM in fact being partly undone by the non-contingent wage increases.

In Tables 6a-6c I report the result of the estimation of equation (9) separately for males, and females and for both groups together. I run a pooled regressions of changes at all of the ninety percentiles (excluding the bottom five and top five) over the four periods of observations and I parameterize the intercept of the model, namely the desired non-contingent wage increase, as a polynomial up to the third power in the percentile variable fully interacted with year dummies. On the right hand side I also experience with a quadratic term in the annualized contingent wage increase to allow for some non-linearity on the correlation between contingent and non-contingent wage changes. Yet, all of the specifications with a quadratic term perform pretty poorly. Standard errors are heteroskedasticity-consistent and consistent with unrestricted auto correlation within each time period.

In the first column, I report a simple regression of contingent wage increases over year dummies. The fit of the regression increases sensibly when I allow for contingent increases on the right hand side. I experience both with a second order and a third order polynomial in the percentile variable and in turn I allow it to be interacted with year dummies. I also estimate a model with no interactions. Interactions always show a significant effect, implying that I can rule out some underlying stationarity in wage inequality. Specification 6, with a quadratic polynomial in the percentile variable fully interacted with year dummies and a linear term in contingent wage increases is my preferred specification for males. This implies a full offsetting of escalated increase on the part of non-escalated ones. For females, specification 10 performs better: this suggest that only around 60% of the effect of the SM was undone by non-contingent wage increases. As far as the pooled estimates are concerned, I consider similar specifications but now I allow all the variables, except contingent wage increases, to vary across sex.

Specifications 6 and 10 give similar values, although specification 10 provides a much more precise point estimate of the parameter of interest. Again, they suggest a value of the elasticity of approximately .6

An obvious objection to the regression analysis hereby conducted is that my estimates of the SM payments can be affected by measurement error. In this case, OLS estimates of the parameter of model (9) are likely to be biased. In particular, since the estimates of non-contingent wage changes (the left hand variable) are obtained as a difference between actual wage changes and ex-ante escalated payments, it can be shown (see appendix B) that in the presence of classical measurement error, an OLS regression of non-contingent wage changes on contingent ones is likely to lead to an estimate of the slope parameter which is biased towards  $-1$ . In this sense my estimates are conservative, since they overestimate the counteracting effect of non-contingent wage changes with respect to contingent ones.

Overall, there is evidence that the SM did in fact bite for females, while, to be cautious, there is evidence that the SM was fully undone for males, although the estimate for males is somehow imprecisely determined. By pooling the observations, I find similar point estimates as for females. If one thinks that not enough variation was left in the distribution of males to identify the effect of SM, then a value of .6 seems a good guideline for both males and females.

In Tables 7 and 8, I decompose respectively the changes in nominal wages and the changes in wage inequality into ex-post contingent and non-contingent wage changes. I use the estimated elasticity from column 10, Table 6c, where I pool observations for males and females, to obtain an estimate of these two sources of the wage changes.

One can see that in the first period of observation, once one has parsed out the counteracting effect of contingent wage increases, non-escalated wage increases tend to compress the distribution of wages. My estimates suggest, that even in the absence of the indexation mechanism, between 1977 and 1980 wage differentials would have compressed, although more so for females. Data in Tables 8a and 8b suggest that the ratio of the extreme deciles would have compressed by more than 3% a year for females and only .5% for males. In the second period, latent wage inequality tends to increase. In 1984, when the two distributions are pretty similar, the estimated desired change in the

ratio is approximately 1% a year for both males and females. In the last period of observation, we see an acceleration of latent wage inequality, which is particularly pronounced for females. Yet, as tables 7a and 7b show, this is the effect of the fact that female workers are relatively more represented among low-wage employees.

To get an idea of the implied change in the latent wage inequality, conditional on the SM being set to zero, in Figure 7 I plot the evolution of the logarithm of the extreme deciles and quartiles of the wage distribution and the implied evolution of the latent wage inequality, obtained as a cumulative sum of the changes from one period to the other. Both series are constructed at fixed distribution of observables and are standardized to zero in 1977.

The results are remarkable. I estimate that in the absence of the SM, wage inequality would have started to increase since the early 80s for both males and females. I estimate that the ratio of the extreme deciles would have increased by 20% for males and by 27% for females. The ratio of the extreme quartiles would have increased respectively by 7% and 13%. Over the whole period of observation, the cumulative changes in the distribution of employment (the differences between the series depicted in Figure 7 and in Figure 1) are responsible for a rise in the ratio of the extreme deciles of around 3% for males and a decline of 2% for females.

## **7. Accounting for employment effects**

Until now I have assumed that density of observables is independent of the distribution of wages. This does not seem a very realistic assumption: firms might react to changes in relative wages by substituting workers whose relative wage has decreased for workers whose relative wage has increased. Again, different points of the distribution will be affected differently, but it is likely that an exogenous reduction in wage differentials implies that some mass moves from the left tail of the distribution to the top tail. In this sense, one might expect that my estimates of the impact of the SM are somehow downward biased: by inducing some employment losses among the unskilled relative to the skilled, this would produce an even more compressed observed wage distribution. The magnitude of this effect will depend on the value of the elasticity of substitution across different types of workers as well as the magnitude of relative wage changes.

By an analogous reasoning, it is likely that my estimates of the trend in latent wage dispersion are somehow downward biased. Failure of taking into account the employment effect of the SM implies that when I set the SM at zero, which is my counterfactual, one is failing to purge the series of the employment losses at the bottom of the distribution. By controlling for this compositional effect, one should find that wage dispersion is higher and changes in latent wage dispersion are bigger than previously estimated.

Suppose that wages are exogenous in my setting and that employment is determined along a labor demand curve. I assume that firms face an infinitely elastic labor supply at the given wages. Wages are set based on the SM and the bargaining process, and employment is determined once wages have been set based on the profit maximizing behavior of the firm. This implies that the distribution of employment will depend on the distribution of wages. One can think of changes in employment being due to either exogenous changes in wages (shifts along a labor demand curve, identified by movements of the labor supply curve) and changes in some relative demand shifts (movements of the demand curve along a flat labor supply). In order to account for the employment effects of the SM, we need to separately identify these sources of changes and attribute to the SM only changes along a labor demand curve.

Let us introduce a last bit of notation. Let us define

$$f_{s,t,r}(w) \equiv f(w | t_w = s, t_z = t, D_r) \quad (18)$$

where  $D$  is a (vector of) demand shifter(s). This notation is somehow redundant since the density of the observables is completely defined for any pair of values of  $D$  and  $t_w$  or for any value of  $t_z$ . For example,  $f_{s,,s}(w) \equiv f_{.,s,}(w)$ . Yet it will prove useful to compute my counterfactuals. With obvious notation  $f_{s,s,s}(w) \equiv f_{s,s}(w) \equiv f_s(w)$ . Note that movements of the labor demand curve affect the observed density of wages only through changes in the composition of employment.

Suppose we ask what the distribution of wages would have looked like had individuals observed at time  $t$  been awarded contingent wage increases and the composition of employment had varied accordingly. This can be written as

$$\begin{aligned}
f(w|t_w = *, D_t) &= \int f(w|t_w = *, z) dF(z|t_w = t^*, D_t) = \\
&= \int f(w|t_w = *, z) \kappa(z) dF(z|t_z = t)
\end{aligned}
\tag{19}$$

where

$$\kappa(z) = \frac{dF(z|t_w = *, D_t)}{dF(z|t_w = t, D_t)}
\tag{20}$$

Equation (20) suggests then that if we want to assess the overall impact of the SM on the wage distribution, we can simply compute the artificial wages  $w^*$  and estimate a kernel density on this artificial distribution at time  $t$ , where each individual observation is reweighted by  $\kappa(z)$ .

Analogously, one can ask what the structure of wages would have looked like if individuals had been awarded contingent wage increases but employment were set at the level implied by the level of demand at time  $s$ . This is equivalent to compute

$$\begin{aligned}
f(w|t_w = *, D_s) &= \int f(w|t_w = *, z) dF(z|t_w = *, D_s) = \\
&= \int f(w|t_w = *, z) \varphi(z) dF(z|t_z = t)
\end{aligned}
\tag{21}$$

where

$$\varphi(z) = \frac{dF(z|t_w = *, D_s)}{dF(z|t_w = t, D_t)}
\tag{22}$$

Note that this is a different question from asking what the structure of wages would have looked like if individuals had been awarded only contingent wage increases but the distribution of employment was the one which actually occurred at time  $s$ . The two

distributions are identical only to the extent that no employment change from  $t$  to  $s$  can be ascribed to non-escalated wage changes. This distribution is reported in equation (13).

One can therefore rewrite the overall change in wages at a given percentile from time  $t$  to time  $s$  as

$$w_s^q - w_t^q = (w_{s,s,s}^q - w_{*,s,s}^q) + (w_{*,s,s}^q - w_{*,t,s}^q) + (w_{*,t,s}^q - w_{*,t,t}^q) + (w_{*,t,t}^q - w_{t,t,t}^q) + (w_{t,t,t}^q - w_{t,t,t}^q) \quad (23)$$

i.e. it can be decomposed into five elements (in the reverse order):

- a. the change due to the varying distribution of wages because of escalated wage increases at given distribution of attributes;
- b. the change due to the employment effect of the escalated wage changes;
- c. the change due to demand shifts;
- d. the change due to the employment effects of the non-escalated wage changes;
- e. the change due to non-contingent wage changes, at given distribution of attributes.

In essence, we have decomposed the change in relative employment of section 4 into a component due to the contingent wage changes, a component due to exogenous shifts in the (relative) demand function and a last part due to non-contingent wage changes.

One can estimate each of the densities (19), and (21) via means of kernels, with the weights given by equations (20) and (22).

Since my interest here is only on the employment effect of the SM I do not identify separately b from c in the above decomposition, although there is no obstacle to doing so.

If one is ready to make some assumptions over the firm's production technology, estimation of the weights is pretty straightforward. Observe that for  $z$  varying over some discrete support, the weights in (20) can be rewritten as

$$\kappa(z) = \exp\left(\ln \Pr(z | t_w = t^*, D_t) - \ln \Pr(z | t_w = t, D_t)\right) \quad (24)$$

i.e. they turn out to be proportional to the relative change in the employment share induced by the SM. Suppose that the variable  $z$  defines  $Z$  disjoint groups and that the firm



employs these labor inputs to produce an output  $Y$  with a CES technology under constant returns to scale.

$$Y = A \left( \sum_{z=1}^Z L_z^\rho \right)^{\frac{1}{\rho}} \quad \rho < 1 \quad (25)$$

where  $L$  is employment,  $A$  some state of aggregate technology and  $Y$  is total output, which equals the wage bill.

If markets are competitive, the employment probability of workers with characteristics  $z$  is

$$\ln \Pr(z | t_w = t, D_t) = -\sigma \bar{w}_{zt} + \bar{w}_s + a_t \quad (26)$$

where  $\sigma = 1/(1 - \rho)$  is the elasticity of substitution,  $\bar{w}_z$  is group  $z$ 's average wage,  $\bar{w}$  is the average wage in the economy and small letters denote logarithms.

Changes in demand between two consecutive times rewrite as

$$\ln \frac{\Pr(z | t_w = s, D_s)}{\Pr(z | t_w = t, D_t)} = -\sigma (\bar{w}_{zs} - \bar{w}_{zt}) + (\bar{w}_s - \bar{w}_t) + (a_s - a_t) \quad (27)$$

The first two terms on the right hand side pick up the effect of changes in the wage structure, while the last term pick up demand shifts.

In order to obtain an estimate of  $\sigma$ , one can then estimate a regression of relative employment changes between  $s$  and  $t$  over changes in wages and year dummies (and possibly group specific fixed effects to account for input specific productivity changes).

If the error term were orthogonal to the regressors, one could estimate the parameters of the model consistently by OLS and adjust the standard errors for the fact that the left hand side variable is a proportion variable. Yet, the orthogonality condition is likely to fail and OLS estimates will be biased. This is the well known simultaneity bias problem: one cannot identify a demand equation by simple knowledge of equilibrium points. Yet,

contingent wage changes candidate as a valid instrument: by shifting the labor supply, they identify the demand equation.<sup>2</sup>

At this stage, and in order to simplify the analysis I assume that the value of the elasticity of substitution is known. I have done this exercise on my data and I have computed for each group defined by the  $z$  variable (interaction of age, education, region, industry and occupation) the ex-post change due to the SM. I estimate the weights in (20) based on my estimated of ex-post contingent wage changes for each group. I have then reweighted the density of  $w^*$  by these new weights and by comparison with the density in (12), I have finally estimated the employment effect of the ex-post contingent changes at each percentile of the wage distribution.

The results of my exercise are reported in Tables 9a and 9b, where I provide the impact of the employment effect of the SM over different measures of inequality for values of the elasticity of substitution between .5 and 4. When firms operate with a Cobb-Douglas production function, the weights are simply the antilogarithm of the opposite of relative wage changes.

The first observation is that a general rule the employment effect grows as the elasticity of substitution increase, although this does not always grows monotonically with the level of wages. Second, the effect of employment changes for males are negligible. A more interesting picture emerges for women: changes in the composition of the observables are potentially able to explain sizeable changes in wage inequality. I estimate that for males the implied reduction in the ratio between the ninth and the first decile ranges between 2.5% and almost 6% a year during the first period of observation. As time passes and the SM is curbed, its effect becomes relatively less appreciable.

The general conclusion I draw for this exercise is that indeed part of the compression of wages which occurred in until the late 70s for women can be attributed to the employment effects of the SM. If any, in the absence of the indication mechanism, wage inequality would have increased even more dramatically than I estimated in section 6. To get an idea of the magnitudes involved, with an elasticity of substitution of .5 I estimate that the ratio of the extreme deciles would have been 16% higher in 1993 than it was in 1977.

## 8. Conclusions

It is often heard that wage inequality “failed: to increase in continental Europe in the last decade, while it rose substantially in the US and UK. In this paper I have used individual data on earnings for Italy to document the trends in wage inequality between 1977 and 1993 and to assess the role that institutions, and in specifically the *Scala Mobile*, played in shaping these trends. First of all, I have shown that after a marked compression, starting from the late 80s *observed* wage inequality has started to increase. In 1993 inequality was at the same level as in 1977. Secondly, I have shown that the *Scala Mobile* had a pretty strong redistributive effect. Around 60% of the change implied by the indexation mechanism translated into actual wage changes. I conclude that this institution did matter: market forces did not completely undo the effect of the SM. Finally, I show that starting from the early 80s, *latent* wage inequality started to increase in Italy. As the SM was curbed, observed wage inequality tended to increase, too.

An interesting result is that once I purge the trends in wage inequality of the effect of the indexation mechanisms and changes in the composition in employment, males and female wages show a remarkably similar trend in dispersion.

This suggests that gender differences can be used to identify the impact of the SM on the distribution of wages. In turn, one could try and experiment with other grouping estimators (say based on education or region) to identify separately the effect of the escalator from a trend in latent wage inequality.

I have also shown that trends in observed wage inequality were somehow affected by changes in the composition of employment. For this purpose I use the procedure suggested by DiNardo *et al.* (1996). I show how one can extend their procedure by allowing the weights to vary endogenously with changes in the wage structure and I have used this procedure to estimate the impact of the SM on the distribution of wages through its effect on changes in demand via variations in relative wages. Potentially, the SM could have produced sizeable employment losses among females workers, disproportionately concentrated in the left tail of the unconditional wage distribution. I

conclude that, if any, my estimate of the trend in latent wage inequality is downward biased.

The finding that in fact escalated wage increases were not fully undone by other sources of wage changes suggest that the SM implied exogenous changes in the wage structure, and its effect varied along the wage distribution This in turn suggests that one can use the SM as an instrument to identify an elasticity of labor demand across different labor inputs. The exercise, which is next on the agenda, might help and understand whether in fact exogenous rises in wages bear the responsibility for the rise in unemployment in Italy over the period of observation.

## **Appendix A. Imputation of SM payments.**

The structure of the typical compensation package in Italy is pretty complicated. In Table A1 I report the voices which concur to the determination of take home annual pay. As discussed in section 1, minimum contractual wages are set at the industry level for different skill levels. The sum of the contractual minimum and the cumulated contingent wage increases gives the contractual compensation. This does not include the automatic seniority payments, and the superminima, either individual or collective, bargained at the firm level or conceded unilaterally by the firm. The sum of these non-escalated wage increases plus the contractual compensation gives the monthly compensation. Thirteen times the monthly compensation (in some sectors a fourteenth or even a fifteenth wage is awarded but I ignore this) gives total annual compensation. If from this we subtract income taxes and workers' social security contributions and we add any family allowances, this gives the take home annual pay, which is my measure of earnings.

As far as the SM is concerned, although already in existence before 1977, in that year the indexation mechanism was made universal. During the course of its life the *Scala Mobile* underwent a number of reforms. These reforms and their timing are summarized in Table A2.

In its original formulation, which I illustrate in section 1, the *Scala Mobile* granted a quarterly flat increase in nominal wages for each percentage point increase in a special consumer price index (*Indice sindacale*) rounded to the nearest integer. The *Scala Mobile* point was originally set to 2,389 lit and price index was calculated with a base August-October 1974=100. The system was universal and implied the same adjustment for all employees, with the exception of those in the public sector where the adjustment took place every six months. In 1980 the two systems were unified.

In 1983 the system was reformed: Price increases were computed based on a price index with base August-October 1982=100 and the SM point was raised to 6,800 lit.

In 1986 a new system was introduced which established that the adjustment of wages due to changes in the price level were to take place every six months rather than every three. It also guaranteed a 100% coverage of a given minimum wage indexed itself,  $a'$ , plus a 25% coverage of the difference between the contractual minimum plus cumulated SM

payments (monthly contractual wage) and the minimum wage. In formulas and for wages above the threshold, changes in wages between time  $t$  and time  $s$  can be written

$$SM_s = \left( .75a_t' + .25CW_t \right) dp_s$$

$$a_s' = a_t' \left( \frac{P_s}{P_t} \right) = a_0' \left( \frac{P_s}{P_0} \right) \quad (A1)$$

where the  $CW$  is the contractual wage. For wages below the threshold, the guaranteed increase in nominal wages is instead  $dw_t = dp_t$ , i.e. a full protection.

Again equation (A1) can be expressed as a constant elasticity formula for relatively small changes in wages and prices

$$\ln \frac{SM_s + W_t}{W_t} = e_t' dp_s$$

$$e_t' = \left( .75 \frac{a_t'}{W_t} + .25 \frac{CW_t}{W_t} \right) \quad (A2)$$

With the renewed mechanism, wage growth responds to price growth partly according to the old mechanism but with a coefficient of  $\frac{3}{4}$ . A residual part depends instead on the ratio between the contractual and the actual wage. The same rules as before apply but in addition, coverage decreases as wages increase, given that the contracted part of the wage becomes proportionally smaller. Compared to the old system, for a given wage level, coverage decreases or increases according to whether the contracted wage is below or above the minimum wage. For very low wages, coverage decreases since while under the old system they were granted more than proportional increases, now they are just given full coverage.

The minimum wage was set at lit 580,000 for a start and the price index was still computed with base August-October 1982=100. In 1991 the system was abolished. In 1993 workers received a lump sum wage increase for failed protection against past inflation.

In order to compute the contingent increase due to the SM for each individual, I combine the individual information of earnings from the SHIW with data on escalated wage increases due to the SM. These data are published by the Italian Statistical Bureau and reported in Tables A3 to A5. To derive the effect on net labor income, I combine this information with data on the composition of gross labor income by decile estimated on SHIW data obtained in 1989 (Di Biase and Di Marco ,1995). The data are reported in Table A6.

### **1977-1985**

I first compute implied gross increases in wages from one year to another which would trigger because of the SM. To do so, I simply compute the sum of payments at the end of the year, allowing for thirteenth wage, based on Tables A3 and A4. If, say, the SM triggers a wage increase of  $l$  lit. starting in month  $m$  of a given year, I assume that this contributes to an increase of  $(14-m)l$  lit. in gross pay. Once I have done this, I work out the net increase according to the position of the individual in the wage distribution of the distribution of wages unconditional on sex, using the tax brackets reported in Table A6. Given the fact the before 1984 tax brackets were not indexed to inflation, this implied that the effect of the SM was partly neutralized by the counteracting effect of tax system (a phenomenon known as fiscal drag). To account for this, for individuals observed in 1980 I use the tax brackets implied by their relative position in the wage distribution in 1977. I make separate (but similar) calculations for public sector workers.

### **1986-1993**

The data for calculations are in Table A5. The variable in column (2) is the value of the minimum wage  $a_i$ '. Because of the continuous updating of this value according to past inflation, this changes from semester to semester and can be computed starting from an initial value of 580,000 lit. and updated by the inflation rate over the preceding six months, which is reported in column (3). This is computed as the proportional change in prices which are reported in column (1). Recall that for wages below the minimum wage, protection against inflation was full.

Price changes were computed in the months of April and October and wage increases were awarded starting from the following month (respectively May and November). So if by  $CW_1$  we denote the contractual wage in month 1 and by  $SM_5$  and  $SM_{11}$  the contingent increases awarded in May and November respectively, it follows

$$SM_{t,5} = (.75a_{t-1,11} + .25CW_1) dp_{t,5}$$

$$SM_{t,11} = (.75a_{t,5} + .25(CW_1 + SM_{t,5})) dp_{t,11}$$

where  $dp$  is the inflation rate in the preceding six months. Suppose we want to estimate the increase in wages which is triggered in May 1987. This is equal to the product of the inflation rate from October 1985 to April 1986 (2.72%) times the sum of  $\frac{3}{4}$  of the minimum wage (580,000 lit.) plus  $\frac{1}{4}$  of the contractual wage in January of that year.

In order to compute SM payments one has to make some assumptions on the way contractual wages relate to actual ones. A simple assumption is that this is some fixed proportion of the individual's monthly wage in the previous year. In the absence of any a priori on the value of the ratio between contractual and actual wages, I assume that this proportion is equal to the complement to one of the tax rate (including social security contributions and excluding family allowances). Since there is evidence of contractual wages being inversely related to the actual wages (Erickson and Ichino (1992), inter alia) this choice has the advantage of simplifying calculations. Implicitly, in formulas, assume

$$CW_{t,1} = \frac{W_{t-1}}{13} (1 - \tau)$$

where  $W$  is the annual gross pay and  $\tau$  the tax rate. I can then compute the contingent increases in May of year  $t+1$  and iteratively compute the escalated wage increases up to year  $s$ . I use the tax rate at the beginning of the period as the value of  $\tau$ . Implicitly, I am assuming that there is no contract renewal over the period of observation. Since contract renewals generally tended to counteract the compressionary effect of the SM and



therefore reestablish the differential in the contractual wages, it is likely that I am underestimating the impact of the SM.

Observe that the estimated increases refer to gross wages. One can simply rescale the data to net wages using the information in Table A6.

### Appendix B. Measurement error

Consider model (7), where I regress non-contingent wage changes over contingent ones and some time varying mean which is opportunely parameterized. Recall that non-contingent wage changes are obtained as a difference between actual wage changes and contingent ones (the right hand variable).

Rewrite model (7) as

$$(w_s - w_t) - (w^* - w_t) = \beta_0' d_s + \gamma_1 (w^* - w_t) + u_s \quad (\text{B1})$$

where I have omitted the  $q$  superscript for simplicity.  $u$  is a random error which I assume uncorrelated with the regressors.  $\gamma_1 = (\beta_1 - 1)$  and  $d$  is a set of other variables. Rewrite equation (B1) as

$$y_s - x_s = \beta_0' d_s + \gamma_1 x_s + u_s \quad (\text{B2})$$

where  $x$  is contingent wage changes,  $y$  is total wage changes and  $z$  Suppose now that we only have some error ridden measure of contingent wage changes

$$\tilde{x}_s = x_s + \delta_s \quad (\text{B3})$$

where  $\delta$  is a measurement error which is uncorrelated with  $x$ . If we use this error ridden measure of  $x$ , we are in fact estimating the model

$$y_s - \tilde{x}_s = \beta_0' d_s + \gamma_1 \tilde{x}_s - (1 + \gamma_1) \delta_s + u_s \quad (\text{B4})$$

The probability limit of the OLS estimator of  $\gamma_1$  is then

$$plim \hat{\gamma}_1 = \gamma_1 - (1 + \gamma_1) plim \left( \frac{\tilde{X}' M_{dd} \tilde{X}}{N} \right)^{-1} \frac{\tilde{X}' M_{dd} \delta}{N} = \gamma_1 - (1 + \gamma_1) R$$

$$M_{dd} = (I - d(d' d)^{-1} d)$$

$$R = \frac{var(\delta | d)}{var(X | d) + var(\delta | d)}$$
(B5)

where  $N$  is the sample size and  $M$  is the transformation matrix of residuals of a regression onto the  $d$  variables and  $R$  is the reliability ratio, conditional on  $d$ . Since  $0 \leq R \leq 1$ , it is easy to show that

$$plim \hat{\gamma}_1 \leq \gamma_1 \quad \gamma_1 \geq -1$$
(B6)

In other terms, the OLS estimator is asymptotically downward biased for a true value of the parameters above minus one. This is the classical attenuation problem which arises when the right hand side variable is affected by measurement error. Given the fact that the left hand variable is itself a function of this error-ridden measure with a coefficient of  $-1$ , the measurement errors tends to bias the OLS estimates of the slope parameter towards  $-1$  rather than  $0$ , as in the classical case.

## References

- Banca d'Italia, *Supplemento al Bollettino Statistico su "I bilanci delle famiglie italiane"*, various issues.
- Blau, F. and L. Kahn (1996), 'International Differences in Male Wage Inequality: Institutions versus Market Forces', *Journal of Political Economy*, 104, 791-837.
- Card D. (1983), 'Cost of living escalators in major union contracts', *Industrial and Labor Relations Review*, 37, 1, 34-48.
- Card D. (1986), 'An Empirical Model of Wage Indexation Provisions in Union Contracts', *The Journal of Political Economy*, 94, S144-S175.
- Card D. (1990), 'Unexpected Inflation, Real Wages and Employment Determination in Union Contracts', *American Economic Review*, 80, 4, 669-688.
- Card D. and A. Krueger, (1994), 'Minimum Wages and Employment. A Case Study of the fast-food Industry in New Jersey and Pennsylvania', *American Economic Review*, 84 (4), 772-793.
- Cella, P. and T. Treu (1989), *Relazioni Industriali*, il Mulino, 1982.
- DiNardo, J., N. Fortin, and T. Lemieux (1996), 'Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach', *Econometrica*, 64, 1001-1044.
- Erickson, C. and A. Ichino (1995), 'Wage Differentials in Italy: Market Forces, Institutions, and Inflation', in *Differences and Changes in The wage Structure*, Freeman, R. and Katz, L. (ed.s), The University of Chicago Press.
- Feenstra and Hanson, (1996), 'Globalization, Outsourcing and Wage inequality', *American Economic Review*, 86, 240-245.
- Juhn, C., K. Murphy and B. Pierce (1993), 'Wage Inequality and the Rise in Returns to Skills', *Journal of Political Economy*, 101, 410-442.
- Katz, L. and K. Murphy, (1992), 'Changes in Relative Wages, 1963-1987: Supply and Demand Factors', *Quarterly Journal of Economics*, 107, 35-78.
- Krugman, P. (1994), 'Past and Prospective Causes of High Unemployment', in *Reducing Unemployment: Current Issues and Policy Options*, Jackson Hole Conference, WY.

- Lee D. (1998), Wage inequality in the US during the 1908s: Rising dispersion or falling minimum wage?, *mimeo*, Princeton University.
- Machin S., Manning A. (1994), 'The effects of minimum wages on wage dispersion and unemployment: Evidence from UK wage councils', *Industrial and Labor Relations Review*, 47, 2, 312-29.
- OECD (1996), *Employment Outlook*, Paris.
- Treu, T. (1991) (ed.) *European Employment and Industrial Relations Glossary: Italy*, Sweet and Maxwell Luxembourg.

Table 1a  
Summary statistics: means/proportions  
Males

	77	80	84	89	93	Total
n. obs	1,640	1,560	1,964	4,065	3,307	12,536
nominal yearly earnings/1000	4,546	7,388	13,231	19,667	24,634	16,463
log (real earnings/1000)	3.748	3.804	3.835	3.933	3.923	3.873
<u>occupation</u>						
white collars	31.08	43.29	41.82	50.15	48.63	45.09
blue collars	68.92	56.71	58.18	49.85	51.37	54.91
<u>education (nr. of years)</u>						
college (18)	5.02	7.31	7.19	7.26	7.41	7.00
high sch. (13)	19.24	26.02	31.38	33.96	31.87	30.07
junior high (8)	29.84	34.20	36.41	37.48	44.07	37.66
elementary (5)	38.63	28.65	23.03	19.30	15.60	22.60
no schooling	5.71	3.35	1.99	1.65	1.06	2.29
<u>age</u>						
18-20	3.53	3.12	1.93	2.50	1.82	2.45
21-30	24.31	23.94	21.57	24.56	21.43	23.16
31-40	26.79	26.27	29.75	25.38	30.63	27.75
41-50	24.49	25.56	26.56	29.74	29.77	28.05
51-65	20.88	21.11	20.18	17.81	16.34	18.60
<u>industry</u>						
agriculture	2.24	1.66	2.47	3.87	2.57	2.82
manufacturing	49.36	49.54	35.20	42.02	43.24	43.20
public	20.28	24.97	26.06	29.92	35.62	28.96
retail trade	6.76	6.20	9.94	8.01	7.22	7.71
transp., comm.	12.05	8.34	12.14	9.31	5.85	9.06
banking	3.57	4.28	5.16	4.50	3.11	4.08
other services	5.51	5.01	9.02	2.38	2.37	4.14
<u>region</u>						
1	16.72	13.73	14.75	14.47	11.21	13.85
2	20.35	22.09	18.58	19.50	19.09	19.68
3	11.82	11.02	9.79	12.07	12.16	11.58
4	7.62	6.82	5.84	6.27	8.09	6.94
5	10.37	12.80	10.03	10.71	11.09	10.92
6	9.31	8.52	9.99	10.25	10.14	9.84
7	8.00	8.19	10.16	6.82	7.04	7.72
8	6.83	6.01	8.27	7.75	8.34	7.65
9	2.67	3.03	3.90	3.88	3.54	3.53
10	6.32	7.78	8.71	8.28	9.29	8.29

Notes. Source: SHIW. Sample selection: employees in full-year employment, aged 18-65. Earnings definition: net annual take-home pay, inclusive of overtime, bonuses and 13<sup>th</sup> wage. Proportions might not add up because of missing values. Regions are defined as follows: (1) Piemonte - Val d'Aosta - Liguria, (2) Lombardia, (3) Trentino Alto Adige - Veneto - Friuli Venezia Giulia, (4) Emilia Romagna, (5) Toscana - Umbria - Marche, (6) Lazio, (7) Campania, (8) Abruzzi - Molise - Puglia, (9) Basilicata - Calabria, (10) Sicilia - Sardegna. Wages are deflated by the consumer price index (1977=100) *Numeri indici dei prezzi al consumo per le famiglie di operai e impiegati*. Source: *Anuario Statistico Italiano*, ISTAT, various issues.

Table 1b  
Summary statistics: means/proportions  
Females

	77	80	84	89	93	Total
n. obs	707	806	1,079	2,226	1,975	6,813
nominal yearly earnings/1000	3,309	6,050	10,717	16,669	20,000	14,018
log (real earnings/1000)	3.398	3.588	3.616	3.772	3.710	3.669
<u>occupation</u>						
white collars	41.35	60.01	57.92	63.86	67.27	61.14
blue collars	58.65	39.99	42.08	36.14	32.73	38.86
<u>education (nr. of years)</u>						
college (18)	7.19	10.51	14.09	13.05	13.44	12.40
high sch. (13)	28.61	41.31	43.46	44.35	46.36	42.79
junior high (8)	30.94	28.69	27.53	29.66	31.45	29.87
elementary (5)	28.88	16.29	13.39	12.06	8.00	13.35
no schooling	4.38	3.09	1.53	0.54	0.75	1.46
<u>age</u>						
18-20	7.92	5.03	4.23	5.48	3.05	4.79
21-30	37.94	36.08	29.90	31.64	27.13	31.27
31-40	24.40	25.17	34.28	28.83	33.06	29.97
41-50	19.46	22.06	21.99	23.81	27.50	23.93
51-65	10.28	11.66	9.61	10.23	9.26	10.04
<u>industry</u>						
agriculture	0.45	0.47	1.06	1.60	1.11	1.12
manufacturing	35.72	27.71	19.31	27.52	26.01	26.72
public	26.62	41.41	44.62	48.90	54.78	46.72
retail trade	11.72	14.85	14.85	13.42	10.34	12.74
transp., comm.	3.82	3.96	3.68	2.12	0.89	2.40
banking	2.26	2.62	2.89	4.16	3.28	3.33
other services	19.27	8.98	13.59	2.29	3.58	6.95
<u>region</u>						
1	20.07	14.26	16.39	17.07	13.61	15.94
2	21.58	24.07	20.84	25.08	23.90	23.61
3	9.97	10.63	11.81	13.12	13.47	12.39
4	9.31	8.02	6.78	6.86	8.54	7.72
5	9.19	11.43	12.09	10.21	11.22	10.83
6	10.31	13.28	8.31	8.19	8.20	9.05
7	6.89	5.88	8.02	5.49	6.03	6.22
8	6.18	6.06	6.36	6.23	6.34	6.25
9	1.52	2.26	2.77	3.25	2.89	2.77
10	4.98	4.12	6.62	4.50	5.80	5.20

Notes. See notes to Table 1a.

Table 2  
The evolution of nominal wages by decile

<u>Deciles</u>	Males					Females				
	77	80	84	89	93	77	80	84	89	93
<u>1</u>	7.951	8.486	9.115	9.471	9.638	7.361	8.218	8.823	9.297	9.306
<u>2</u>	8.107	8.644	9.239	9.589	9.778	7.745	8.438	9.037	9.453	9.570
<u>3</u>	8.203	8.736	9.327	9.677	9.878	7.905	8.550	9.145	9.543	9.698
<u>4</u>	8.279	8.808	9.399	9.755	9.966	8.013	8.634	9.223	9.621	9.798
<u>5</u>	8.351	8.874	9.465	9.825	10.048	8.105	8.708	9.293	9.687	9.886
<u>6</u>	8.431	8.940	9.527	9.895	10.126	8.189	8.778	9.359	9.751	9.968
<u>7</u>	8.519	9.008	9.597	9.975	10.210	8.275	8.852	9.427	9.815	10.050
<u>8</u>	8.623	9.092	9.687	10.079	10.318	8.375	8.936	9.501	9.889	10.140
<u>9</u>	8.763	9.226	9.841	10.235	10.504	8.523	9.056	9.607	9.995	10.262
<u>price index</u>	4.61	5.05	5.61	5.91	6.12	4.61	5.05	5.61	5.91	6.12

Notes. The table reports the log of nominal wages at each decile of the distribution, as well as the logarithm of the consumer price index.

Table 3a  
Measures of wage dispersion at selected points in time  
Males

Measures of <u>inequality</u>	<u>Levels</u>					<u>Annualized changes (x 100)</u>			
	77	80	84	89	93	77-80	80-84	84-89	89-93
<u>SD</u>	0.363	0.343	0.318	0.318	0.372	-0.66	-0.64	0.01	1.35
<u>95-05</u>	1.110	1.066	0.992	1.002	1.158	-1.47	-1.85	0.20	3.90
<u>90-10</u>	0.812	0.740	0.726	0.764	0.866	-2.40	-0.35	0.76	2.55
<u>75-25</u>	0.410	0.354	0.352	0.388	0.430	-1.87	-0.05	0.72	1.05
<u>05-50</u>	-0.568	-0.578	-0.480	-0.456	-0.548	-0.33	2.45	0.48	-2.30
<u>10-50</u>	-0.400	-0.388	-0.350	-0.354	-0.410	0.40	0.95	-0.08	-1.40
<u>25-50</u>	-0.192	-0.180	-0.180	-0.190	-0.218	0.40	0.00	-0.20	-0.70
<u>75-50</u>	0.218	0.174	0.172	0.198	0.212	-1.47	-0.05	0.52	0.35
<u>90-50</u>	0.412	0.352	0.376	0.410	0.456	-2.00	0.60	0.68	1.15
<u>95-50</u>	0.542	0.488	0.512	0.546	0.610	-1.80	0.60	0.68	1.60

**Notes:** The table reports measures of wage dispersion based on the kernelized densities. “SD: is the standard deviation of the logarithm of wages. “95” if the 95<sup>th</sup> percentile of the same distribution, and “95-05” is the difference between the two extreme vingtiles. The other measures are defined similarly.



Table 3b  
Measures of wage dispersion at selected points in time  
Females

Measures of <u>inequality</u>	<u>Levels</u>					<u>Annualized changes (x 100)</u>			
	77	80	84	89	93	77-80	80-84	84-89	89-93
SD	0.467	0.388	0.341	0.312	0.404	-2.63	-1.19	-0.56	2.29
95-05	1.618	1.256	1.122	0.996	1.300	-12.07	-3.35	-2.52	7.60
90-10	1.162	0.838	0.784	0.698	0.956	-10.80	-1.35	-1.72	6.45
75-25	0.488	0.392	0.366	0.350	0.454	-3.20	-0.65	-0.32	2.60
05-50	-1.072	-0.804	-0.712	-0.580	-0.820	8.93	2.30	2.64	-6.00
10-50	-0.744	-0.490	-0.470	-0.390	-0.580	8.47	0.50	1.60	-4.75
25-50	-0.270	-0.208	-0.196	-0.186	-0.246	2.07	0.30	0.20	-1.50
75-50	0.218	0.184	0.170	0.164	0.208	-1.13	-0.35	-0.12	1.10
90-50	0.418	0.348	0.314	0.308	0.376	-2.33	-0.85	-0.12	1.70
95-50	1.618	1.256	1.122	0.996	1.300	-12.07	-3.35	-2.52	7.60

Notes: See notes to Table 3a.

Table 4a  
Decomposing proportional changes in nominal wages  
Ex ante annualized changes (x 100)  
Males

Deciles	77-80			80-84			84-89			89-93			
	Total	SM	z	Total	SM	z	Total	SM	z	Total	SM	z	
1	17.82	11.67 (.65)	0.33 (.02)	15.74	8.6 (.55)	0.2 (.01)	7.11	2.48 (.35)	0.24 (.03)	4.39 (.62)	4.18	1.6 (.38)	0.1 (.02)
2	17.89	9.87 (.55)	0.4 (.02)	14.89	7.35 (.49)	0.15 (.01)	6.99	2.2 (.31)	0.16 (.02)	4.63 (.66)	4.73	1.45 (.31)	0 (.00)
3	17.75	8.93 (.50)	0.47 (.03)	14.79	6.65 (.45)	0.25 (.02)	6.99	2 (.29)	0.16 (.02)	4.83 (.69)	5.03	1.3 (.26)	-0.05 (-.01)
4	17.62	8.27 (.47)	0.53 (.03)	14.79	6.2 (.42)	0.35 (.02)	7.11	1.88 (.26)	0.12 (.02)	5.11 (.72)	5.28	1.2 (.23)	-0.1 (-.02)
5	17.42	7.73 (.44)	0.67 (.04)	14.79	5.85 (.40)	0.4 (.03)	7.19	1.72 (.24)	0.16 (.02)	5.31 (.74)	5.58	1.15 (.21)	-0.15 (-.03)
6	16.95	7.13 (.42)	0.8 (.05)	14.69	5.5 (.37)	0.45 (.03)	7.35	1.68 (.23)	0.16 (.02)	5.51 (.75)	5.78	1.05 (.18)	-0.15 (-.03)
7	16.29	6.53 (.40)	0.87 (.05)	14.74	5.15 (.35)	0.55 (.04)	7.55	1.52 (.20)	0.24 (.03)	5.79 (.77)	5.88	1 (.17)	-0.25 (-.04)
8	15.62	5.73 (.37)	1 (.06)	14.89	4.7 (.32)	0.7 (.05)	7.83	1.36 (.17)	0.32 (.04)	6.15 (.79)	5.98	0.9 (.15)	-0.4 (-.07)
9	15.42	4.8 (.31)	1.13 (.07)	15.39	4.1 (.27)	0.9 (.06)	7.87	1.2 (.15)	0.44 (.06)	6.23 (.79)	6.73	0.8 (.12)	-0.75 (-.11)
inflation	14.82			13.90			6.03				5.43		

Notes. The Table reports the annualized proportional wage changes at each decile of the distribution of wages and the contribution due to ex-ante contingent payments (SM), changes in the distribution of the observables (z) and ex-ante non-contingent payments (NSM). In brackets I report the contribution of each component to total change. The table also reports the price inflation rate calculated as the annualized proportional growth in the consumer price index over each interval.

Table 4b  
Decomposing proportional changes in nominal wages  
Ex-ante annualized changes (x 100)  
Females

Deciles	77-80			80-84			84-89			89-93		
	Total	SM	NSM	Total	SM	NSM	Total	SM	NSM	Total	SM	NSM
1	28.55	20.07 (.70)	3.33 (.12)	15.14	10.9 (.72)	4.44 (.29)	9.47	3.32 (.35)	4.19 (.44)	0.23	2 (8.70)	-2.62 (-11.39)
2	23.09	14.6 (.63)	1.6 (.07)	14.99	9.15 (.61)	6.24 (.42)	8.31	2.76 (.33)	4.63 (.56)	2.93	1.7 (.58)	0.88 (.30)
3	21.49	12.4 (.58)	1.33 (.06)	14.89	8.2 (.55)	6.94 (.47)	7.95	2.44 (.31)	4.95 (.62)	3.88	1.5 (.39)	2.18 (.56)
4	20.69	11 (.53)	1.4 (.07)	14.74	7.5 (.51)	7.39 (.50)	7.95	2.24 (.28)	5.31 (.67)	4.43	1.35 (.30)	2.93 (.66)
5	20.09	9.93 (.49)	1.33 (.07)	14.64	6.85 (.47)	7.84 (.54)	7.87	2.08 (.26)	5.51 (.70)	4.98	1.25 (.25)	3.58 (.72)
6	19.62	8.93 (.46)	1.33 (.07)	14.54	6.3 (.43)	8.24 (.57)	7.83	1.92 (.25)	5.67 (.72)	5.43	1.2 (.22)	4.13 (.76)
7	19.22	8 (.42)	1.2 (.06)	14.39	5.8 (.40)	8.64 (.60)	7.75	1.76 (.23)	5.83 (.75)	5.88	1.15 (.20)	4.63 (.79)
8	18.69	6.93 (.37)	1.33 (.07)	14.14	5.25 (.37)	9.04 (.64)	7.75	1.6 (.21)	6.03 (.78)	6.28	1.05 (.17)	5.13 (.82)
9	17.75	5.67 (.32)	1.47 (.08)	13.79	4.5 (.33)	9.59 (.70)	7.75	1.32 (.17)	6.35 (.82)	6.68	0.95 (.14)	5.58 (.84)
<u>inflation</u>	14.82			13.90			6.03			5.43		

Notes. See notes to Table 4a.

Table 5a  
Decomposing the changes in wage inequality  
Ex-ante annualized changes (x 100)  
Males

Measures of inequality	77-80			80-84			84-89			89-93						
	Total	SM	z	NSM	Total	SM	z	NSM	Total	SM	z	NSM				
<u>90-10</u>	-2.40	-6.87 (2.86)	0.80 (-.33)	3.67 (-1.53)	-0.35	-4.50 (12.86)	0.70 (-2.00)	3.45 (-9.86)	0.76	-1.28 (-1.68)	0.20 (.26)	1.84 (2.42)	2.55	-0.80 (-.31)	-0.85 (-.33)	4.20 (1.65)
<u>75-25</u>	-1.87	-3.27 (1.75)	0.53 (-.29)	0.87 (-.46)	-0.05	-2.05 (41.00)	0.40 (-8.00)	1.60 (-32.00)	0.72	-0.64 (-.89)	0.12 (.17)	1.24 (1.72)	1.05	-0.40 (-.38)	-0.25 (-.24)	1.70 (1.62)
<u>10-50</u>	0.40	3.93 (9.83)	-0.33 (-.83)	-3.20 (-8.00)	0.95	2.75 (2.89)	-0.20 (-.21)	-1.60 (-1.68)	-0.08	0.76 (-9.50)	0.08 (-1.00)	-0.92 (11.50)	-1.40	0.45 (-.32)	0.25 (-.18)	-2.10 (1.50)
<u>25-50</u>	0.40	1.67 (4.17)	-0.27 (-.67)	-1.00 (-2.50)	0.00	1.10	-0.20	-0.90	-0.20	0.36 (-1.80)	0.00 (.00)	-0.56 (2.80)	-0.70	0.20 (-.29)	0.10 (-.14)	-1.00 (1.43)
<u>75-50</u>	-1.47	-1.60 (1.09)	0.27 (-.18)	-0.13 (.09)	-0.05	-0.95 (19.00)	0.20 (-4.00)	0.70 (-14.00)	0.52	-0.28 (-.54)	0.12 (.23)	0.68 (1.31)	0.35	-0.20 (-.57)	-0.15 (-.43)	0.70 (2.00)
<u>90-50</u>	-2.00	-2.93 (1.47)	0.47 (-.23)	0.47 (-.23)	0.60	-1.75 (-2.92)	0.50 (.83)	1.85 (3.08)	0.68	-0.52 (-.76)	0.28 (.41)	0.92 (1.35)	1.15	-0.35 (-.30)	-0.60 (-.52)	2.10 (1.83)

Notes. The table provides the contribution of the ex-ante contingent payments (SM), the observable characteristics (z) and the residual ex-ante non-contingent component (NSM) in explaining changes in different measures of wage inequality. 90-10 is the difference between the 90<sup>th</sup> percentile and the 10<sup>th</sup> decile of the log wage distribution. Other measures are defined similarly. Below each number, giving the annualized change, the proportion explained by each component is reported in brackets.

Table 5b  
Decomposing the changes in wage inequality  
Ex-ante annualized changes (x 100)  
Females

Measures of inequality	77-80			80-84			84-89			89-93						
	Total	SM	z	NSM	Total	SM	z	NSM	Total	SM	z	NSM				
<u>90-10</u>	-10.80	-14.40 (1.33)	-1.87 (.17)	5.47 (-.51)	-1.35	-6.40 (4.74)	-0.10 (.07)	5.15 (-3.81)	-1.72	-2.00 (1.16)	-1.88 (1.09)	2.16 (-1.26)	6.45	-1.05 (-.16)	-0.70 (-.11)	8.20 (1.27)
<u>75-25</u>	-3.20	-6.00 (1.87)	-0.07 (.02)	2.87 (-.90)	-0.65	-3.10 (4.77)	0.25 (-.38)	2.20 (-3.38)	-0.32	-0.92 (2.87)	-0.52 (1.63)	1.12 (-3.50)	2.60	-0.50 (-.19)	-0.15 (-.06)	3.25 (1.25)
<u>10-50</u>	8.47	10.13 (1.20)	2.00 (.24)	-3.67 (-.43)	0.50	4.05 (8.10)	-0.15 (-.30)	-3.40 (-6.80)	1.60	1.24 (.78)	1.68 (1.05)	-1.32 (-.83)	-4.75	0.75 (-.16)	0.70 (-.15)	-6.20 (1.31)
<u>25-50</u>	2.07	3.47 (1.68)	0.00 (.00)	-1.40 (-.68)	0.30	1.75 (5.83)	-0.25 (-.83)	-1.20 (-4.00)	0.20	0.52 (2.60)	0.40 (2.00)	-0.72 (-3.60)	-1.50	0.30 (-.20)	0.15 (-.10)	-1.95 (1.30)
<u>75-50</u>	-1.13	-2.53 (2.24)	-0.07 (.06)	1.47 (-1.29)	-0.35	-1.35 (3.86)	0.00 (.00)	1.00 (-2.86)	-0.12	-0.40 (3.33)	-0.12 (3.33)	0.40 (-3.33)	1.10	-0.20 (-.18)	0.00 (.00)	1.30 (1.18)
<u>90-50</u>	-2.33	-4.27 (1.83)	0.13 (-.06)	1.80 (-.77)	-0.85	-2.35 (2.76)	-0.25 (.29)	1.75 (-2.06)	-0.12	-0.76 (6.33)	-0.20 (1.67)	0.84 (-7.00)	1.70	-0.30 (-.18)	0.00 (.00)	2.00 (1.18)

Notes. See notes to Table 5a.

Table 6a  
Elasticity of non-contingent wage increases with respect to contingent wage increases  
Dependent variable: ex-ante non-contingent wage increases

Variables	Males										
	1	2	3	4	5	6	7	8	9	10	11
Contingent increase		-.635	-1.400	-.118	1.266	-1.095	-.985	-.061	1.615	-.520	.699
		(.121)	(1.030)	(.144)	(.687)	(.387)	(.934)	(.156)	(.647)	(.599)	(.989)
(Contingent increase) <sup>2</sup>			5.102		-7.539		-.578		-9.061		-4.944
			(6.477)		(3.356)		(3.934)		(3.105)		(2.748)
<u>period dummies</u>											
80-84	.001	-.011	-.010	-.001	.003	-.018	-.018	.000	.006	.015	.018
	(.000)	(.002)	(.001)	(.003)	(.004)	(.013)	(.012)	(.003)	(.004)	(.022)	(.018)
84-89	-.031	-.069	-.084	-.038	-.001	-.116	-.114	-.035	.010	-.043	.004
	(.000)	(.007)	(.022)	(.009)	(.021)	(.038)	(.044)	(.009)	(.020)	(.066)	(.068)
89-93	-.039	-.082	-.100	-.047	-.003	-.145	-.143	-.043	.010	-.079	-.023
	(.000)	(.008)	(.027)	(.010)	(.025)	(.041)	(.050)	(.010)	(.024)	(.072)	(.076)
(pct)				.048	.050	-.002	-.005	.148	.170	.211	.251
				(.023)	(.016)	(.044)	(.041)	(.077)	(.062)	(.154)	(.134)
(pct) <sup>2</sup>				-.017	-.003	-.048	-.043	-.245	-.273	-.414	-.467
				(.022)	(.007)	(.014)	(.027)	(.141)	(.117)	(.224)	(.192)
(pct) <sup>3</sup>								.149	.179	.228	.279
								(.081)	(.074)	(.134)	(.121)
<u>(pct)* period dummies</u>											
80-84					-.063	-.060				-.218	-.172
					(.012)	(.026)				(.036)	(.028)
84-89					.004	.008				-.210	-.206
					(.036)	(.039)				(.127)	(.099)
89-93					.033	.037				-.069	-.072
					(.039)	(.039)				(.133)	(.106)
<u>(pct)<sup>2</sup>* period dummies</u>											
80-84					.096	.093				.421	.345
					(.001)	(.022)				(.045)	(.041)
84-89					.053	.048				.447	.435
					(.012)	(.028)				(.185)	(.143)
89-93					.051	.047				.173	.169
					(.012)	(.029)				(.192)	(.150)
<u>(pct)<sup>3</sup>* period dummies</u>											
80-84										-.214	-.182
										(.029)	(.021)
84-89										-.249	-.259
										(.110)	(.090)
89-93										-.069	-.085
										(.115)	(.095)
constant	.084	.134	.161	.075	.010	.186	.182	.059	-.022	.100	.021
	(.000)	(.010)	(.038)	(.017)	(.038)	(.048)	(.064)	(.023)	(.040)	(.083)	(.094)
R2	.757	.903	.915	.959	.968	.992	.992	.968	.981	.997	.997

**Notes:** The table reports the results of a regression of nominal ex-ante non-contingent wage changes on nominal ex-ante contingent ones at each percentile over the whole period of observation. Top and bottom five percentiles are excluded. Both wage changes are expressed in proportional terms, multiplied by 100 and annualized. *Pct* is the percentile variable divided by 100 (.06 for the sixth percentile, .07 for the seventh, etc.) Standard errors in parenthesis are heteroskedasticity-consistent and consistent with unrestricted auto correlation within each time period. Number of observations 360.

Table 6b  
Elasticity of non-contingent wage increases with respect to contingent wage increases  
Dependent variable: ex-ante non-contingent wage increases

Variables	Females										
	1	2	3	4	5	6	7	8	9	10	11
Contingent increase		-.524	-1.217	-.094	.254	-.445	-1.193	-.063	.281	-.649	-1.046
		(.117)	(.511)	(.174)	(.400)	(.138)	(.844)	(.188)	(.405)	(.093)	(.471)
(Contingent increase) <sup>2</sup>			2.908		-1.219		2.083		-1.204		.920
			(1.939)		(.876)		(2.162)		(.901)		(.994)
<u>period dummies</u>											
80-84	-.010	-.029	-.031	-.013	-.010	-.047	-.054	-.012	-.009	-.088	-.097
	(.000)	(.004)	(.003)	(.006)	(.008)	(.014)	(.014)	(.007)	(.008)	(.012)	(.016)
84-89	-.032	-.077	-.099	-.040	-.026	-.083	-.126	-.037	-.023	-.137	-.170
	(.000)	(.010)	(.019)	(.015)	(.024)	(.025)	(.057)	(.016)	(.024)	(.021)	(.044)
89-93	-.056	-.105	-.132	-.065	-.048	-.163	-.215	-.062	-.046	-.238	-.275
	(.000)	(.011)	(.022)	(.016)	(.026)	(.027)	(.068)	(.018)	(.027)	(.022)	(.051)
(pct)				.110	.112	-.016	-.031	.226	.228	-.237	-.292
				(.059)	(.059)	(.047)	(.039)	(.121)	(.121)	(.069)	(.091)
(pct) <sup>2</sup>				-.058	-.053	.013	-.010	-.323	-.317	.408	.471
				(.035)	(.032)	(.025)	(.012)	(.180)	(.178)	(.105)	(.117)
(pct) <sup>3</sup>								.173	.173	-.236	-.276
								(.096)	(.096)	(.058)	(.070)
<u>(pct)* period dummies</u>											
80-84					.067	.042				.309	.306
					(.028)	(.015)				(.043)	(.017)
84-89					.036	.027				.261	.288
					(.042)	(.012)				(.061)	(.057)
89-93					.212	.210				.603	.640
					(.043)	(.021)				(.064)	(.069)
<u>(pct)<sup>2</sup>* period dummies</u>											
80-84					-.043	-.010				-.534	-.517
					(.017)	(.026)				(.067)	(.015)
84-89					-.017	.014				-.439	-.460
					(.023)	(.022)				(.094)	(.067)
89-93					-.130	-.099				-.935	-.971
					(.024)	(.021)				(.098)	(.084)
<u>(pct)<sup>3</sup>* period dummies</u>											
80-84										.307	.300
										(.037)	(.010)
84-89										.256	.272
										(.052)	(.041)
89-93										.509	.534
										(.054)	(.052)
constant	.086	.142	.178	.059	.035	.138	.205	.043	.019	.198	.245
	(.000)	(.013)	(.029)	(.037)	(.051)	(.030)	(.085)	(.046)	(.058)	(.024)	(.062)
R2	.619	.823	.854	.939	.942	.991	.946	.949	.997	.997	

Notes. See notes to Table 6a.

Table 6c  
Elasticity of non-contingent wage increases with respect to contingent wage increases  
Dependent variable: ex-ante non-contingent wage increases  
Males and females

Variables	1	2	3	4	5	6	7	8	9	10
Contingent increase	-.080 (.150)	.320 (.410)	-.480 (.110)	(1.130) .450	-.540 (.100)	-1.420 (.360)	-.060 (.160)	.380 (.400)	-.630 (.020)	-.750 (.220)
(Contingent increase) <sup>2</sup>		-1.520 (1.050)		(2.960) 1.920		-2.630 (.980)		-1.650 (.990)		.270 (.500)
<u>period dummies</u>										
80-84	-.010 (.000)	.000 (.010)	-.020 (.000)	(.020) .000	-.060 (.010)	-.060 (.000)	-.010 (.000)	.000 (.010)	-.090 (.000)	-.090 (.010)
84-89	-.040 (.010)	-.020 (.020)	-.070 (.010)	(.090) .010	-.100 (.020)	-.140 (.020)	-.040 (.010)	-.020 (.020)	-.130 (.000)	-.140 (.020)
89-93	-.050 (.010)	-.040 (.020)	-.090 (.010)	(.110) .020	-.180 (.020)	-.230 (.030)	-.050 (.010)	-.030 (.020)	-.230 (.000)	-.240 (.020)
(pct)	.080 (.040)	.080 (.040)	.000 (.010)	(.000) .000	-.050 (.030)	-.040 (.010)	.190 (.080)	.200 (.080)	-.230 (.010)	-.240 (.030)
(pct) <sup>2</sup>	-.040 (.020)	-.030 (.020)	.130 (.010)	(.160) .020	-.030 (.020)	-.010 (.010)	-.290 (.130)	-.290 (.120)	.390 (.020)	.400 (.040)
(pct) <sup>3</sup>							.160 (.070)	.170 (.070)	-.230 (.010)	-.230 (.030)
<u>male* period dummies</u>										
77-80					-.100 (.010)	-.090 (.000)			-.140 (.000)	-.140 (.000)
80-84					-.040 (.000)	-.050 (.000)			-.040 (.000)	-.040 (.000)
84-89					-.060 (.000)	-.060 (.000)			-.060 (.000)	-.060 (.000)
(pct) * period dummies										
80-84					-.090 (.020)	-.040 (.010)			.300 (.010)	.300 (.000)
84-89					-.060 (.030)	-.030 (.000)			.250 (.010)	.260 (.020)
89-93					-.240 (.030)	-.220 (.000)			.590 (.010)	.600 (.020)
(pct) <sup>2</sup> * period dummies										
80-84					-.050 (.010)	-.010 (.010)			-.520 (.010)	-.510 (.010)
84-89					-.030 (.020)	-.020 (.010)			-.420 (.020)	-.420 (.020)
89-93					-.150 (.020)	-.100 (.010)			-.920 (.020)	-.920 (.030)
(pct) <sup>2</sup> * period dummies										
80-84									.300 (.010)	.300 (.000)
84-89									.250 (.010)	.250 (.010)
89-93									.500 (.010)	.500 (.020)



Table 6c: continued

Variables	1	2	3	4	5	6	7	8	9	10
<u>male*(pct) * period</u>										
<u>dummies</u>										
77-80					-.110	-.080			.410	.410
					(.020)	(.010)			(.010)	(.010)
80-84					-.060	-.050			-.110	-.100
					(.000)	(.000)			(.000)	(.010)
84-89					.000	-.010			-.030	-.030
					(.000)	(.010)			(.000)	(.010)
89-93					-.150	-.150			-.230	-.230
					(.000)	(.000)			(.000)	(.000)
<u>male*(pct)<sup>2</sup> * period</u>										
<u>dummies</u>										
77-80					-.100	-.060			-.760	-.750
					(.010)	(.010)			(.010)	(.000)
80-84					-.050	-.050			.170	.170
					(.000)	(.000)			(.000)	(.000)
84-89					-.010	.000			.070	.070
					(.000)	(.000)			(.000)	(.010)
89-93					-.120	-.110			.290	.290
					(.000)	(.000)			(.000)	(.000)
<u>male*(pct)<sup>3</sup> * period</u>										
<u>dummies</u>										
77-80									.430	.420
									(.010)	(.000)
80-84									-.080	-.080
									(.000)	(.000)
84-89									-.050	-.040
									(.000)	(.010)
89-93									-.120	-.120
									(.000)	(.000)
male	.000	.010			-.050	-.050	.000	.010	.060	.060
	(.010)	(.010)			(.000)	(.000)	(.010)	(.010)	(.000)	(.000)
constant	.060	.040			-.160	-.230	.050	.020	.190	.210
	(.030)	(.040)			(.020)	(.030)	(.030)	(.050)	(.000)	(.030)
R2	.802	.831	.910	.913	.990	.992	.918	.922	.997	.997

Notes. Data refer to males and females. *Male* is a dummy variable equal to one for males. Number of observations 720. See also notes to Table 6a.

Table 7a  
Decomposing the changes in nominal ages  
Ex-post annualized changes (x 100)  
Males

Deciles	SM		NSM		SM		NSM		SM		NSM	
	SM	NSM	SM	NSM	SM	NSM	SM	NSM	SM	NSM	SM	NSM
1	4.28 (.24)	13.00 (.73)	3.15 (.20)	12.40 (.79)	0.91 (.13)	5.96 (.84)	0.59 (.14)	3.40 (.81)				
2	3.62 (.20)	13.84 (.77)	2.69 (.18)	12.22 (.82)	0.81 (.12)	6.02 (.86)	0.53 (.11)	4.19 (.89)				
3	3.27 (.18)	14.18 (.80)	2.44 (.16)	12.11 (.82)	0.73 (.10)	6.12 (.88)	0.48 (.09)	4.69 (.93)				
4	3.03 (.17)	14.14 (.80)	2.27 (.15)	12.08 (.82)	0.69 (.10)	6.27 (.88)	0.44 (.08)	5.00 (.95)				
5	2.83 (.16)	13.85 (.80)	2.14 (.14)	12.12 (.82)	0.63 (.09)	6.43 (.89)	0.42 (.08)	5.22 (.94)				
6	2.61 (.15)	13.42 (.79)	2.02 (.14)	12.22 (.83)	0.62 (.08)	6.60 (.90)	0.38 (.07)	5.44 (.94)				
7	2.39 (.15)	12.98 (.80)	1.89 (.13)	12.38 (.84)	0.56 (.07)	6.77 (.90)	0.37 (.06)	5.74 (.98)				
8	2.10 (.13)	12.65 (.81)	1.72 (.12)	12.60 (.85)	0.50 (.06)	6.90 (.88)	0.33 (.06)	6.24 (1.04)				
9	1.76 (.11)	12.55 (.81)	1.50 (.10)	12.88 (.84)	0.44 (.06)	7.00 (.89)	0.29 (.04)	7.01 (1.04)				

Notes. The table reports the decomposition of total changes in inequality into contingent and ex-post non contingent wage changes. Data are obtained based on the results of specification 10 in Table 6c. In brackets I report the same quantities expressed as a proportion of the total change.

Table 7b  
Decomposing the changes in nominal ages  
Ex-post annualized changes (x 100)  
Females

Deciles	SM		NSM		SM		NSM		SM		NSM	
	SM	NSM	SM	NSM	SM	NSM	SM	NSM	SM	NSM	SM	NSM
1	7.36 (.26)	17.53 (.61)	4.00 (.26)	11.45 (.76)	1.22 (.13)	6.26 (.66)	0.73 (3.19)	-0.81 (-3.52)				
2	5.35 (.23)	16.29 (.71)	3.35 (.22)	11.87 (.79)	1.01 (.12)	6.43 (.77)	0.62 (.21)	1.47 (.50)				
3	4.55 (.21)	15.56 (.72)	3.01 (.20)	12.12 (.81)	0.89 (.11)	6.57 (.83)	0.55 (.14)	3.02 (.78)				
4	4.03 (.19)	15.20 (.73)	2.75 (.19)	12.24 (.83)	0.82 (.10)	6.67 (.84)	0.49 (.11)	4.00 (.90)				
5	3.64 (.18)	15.08 (.75)	2.51 (.17)	12.27 (.84)	0.76 (.10)	6.76 (.86)	0.46 (.09)	4.58 (.92)				
6	3.27 (.17)	15.06 (.77)	2.31 (.16)	12.27 (.84)	0.70 (.09)	6.85 (.87)	0.44 (.08)	4.93 (.91)				
7	2.93 (.15)	15.01 (.78)	2.13 (.15)	12.26 (.85)	0.65 (.08)	6.95 (.90)	0.42 (.07)	5.20 (.89)				
8	2.54 (.14)	14.79 (.79)	1.92 (.14)	12.31 (.87)	0.59 (.08)	7.06 (.91)	0.38 (.06)	5.57 (.89)				
9	2.08 (.13)	14.27 (.93)	1.65 (.11)	12.46 (.81)	0.48 (.06)	7.22 (.92)	0.35 (.05)	6.19 (.92)				

Table 8a  
 Decomposing the changes in wage inequality  
 Ex-post annualized changes (x 100)  
 Males

Measures of inequality	77-80		80-84		84-89		89-93	
	SM	NSM	SM	NSM	SM	NSM	SM	NSM
<u>90-10</u>	-2.52 (1.05)	-45 (.19)	-1.65 (4.71)	.48 (-1.37)	-47 (-.62)	1.04 (1.37)	-.29 (-.11)	3.60 (1.41)
<u>75-25</u>	-1.20 (.64)	-1.27 (.68)	-.75 (15.00)	.33 (-6.60)	-.23 (-.32)	.77 (1.07)	-.15 (-.14)	1.49 (1.42)
<u>10-50</u>	1.44 (3.60)	-.85 (-2.13)	1.01 (1.06)	.28 (.29)	.28 (-3.50)	-.47 (5.88)	.16 (-.11)	-1.82 (1.30)
<u>25-50</u>	.61 (1.53)	.21 (.53)	.40	.04	.13 (-.65)	-.37 (1.85)	.07 (-.10)	-.75 (1.07)
<u>75-50</u>	-.59 (.40)	-1.05 (.71)	-.35 (7.00)	.37 (-7.40)	-.10 (-.19)	.41 (.79)	-.07 (-.20)	.74 (2.11)
<u>90-50</u>	-1.08 (.54)	-1.30 (.65)	-.64 (-1.07)	.76 (1.27)	-.19 (-.28)	.57 (.84)	-.13 (-.11)	1.79 (1.56)

Notes. See notes to Table 7a.

Table 8b  
Decomposing the changes in wage inequality  
Ex-post annualized changes (x 100)  
Females

Measures of inequality	77-80		80-84		84-89		89-93	
	SM	NSM	SM	NSM	SM	NSM	SM	NSM
<u>90-10</u>	-5.28 (.49)	-3.27 (.30)	-2.35 (1.74)	1.01 (-.75)	-.73 (.42)	.96 (-.56)	-.38 (-.06)	7.00 (1.09)
<u>75-25</u>	-2.2 (.69)	-.94 (.29)	-1.14 (1.75)	.27 (-.42)	-.34 (1.06)	.50 (-1.56)	-.18 (-.07)	3.04 (1.17)
<u>10-50</u>	3.71 (.44)	2.45 (.29)	1.48 (2.96)	-.82 (-1.64)	.45 (.28)	-.50 (-.31)	.27 (-.06)	-5.39 (1.13)
<u>25-50</u>	1.27 (.61)	.79 (.38)	.64 (2.13)	-.26 (-.87)	.19 (.95)	-.26 (-1.30)	.11 (-.07)	-2.26 (1.51)
<u>75-50</u>	-.93 (.82)	-.15 (.13)	-.49 (1.40)	.01 (-.03)	-.15 (1.25)	.24 (-2.00)	-.07 (-.06)	.78 (.71)
<u>90-50</u>	-1.56 (.67)	-.81 (.35)	-.86 (1.01)	.19 (-.22)	-.28 (2.33)	.45 (-3.75)	-.11 (-.06)	1.61 (.95)

Notes. See notes to Table 8a.

Table 9a  
The employment effect of the SM on wage inequality  
Annualized changes (x 100)  
Males

Measures of inequality	77-80					80-84					84-89					89-93				
	.5	1	2	4		.5	1	2	4		.5	1	2	4		.5	1	2	4	
	Elasticity of substitution					Elasticity of substitution					Elasticity of substitution					Elasticity of substitution				
<u>90-10</u>	-20 (-25)	-20 (-25)	-20 (-25)	.27 (.34)		-20 (-29)	-35 (-50)	-40 (-57)	-10 (-14)		-08 (-40)	-12 (-60)	-16 (-80)	-20 (-1.00)		.00 (.00)	.00 (.00)	.00 (.00)	.00 (.00)	
<u>75-25</u>	.00 (.00)	.00 (.00)	.13 (.25)	.40 (.75)		-05 (-13)	-10 (-25)	-10 (-25)	-05 (-13)		-04 (-33)	-08 (-67)	-12 (-1.00)	-20 (-1.67)		.00 (.00)	.00 (.00)	.00 (.00)	.05 (-.20)	
<u>10-50</u>	.20 (-.61)	.27 (-.82)	.40 (-1.21)	.20 (-.61)		.25 (-1.25)	.45 (-2.25)	.65 (-3.25)	.85 (-4.25)		.08 (1.00)	.12 (1.50)	.20 (2.50)	.32 (4.00)		.05 (.20)	.05 (.20)	.05 (.20)	.10 (.40)	
<u>25-50</u>	.00 (.00)	.00 (.00)	-.07 (.26)	-.33 (1.22)		.05 (-.25)	.10 (-.50)	.10 (-.50)	.15 (-.75)		.04 (.00)	.04 (.00)	.08 (.14)	.16 (.43)		.05 (.50)	.05 (.50)	.05 (.50)	.05 (.50)	
<u>75-50</u>	.00 (.00)	.00 (.00)	.07 (.26)	.07 (.26)		.00 (.00)	.00 (.00)	.00 (.00)	.10 (.50)		.00 (.00)	-.04 (-.33)	-.04 (-.33)	-.04 (-.33)		.05 (-.33)	.05 (-.33)	.05 (-.33)	.10 (-.67)	
<u>90-50</u>	.00 (.00)	.07 (.15)	.20 (.43)	.47 (1.00)		.05 (.10)	.10 (.20)	.25 (.50)	.75 (1.50)		.00 (.00)	.00 (.00)	.04 (.14)	.12 (.43)		.05 (-.08)	.05 (-.08)	.05 (-.08)	.10 (-.17)	

Notes. The table provides the estimated impact of the employment effect of the ex-post contingent payments to changes in wage inequality for different measures of the elasticity of substitution. See main text for details of calculations. In brackets I report the total change as a proportion of the actual compositional change over the period of observation (see Tables 5a-5b).

Table 9b  
The employment effect of the SM on wage inequality  
Annualized changes (x 100)  
Females

Measures of inequality	77-80					80-84					84-89					89-93				
	.5	1	2	4		.5	1	2	4		.5	1	2	4		.5	1	2	4	
	Elasticity of substitution					Elasticity of substitution					Elasticity of substitution					Elasticity of substitution				
<u>90-10</u>	-2.53 (1.35)	-4.20 (2.25)	-5.47 (2.93)	-5.93 (3.17)		-1.20 (12.00)	-1.85 (18.50)	-2.45 (24.50)	-2.70 (27.00)		-0.56 (.30)	-1.00 (.53)	-1.60 (.85)	-2.40 (1.28)		-0.10 (.14)	-0.20 (.29)	-0.40 (.57)	-0.75 (1.07)	
<u>75-25</u>	-0.60 (8.57)	-0.87 (12.43)	-1.20 (17.14)	-1.13 (16.14)		-0.25 (-1.00)	-0.45 (-1.80)	-0.60 (-2.40)	-0.75 (-3.00)		-0.20 (.38)	-0.28 (.54)	-0.48 (.92)	-0.76 (1.46)		-0.05 (.33)	-0.05 (.33)	-0.10 (.67)	-0.20 (1.33)	
<u>10-50</u>	2.53 (1.27)	4.13 (2.07)	5.53 (2.77)	6.33 (3.17)		1.10 (-7.33)	1.70 (-11.33)	2.25 (-15.00)	2.60 (-17.33)		.44 (.26)	.80 (.48)	1.32 (.79)	1.96 (1.17)		.10 (.14)	.20 (.29)	.35 (.50)	.60 (.86)	
<u>25-50</u>	.47	.67	1.00	1.27		.20 (-.80)	.35 (-1.40)	.45 (-1.80)	.55 (-2.20)		.12 (.30)	.16 (.40)	.32 (.80)	.44 (1.10)		.05 (.33)	.05 (.33)	.05 (.33)	.10 (.67)	
<u>75-50</u>	-0.13 (1.86)	-0.20 (2.86)	-0.20 (2.86)	.13 (-1.86)		-0.05	-0.10	-0.15	-0.20		-0.08 (.67)	-0.12 (1.00)	-0.16 (1.33)	-0.32 (2.67)		.00	.00	-0.05	-0.10	
<u>90-50</u>	.00 (.00)	-0.07 (-.54)	.07 (.54)	.40 (3.08)		-0.10 (.40)	-0.15 (.60)	-0.20 (.80)	-0.10 (.40)		-0.12 (.60)	-0.20 (1.00)	-0.28 (1.40)	-0.44 (2.20)		.00	.00	-0.05	-0.15	

Notes. See notes to Table 8a.

Table A1  
THE STRUCTURE OF THE TYPICAL COMPENSATION PACKAGE

Monthly contractual minimum +cumulated contingent payments =monthly contractual wage +cumulated non-contingent payments (seniority increases, superminima,...) = monthly wage *13 =TOTAL ANNUAL COMPENSATION - income taxes -social contributions +family allowances =TAKE HOME ANNUAL PAY
---

Notes: Adapted for Erickson and Ichino (1992)

Table A2  
The evolution of the *Scala Mobile* mechanism

<i>Time Period</i>	<i>Modifications to SM</i>
<b>1977-1982</b>	Quarterly adjustment of wages to inflation. Universal flat nominal increases
<b>1983-1985</b>	Value of SM point lowered
<b>1986-1991</b>	Adjustment every 6 months rather than every 3 75% coverage of indexed minimum wage, 25% coverage of residual
<b>1991</b>	SM abolished
<b>1993</b>	Across the board lump sum for lack of protection from past inflation



Table A3  
The Scala Mobile from 1977 to 1982

Quarter ending in		Price index	Rounded price index	Change in price index	Nominal increase in Monthly wage (a)	
		(1)	(2)	(3)	(4)	
Year	Month				Private Sector	Public sector
77	1	143.27	143	9	21.5	
77	4	148.93	149	6	14.33	10.29
77	7	154.21	154	5	11.94	
77	10	157.7	158	4	9.56	12.93
78	1	161.91	162	4	9.56	
78	4	167.09	167	5	11.94	14.75
78	7	173.44	173	6	14.33	
78	10	178.02	178	5	11.94	16.89
79	1	183.59	184	6	14.33	
79	4	192.38	192	8	19.11	19.53
79	7	198.40	198	6	14.33	
79	10	205.95	206	8	19.11	22.87
80	1	214.30	214	8		19.11
80	4	226.07	226	12		28.67
80	7	234.38	234	8		19.11
80	10	243.86	244	10		23.89
81	1	255.39	255	11		26.28
81	4	269.25	269	14		33.45
81	7	279.17	279	10		23.89
81	10	287.75	288	9		21.50
82	1	297.33	297	9		21.50
82	4	309.30	309	12		28.67
82	7	322.35	322	13		31.06
82	10	334.83	335	13		31.06

**Notes.** The Scala Mobile granted a flat in increase in nominal wages for each percentage point increase in a special consumer price index (*Indice sindacale*) rounded to the nearest integer. The system was universal and implied the same quarter adjustment for all employees, with the exception of those in the public sector where the features of the system were slightly different until 1979. In 1980 the two systems were unified. This table reports the predicted increase due to contingent payments from 1977 to 1982. Column (1) reports the quarterly price index used for computations (August-October 1974=100). Column (2) reports the rounded value of the price index. Changes in rounded price index are computed in column (3). Column (4) reports the implied contingent increase, which is obtained as the product of the points triggered every quarter and the Scala Mobile point of 2,389 lit.

(a) Figures are in 1,000 lit and refer to gross monthly wages.

Table A4  
The Scala Mobile from 1983 to 1985

Quarter ending in		Price index	Rounded price index	Change in price index	Nominal increase in monthly wage(a)
Year Month		(1)	(2)	(3)	(4)
83	1	104.08	104	4	27.2
83	4	107.14	107	3	20.4
83	7	109.82	109	2	13.6
83	10	112.41	112	3	20.4
84	1	116.91	116	2 (b)	13.6
84	4	120.45	120	2 (b)	13.6
84	7	122.87	122	2	13.6
84	10	124.11	124	2	6.8
85	1	126.89	126	2	13.6
85	4	130.87	130	4	20.4
85	7	133.24	133	3 (c)	20.4
85	10	134.50	134	1	6.80

**Notes.** See notes to Table 3. The system was adjourned starting from 1983. Price increases were computed based on a price index with base August-October 1982=100 (1) and the SM point (the product of columns (3) and (4)) was raised to 6,800 lit.

(a) Figures are in 1,000 lit and refer to gross monthly wages.

(b) Caps on price increase were imposed.

(c) Only two points were awarded in July 1985, but an extra point triggered in August as a compensation for failed coverage in the past.

Table A5  
The Scala Mobile from 1986 to 1991

Year	Semester ending		Price index (1)	Minimum wage (a) (2)	Proportional price change (3)
	Month				
86	4		137.64	595.8	2.72
86	10		141.63	613.0	2.90
87	4		145.33	629.0	2.61
87	10		149.09	645.3	2.59
88	4		153.02	662.3	2.64
88	10		157.05	679.8	2.63
89	4		162.43	703.1	3.43
89	10		167.31	724.2	3.00
90	4		173.47	750.8	3.68
90	10		179.28	776.0	3.35
91	4		187.06	809.7	4.34
91	10		193.63	838.1	3.51
92 (a)	4		198.36	858.6	2.44
92 (a)	10		201.88	873.8	1.77
93 (a)	4		205.22	888.3	1.65
93 (a) (b)	10		210.91	912.9	2.77

Notes. In 1986 a new system was introduced which established that the adjustment of wages due to changes in the price level was to take place every six months rather than every three. Price changes were evaluated on the base on a six-month price index with base August-October 1982=100, reported in column (1). The system became quasi-proportional, guaranteeing a 100% coverage against inflation for a given minimum wage, plus a 25% coverage for the residual difference between the contractual minimum plus accumulated SM payments and the minimum wage. The minimum wage, set to lit 580.000 for a start and indexed itself, is reported in column (2). Wages below the minim wage were fully indexed. See text for details.

(a) Scala Mobile abolished.

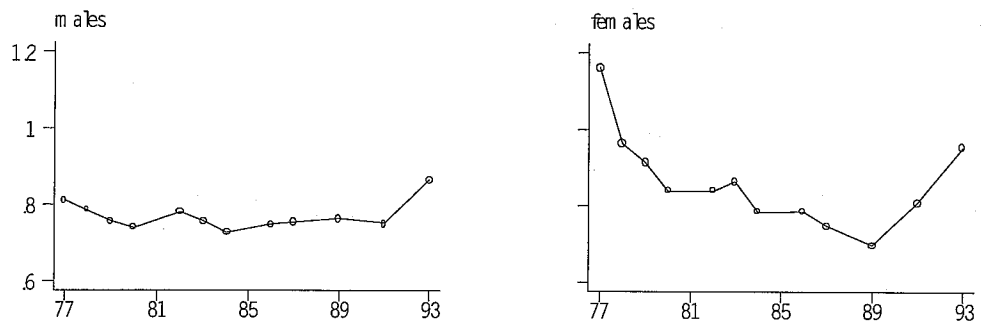
(b) Workers were awarded a flat increase of lit 20,000 as a compensation for failed coverage in the past.

Table A6  
The composition of gross labor income by decile – employees only

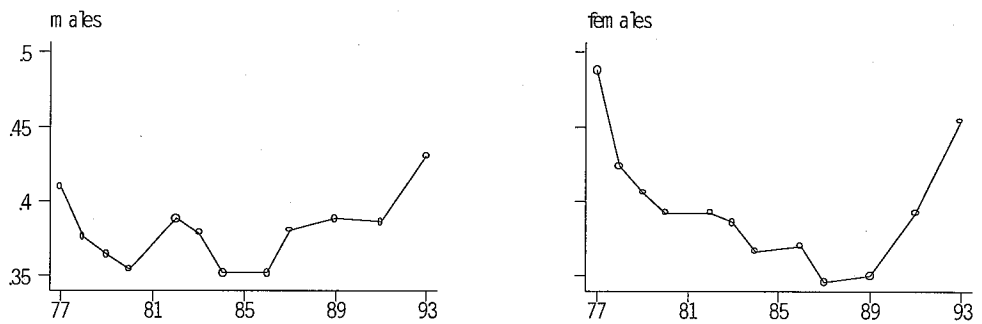
Decile	Employees' social security contributions	Personal income tax	Family allowances	Net labor income plus family allowances
	(1)	(2)	(3)	(4)
1	7.7	3.7	5.4	94.0
2	8.6	10.2	4.6	85.8
3	8.6	12.7	2.1	80.8
4	8.6	13.8	2.1	78.3
5	8.8	14.6	1.5	78.1
6	8.7	15.5	1.1	76.9
7	9.3	15.7	1.0	76.0
8	9.1	16.7	0.5	74.7
9	8.9	17.4	0.5	74.2
10	8.7	21.2	0.1	70.2
Total	8.7	14.1	1.9	79.1

Notes. The table is derived from Di Biase and Di Marco (1995), Table 5, p. 393. Data refer to 1989 and are computed on SHIW data. Column (4) is obtained as  $100 - (1) - (2) + (3)$ .

Figure 1



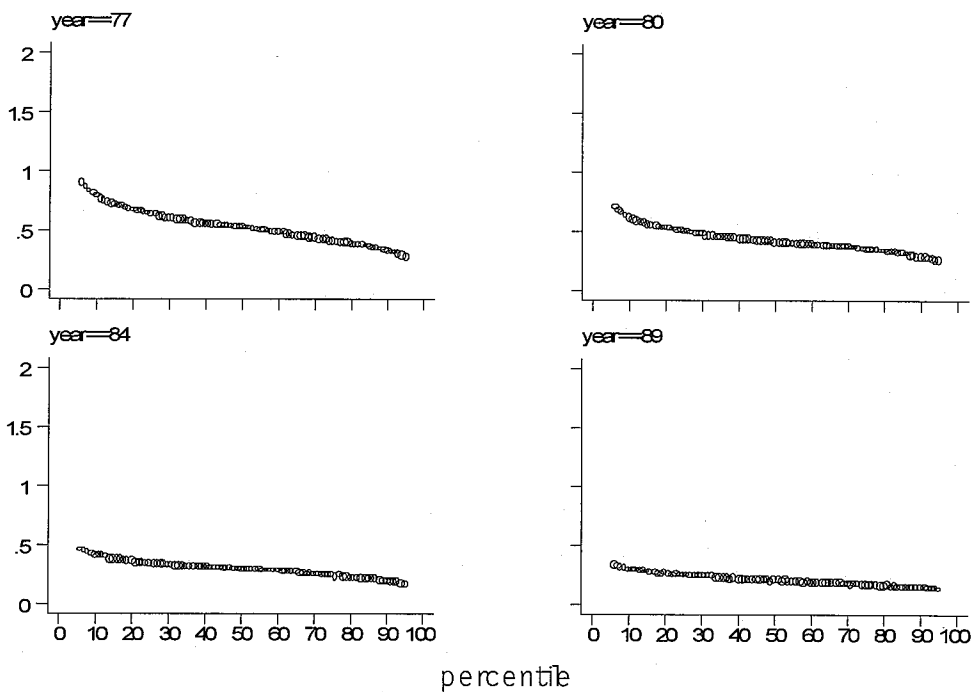
### 9th-1st decile log wages



### 3rd-1st quartile log wages

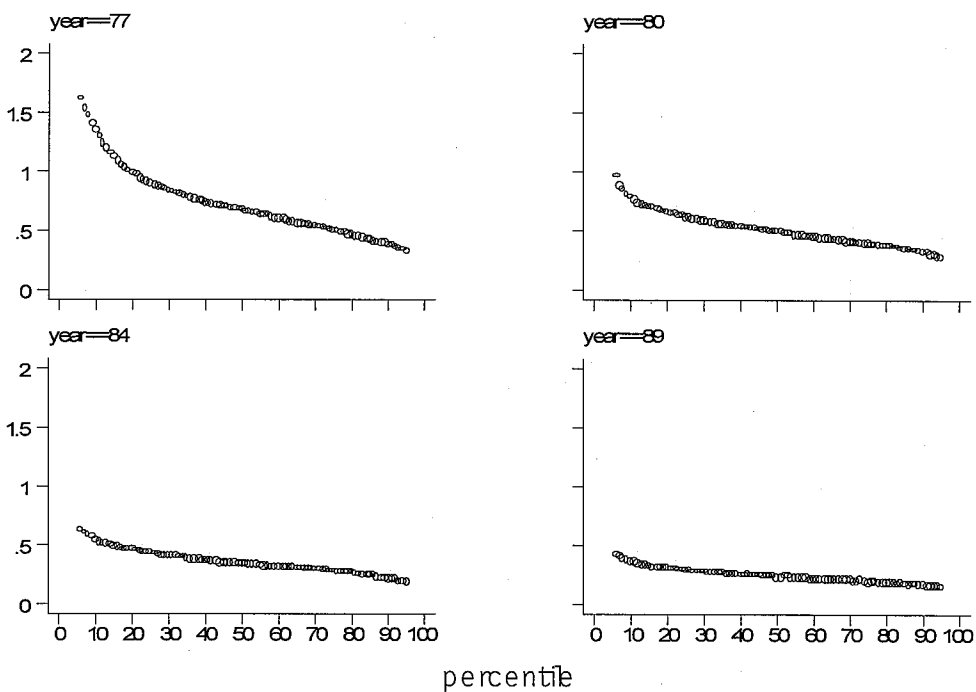
The figure reports the log ratio of the extreme deciles and quartiles of the kernelized distribution of wages. Source: SHIW.

Figure 2  
Males



Scala Mobile coverage at different percentiles

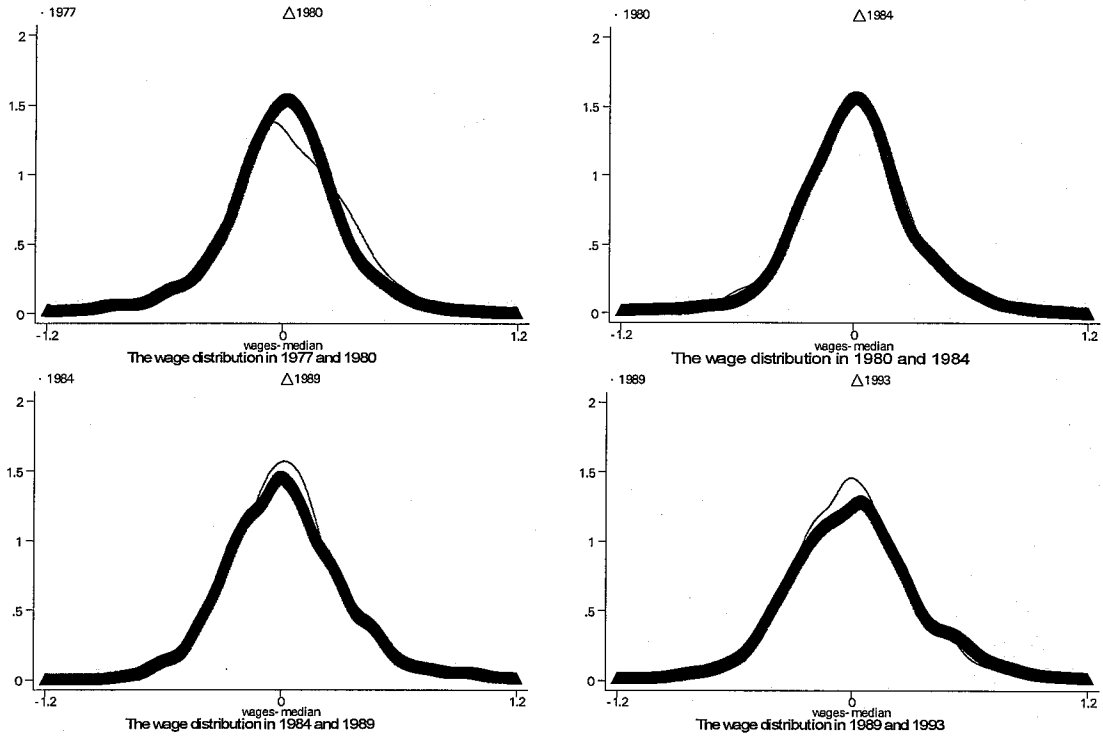
Females



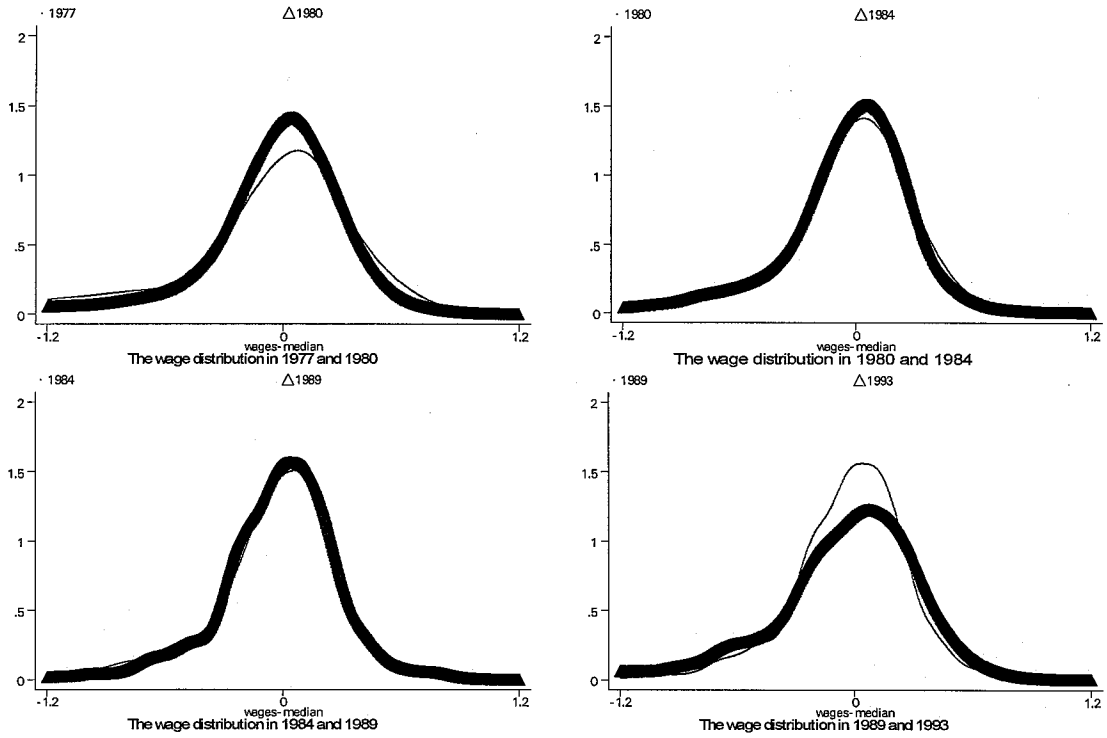
Scala Mobile coverage at different percentiles

Notes. Coverage is defined as the ratio between the ex-ante rate of growth in nominal wages due to the *Scala Mobile* and the growth in prices.

Figure 3  
The evolution of the wage distribution  
Males

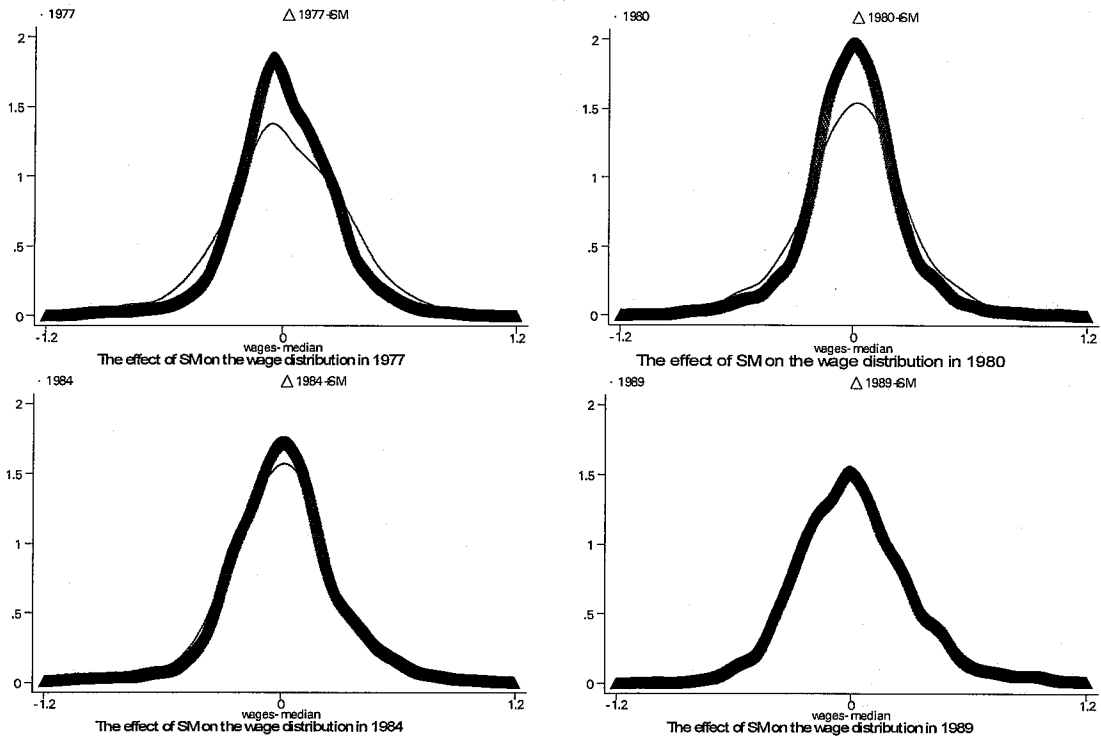


Females

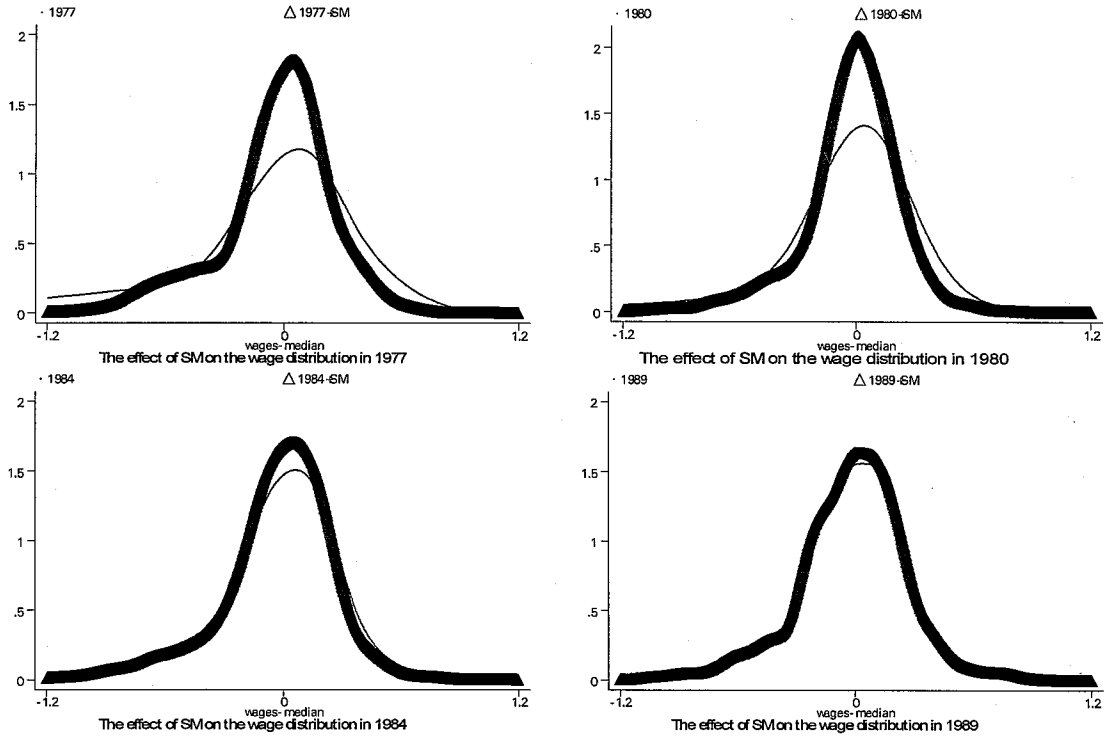


Notes. The figure reports kernel density estimates of the wage distribution at different points in time. The distributions are standardized to the median.

Figure 4  
The ex-ante effect of Scala Mobile on the wage distribution  
Males



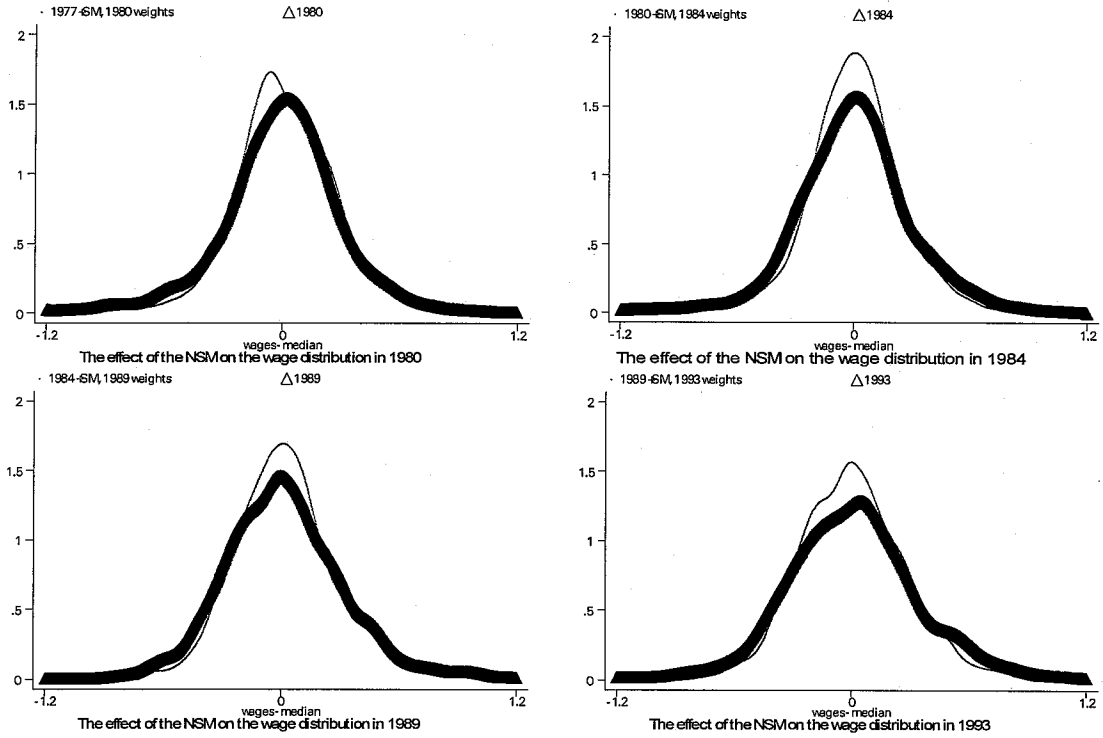
Females



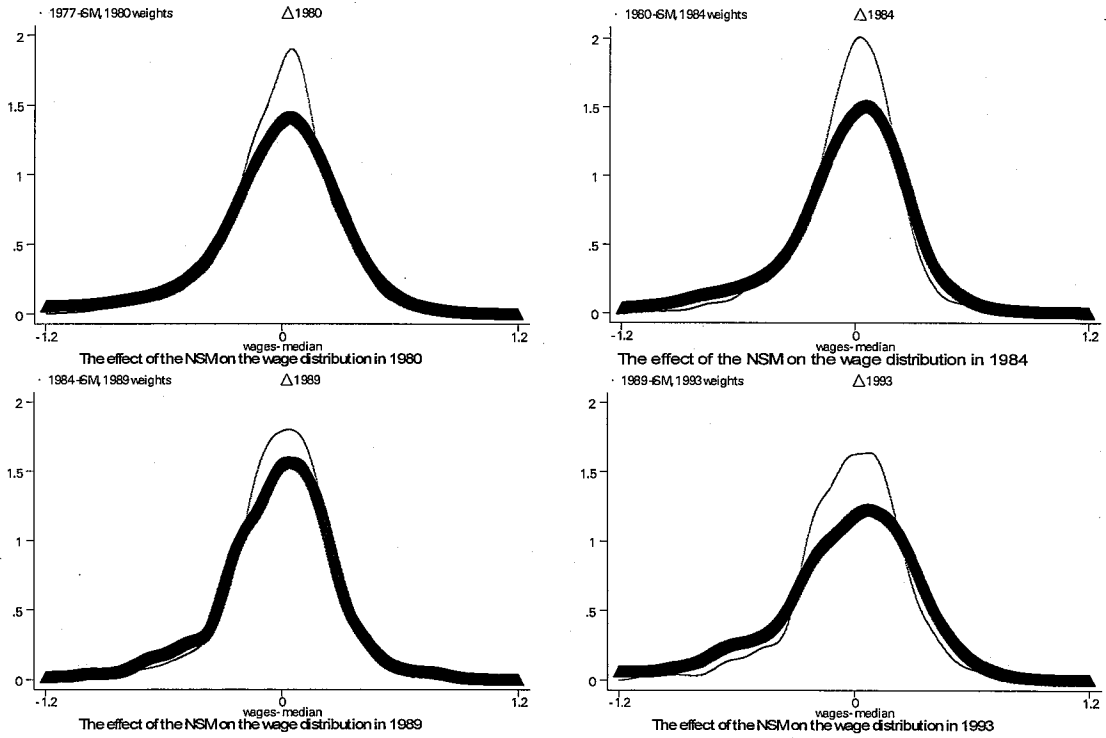
Notes. In each panel the figure reports kernel density estimates of the wage distribution at some initial time  $t$  and the distribution obtained by adding up the escalated wage increases ( $w_*$ ). The distributions are standardized to the median.



Figure 5  
The ex-ante effect of the non-escalated wage increases on the wage distribution  
Males

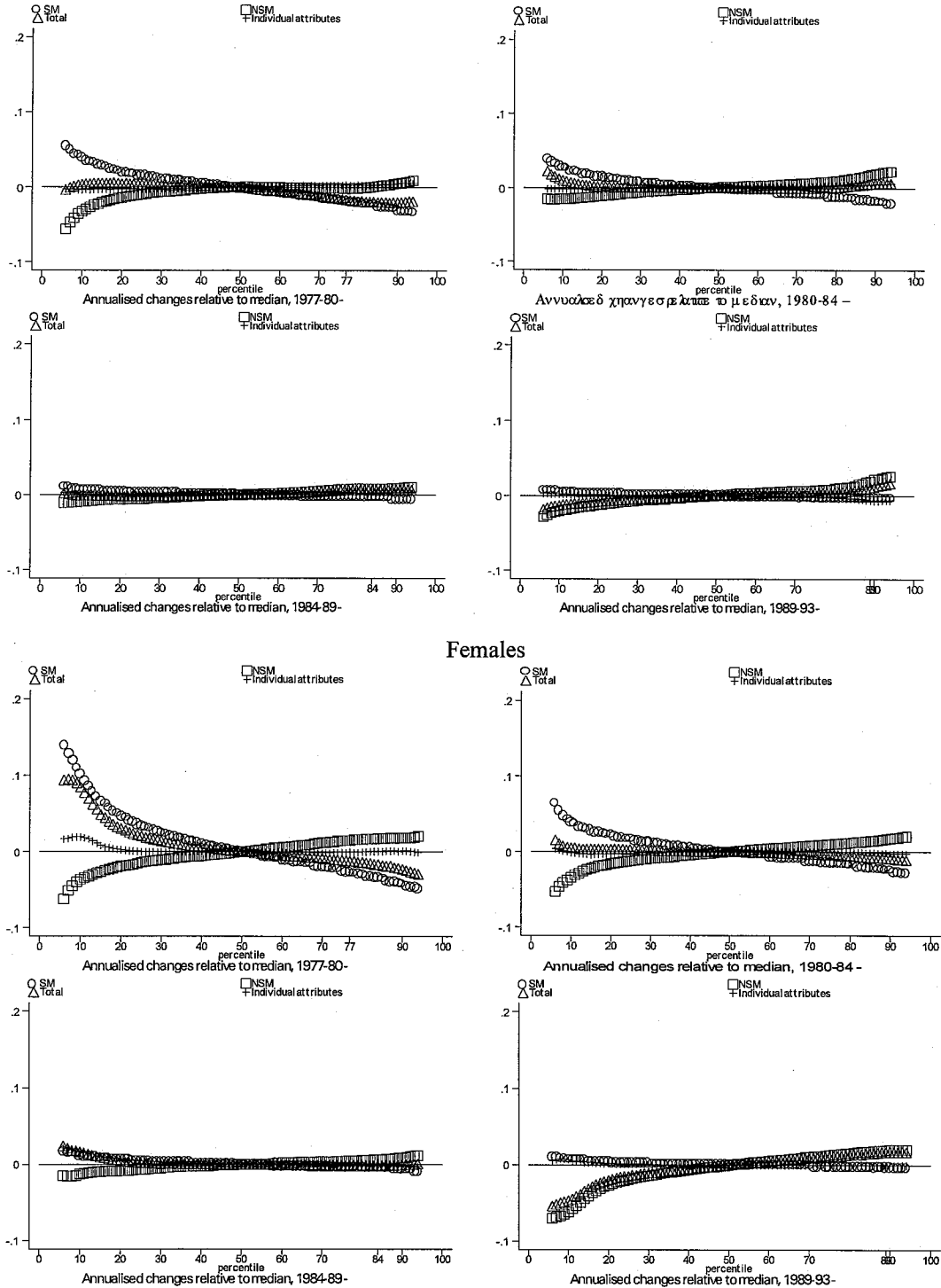


Females



Notes. In each panel the figure reports kernel density estimates of the wage distribution at some initial time  $t$  plus escalated wage increases ( $w_+$ ) and the final distribution at time  $s$ . The distributions are standardized to the median.

Figure 6  
Decomposing changes in the distribution of wages at each percentile: ex-ante effects  
Males



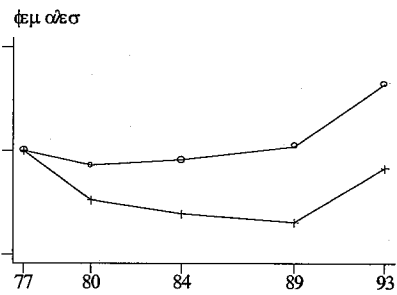
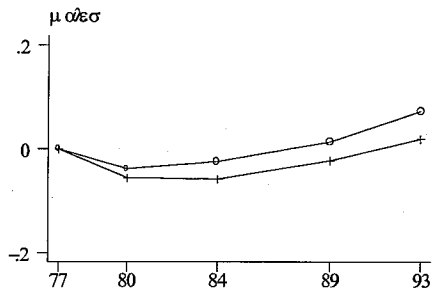
Notes. In each panel the figure reports the ex-ante changes due to each of the component; ex-ante Scala Mobile payments (*SM*), ex-ante non-escalated wage increases (*NSM*) and changes in observables (*z*) to the total changes in wages. See notes to Table 5a. Changes are annualized and standardized to changes at the median

Figure 7

The evolution of latent wage inequality at fixed distribution of the observables

◦ latent

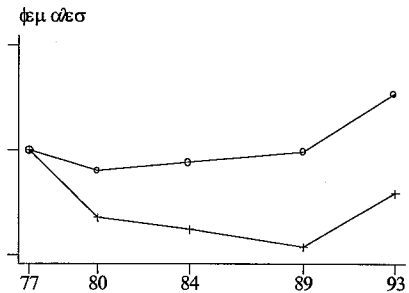
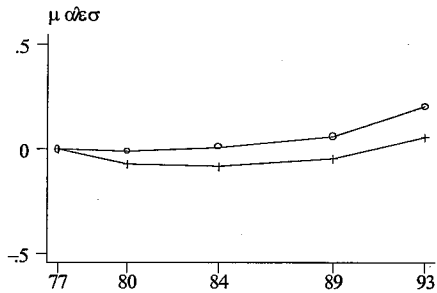
+ actual



3rd-1st quartile log wages

◦ latent

+ actual



9th -1st decile log wages

Notes: The picture reports the estimated series of wage inequality in the absence of indexation (latent wage inequality), as estimated on my data and controlling for changes in observables. For comparison I also report the actual series of wage inequality. Both series are standardized to 1977=0.

---

<sup>1</sup> In 1994 a new system of wage indexation entered in force, which linked contingent wage changes to *expected* inflation.

<sup>2</sup> I am assuming that firms do not anticipate changes in wage differentials induced by the SM.

Alternatively, one could use only the bit of contingent wage changes which is due to price surprises (Card, 1990).