An Empirical Analysis of Changes in the Structure of Wages and Employment in OECD Countries

Thesis submitted for the degree of Doctor of Philosophy (Ph.D.)

by Marco Manacorda

registered at University College London

Abstract

This work uses a variety of micro and macro data sets in order to analyse changes in the wage and employment structures in a number of OECD countries over the 1970s and 1980s. I find evidence of a generalised rise in the relative demand for skilled labour across all countries analysed. The US (in the 1980s) and the UK, however, are the only two countries where a deceleration in the relative supply of skilled labour produced an increased imbalance between the demand and the supply of skills. Such an increased imbalance is able to explain the rise in returns to skills which occurred over the 1980s. As continental Europe is concerned, an analysis of the Italian labour market illustrates that the rising trend in the demand for skills was counteracted by institutional rigidities, which kept the wage structure relatively unchanged. The analysis suggests that wage rigidities and shifts in demand are jointly responsible for the rapid shift towards skilled employment which occurred in continental Europe during the 1980s.

Table of Contents

List of Tables

List of Figures

Chapter 1:

Chapter 2:

Chapter 3:

Chapter 4:

Acknowledgements

In writing this dissertation I have benefited from the help of many people. Steve Machin and Costas Meghir provided me with insightful and dedicated advising. I learnt a great deal from my interaction with both of them. Steve showed me the value of empirical research in economics and a way to make effective use of data within a rigorous theoretical framework. Costas's teaching proved essential to get an understanding of the interplay between econometric techniques and economic theory. The interaction with Costas pushed me to expand my understanding of economics by constantly questioning some of my previous assumptions.

Alan Manning has been a continuous source of inspiration for original research and an enlightening guide throughout my years as a graduate student.

David Card provided me with a unique amount of stimulus and encouragement. His intellectual vivacity and his generosity proved invaluable at several stages of this work. I also wish to thank him for the opportunity to visit the Center for Labor Economics at UC Berkeley. The years at Berkeley have been among the most exciting and productive of my graduate studies.

Marco Pagano and Tullio Jappelli have been generous mentors. Without Marco's initial support and encouragement I would have hardly started an economic career.

At different points of this work I have also benefited from discussions with a number of other people. I wish particularly to thank Richard Blundell and Steve Nickell.

Most of this work would have not been possible without the years spent the Center for Economic Performance at the LSE. I wish to thank Richard Layard for having made this possible. During the years at the CEP, I have benefited enormously from the interaction with fellow researchers. Among them I wish to thank Donna Brown, Richard Dickens, Jan

Eeckhout, Maia Guell, Paul Gregg, Steve McInsotsh, Barbara Petrongolo and Jonathan Wadsworth.

Introduction

This dissertation analyses the performances of the labour markets in Europe and the US in the 1970s and 1980s. The objective of this analysis is to get an understanding of the interplay between market forces (supply and demand for skills) and institutions in shaping the evolution of the wage and employment structures on the two sides of the Atlantic over this time period. For this purpose a variety of micro and macro data sets for as many as eleven OECD countries are used.

The basic motivation for this study comes from a few well known stylised facts. While over the period of observation the US experienced a remarkable rise in the level of wage inequality, unemployment in this country stayed essentially untrended. The reverse seems to have happened in continental Europe, where the wage structure - more equal for a start - remained broadly unchanged or compressed over the 1970s and 1980s, while unemployment grew dramatically, especially among the unskilled. The UK stands somewhat between these two extremes, with some rise in unemployment and some rise in wage inequality.

Some questions arise naturally. Can the different experiences on the two sides of the Atlantic be rationalised in terms of different responses to similar shocks? What is the role of labour market institutions in shaping these different outcomes? And what can we learn about the functioning of the labour market by comparing countries with different (changes in) institutional arrangements and different (changes in) economic forces?

Chapters 1 and 2 test the hypothesis that an increase in the gap between demand and supply of skills has been a generalised phenomenon across the OECD, and that this can explain the rise in aggregate unemployment in Europe over the 1970s and 1980s. This has long been offered as the most plausible explanation for the rise in wage inequality in the US during the 1980s. A number of authors have suggested that this could in principle be the driving force behind the changes in the employment structure in Europe. The basic idea being that if wages are rigid - as it is sometimes held to be the case in Europe - the failure of the supply of skills to keep the pace with changes in demand would essentially translate into changes in the employment structure (as opposed to changes in the wage structure), and possibly into changes in aggregate unemployment.

Chapter 1, written together with Barbara Petrongolo, develops a simple model of the labour market with two types of labour and uses evidence on employment, labour force and wage differentials by education (high and low) for several OECD countries to investigate the occurrence and the consequences of such an increased imbalance.

In chapter 2, co-authored with Alan Manning, the analysis of chapter 1 is extended by studying the fortunes of those at any given position in the skills distribution, as opposed to those with any given level of education. The advantage of this approach over the one in chapter 1 is double. First, it allows to circumvent the problem of defining comparable levels of education across countries. Second, it accounts for the circumstance that the secular trend towards higher educational attainment in the population implies that the same level of education corresponds to a different relative position in the distribution of skills as time goes on. Under some parametric assumptions about the (continuous) distribution of human capital in the population, it is shown how one can derive a one-dimensional measure of imbalance between supply and demand for skills which in principle does not rely on having comparable measures of skills across countries or over time. Also, it is shown how in the presence of data for (more than two) educational inputs, one can test for the validity of the model. The empirical analysis focuses on the experience of five countries, a subset of the ones which are analysed in chapter 1, chosen based on the availability of data on prices and quantities for at least four educational groups.

Chapters 3 and 4 explore the hypothesis that (changes in) wage institutions primarily explain the different trends in the wage structure on the two sides of the Atlantic.

Chapter 3 uses SHIW and CPS micro data to examine changes in the wage structure in Italy between the late 1970s and the early 1990s and explicitly compare these changes with those that occurred in the US over the same period. The analysis concentrates on the effect of a wage indexation clause – the Scala Mobile – on the evolution of earnings inequality. By granting the same absolute wage increase to all employees as prices rose, this institution had a potential to compress the distribution of wages. The assumption that, in the absence of this institution, inequality would have evolved similarly for men and women allows to identify the effect of the Scala Mobile on changes in the earnings structure separately from market forces.

A problem with the analysis in chapter 3 is that the effect of the decline in the Scala Mobile over the trend in the wage structure is observationally equivalent to the effect of skill-biased (technological) change. To cope with this problem, chapter 4 studies changes in returns to education in Italy and estimates a model which accounts simultaneously for changes in supply and demand for skills as well as for changes in institutions (Scala Mobile). In order to carry out this exercise, the data in chapter 3 are integrated with published data on employment and labour force participation for workers with different levels of education. As a consistency check for the results in chapter 3, a different identification strategy for the Scala Mobile is used, namely that, in its absence, the gender earnings gap would have varied at a constant rate over the period of observation.

Finally, chapter 5 provides a very stylised model of the labour market with two heterogeneous inputs (skilled and unskilled labour) which is broadly able to account for the different results found throughout this dissertation. It is shown how one can reconcile the different labour market performances on the two sides of the Atlantic during the 1980s in terms of similar (exogenous) changes in market forces coupled with different values of the parameters of the model.

Chapter 1

Skill-Biased Change and Labour Market Performance in OECD Countries

Evidence on labour market performance in OECD countries over the last two and a half decades delivers two well-known stylised facts.

First, following the two oil shocks of the 1970s, most OECD countries experienced remarkable rises in their unemployment rates. In the late 1980s, no more than two decades after the first oil shock, the unemployment rate in the United States had reverted to its pre-shock level, while in the countries of the European Union it was still two to three times as high as it was at the beginning of the previous decade, and showed a remarkable degree of persistence. These different trends in the evolution of unemployment across the OECD are documented in the existing literature, and have been the subject of a vast debate (see Bean, 1994 for a survey). Secondly, wage inequality - both overall and between a number of dimensions - has been steadily increasing in the US over the 1980s. This dramatic increase in wage inequality does not appear in most European countries. With the exception of the UK, where wage differentials widened during the 1980s, European countries experienced a pretty stable - if not declining - dispersion of earnings over this period (see for example OECD, 1993 and the evidence in chapters 3 and 4).[1]

It has been suggested that these pieces of evidence can be rationalised in terms of the same driving force. Krugman (1994) argues that the rise in European unemployment and the widening wage dispersion in the US might be interpreted as "two sides of the same coin", namely a pressure towards a rise in the inequality of market wages. The different outcomes in terms of unemployment versus wage inequality would then depend on the institutional setting dominating a country's labour market. In flexible labour markets this pressure would translate into an actual widening of the wage distribution. In highly regulated labour markets, the forces that prevent the widening of earnings dispersion would instead translate the rise in the inequality of market wages into higher unemployment dispersion and via this into higher aggregate unemployment. One plausible cause of a tendency towards greater inequality is skill-biased technological progress, increasing the relative demand for skilled labour at the expenses of the less-skilled.

Any increase in the relative demand for skilled labour would not cause major labour market problems if it were matched by a parallel adjustment of supply. Along these lines, this chapter is an attempt to evaluate whether and to what extent any imbalance between the demand and the supply of skills - that we refer to as skill mismatch - can be held responsible for the secular rise in European unemployment.

Our analysis provides two new contributions to the debate.

The first is an explicit description of how wage inequality and unemployment interact in an economy with heterogeneous labour (skilled and unskilled), in which institutions of varying power govern the wage-setting process. The framework that we adopt is based on the widely accepted idea, first expressed in Lipsey (1960), that wages are relatively more responsive to unemployment when unemployment is low. The presence of such a convex wage-unemployment relationship implies that a given asymmetric shock, hitting two different types of labour and generating greater unemployment (and wage) dispersion, will also generate higher aggregate

[1] The issue of the source of increased wage inequality has generated some debate between those who explain it as being mainly induced by the \third world competition in those industries which are less skill intensive (see for example Murphy and Welch, 1992 and Wood, 1994), and those who reckon instead that it was mainly due to skill-biased technological progress (for some evidence in this direction see Katz and Murphy, 1992; Berman *et al.*, 1994; and Machin, 1994). Others stress instead the role played by the declining power of labour market institutions (see Goslin and Machin, 1994; and DiNardo *et al.*, 1996).

unemployment. In the same framework we show that the impact of a given shock on unemployment is negatively related to real wage flexibility.

The second element concerns the empirical documentation of the driving force at the basis of the recent major developments in unemployment and wage inequality. By focusing on the evolution of prices and quantities of different educational inputs for as many as 11 OECD countries we try to determine whether a net relative demand shift between different skill groups has in fact occurred, to distinguish its demand and supply components, to assess its magnitude, and finally to discuss its relationship with aggregate unemployment.

Although most of the related literature follows a similar approach to the one presented here, the interpretation of the data and the conclusions drawn are sometimes quite different. For example, Krugman (1994) points to the larger rise in unemployment rates for the unskilled in Europe, while Nickell and Bell (1995) point out to the circumstance that relative unemployment rates by education show similar trends across countries. The existing literature does not provide very clear guidance on what evidence should be given most weight (e.g. should one pay more attention to absolute or relative differences in unemployment rates by education) and it is difficult to know what to make of these disparate pieces of evidence. The contribution of this chapter is then to provide some guidance on how to analyse the basic data.

The chapter is organised as follows. Section I presents some descriptive evidence on the evolution of unemployment and wage differentials by education in a set of OECD countries, characterised by different labour market performances. Section II introduces the labour demand side of the economy. A simple Cobb-Douglas specification of technology delivers testable predictions in terms of the relationship between relative wages and relative employment, and it is not rejected by our data. This section also provides some estimates for the growth in demand and supply of skills in our set of countries over the past two decades. Section III closes the model by introducing a wage function that relates skill-specific wages to skill-specific unemployment. Here we show that labour demand and supply imbalances hitting those workers with the poorest labour market prospects can in fact worsen the aggregate performance of the economy, by increasing the aggregate unemployment rate. Finally, in the same section we evaluate the impact of increased skill mismatch on aggregate unemployment. Section IV concludes the chapter and states our main findings.

I. Unemployment and Wage Differentials by Skill: Some Evidence

In this section we introduce some descriptive evidence on the evolution of wages and unemployment by skill in a set of OECD countries for which data are available. The aim of this section is to highlight whether any sign of increasing inequality in wages and/or employment opportunities across skills can be detected and to assess whether this is a generalised phenomenon across the OECD. At this stage we are not able to evaluate to what extent a shift in relative demand towards the skilled has occurred, and in order to do so in the next section we develop an appropriate framework for thought.

Figure 1 plots the standardised unemployment rate for 11 OECD countries over the past two and a half decades. The countries are Australia, Canada, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, United Kingdom and United States.

These countries differ substantially in their unemployment experiences. One subset, made up of EU countries, Australia and Canada, shows an overall upward trend in the unemployment rate over the period considered. Here unemployment increases roughly monotonically until it reaches a peak around mid-1980s, then has a local minimum in the late 1980s, followed by a further recession. Note however that the recovery of the second half of the 1980s does not bring unemployment back to the level where it started before the first oil shock. In the US, on the other hand, the unemployment rate experiences pronounced cycles, without any definite trend. Lastly, in the Scandinavian countries, unemployment is stable and very low until the late 1980s, and then peaks during the last recession.

While these aggregate trends are well documented in the literature, less evidence has been provided with regard to the skill composition of employment and the labour force. The educational attainment of individuals is used here as the relevant indicator of skill. Since education is arguably only imperfectly correlated with human capital, in the next chapter we extend the analysis of this chapter to allow for this imperfect correlation. In addition, cross-country comparisons by education can be quite problematic since educational systems vary widely across countries. In this sense, the evidence presented below should be treated with some care, as far as international comparisons are concerned. Again, we will try to deal with this issue in the next chapter. Despite these caveats, we hope to be able to highlight some basic trends and to show that they are robust to the classification used.

In what follows we adopt a dichotomous classification of skills. We generally define as skilled those individuals who have completed their upper secondary education (or equivalent vocational qualification), and unskilled all the others (see the Data Appendix for a more detailed definition of skill categories across countries and for data sources). Two exceptions have been made to this taxonomy, for the US and Spain, where skilled individuals are those who have at least some college education. For the US this procedure provides a more balanced partition between skill levels. For most countries, in fact, there is a point in the sample period at which the two groups are approximately equally sized. This allows us to keep to a "relative" definition of skills, in which skilled individuals are defined as those who have an education attainment above the median. The exception for Spain is due to the very poor disaggregation between skill levels in the original data that does not allow the same skill partition obtained for other European countries.

Figure 2 plots the percentage of skilled people in the population of working age (where available), labour force and employment for each country. The relative size of the skilled group grows monotonically over the whole period in all countries, showing a definite and generalised trend towards higher educational attainment.

To evaluate whether the general tendency towards a skill-upgrading was balanced in its demand and supply components, we look at the evolution of skill-specific unemployment rates. Figure 3 plots the evolution of the unemployment rates by education for our set of countries. For ten of the eleven countries considered the unemployment rate of the unskilled is above that of the skilled. The only exception is Italy, where unemployment is more concentrated among highly educated workers.

Although we will make this point formally in the next section, it can be shown that, for given relative wages, an increase in the imbalance between the demand and the supply of skills can be identified by looking at the evolution of the <u>difference</u> between the unemployment rates of the two groups.

We can detect two main patterns in the evolution of skill-specific unemployment rates. There is in fact a group of countries where the secular increase in unemployment is mainly concentrated among the unskilled. This is the case for the US and most EU countries: UK, France, Germany, Italy, the Netherlands and Spain. On the other hand, in Australia, Canada and the Scandinavian countries (with the exception of Norway in the last recession) no remarkable change in the difference between skill-specific unemployment rates has taken place. Overall, no clear correlation between the difference in the unemployment rates and aggregate unemployment can be detected in our data.

It is interesting to notice at this stage that the remarkably close behaviour of population shares to labour force shares (see Figure 2) implies that non-employment rate differentials move very much in line with unemployment rate differentials. We therefore rule out the possibility that the different patterns of unemployment differentials in the various countries are driven by different patterns of labour force participation across skills.

Turning finally to wage differentials, the recent evolution of wage inequality across a number of dimensions - among which education - is extensively documented in the literature,[2] and has produced global consensus on the recognition of a few stylised facts. Below we will simply describe the evolution of wage differentials between the two educational groups already defined for our set of countries.

Figure 4 plots the evolution of the skilled to unskilled wage ratio for a subset of countries for which consistent time series for wages are available: UK, Germany, France, Italy, the Netherlands and the US. In no country except the UK and the US - two countries where the differentials are higher in levels - can any appreciable evidence of widening wage differentials by skill be found. In the remaining countries, wage differentials stay basically unchanged or even fall. For Australia, Canada, Norway and Sweden, indirect evidence based on OECD (1993,1994b Table 7.A.1) shows that in none of them (with the exception of Sweden in the late 1980s, when differentials increased moderately) can any sign of increasing dispersion be detected.

Given our evidence, we can tentatively conclude that there seems to be some sign of a relative demand shift (net of supply) towards skilled labour in the UK, France, Germany, Italy, Spain and the US. Evidence of this shift is represented by changes in the skill distribution of unemployment and/or in wage differentials. It is instead more difficult to detect any sign of this kind in other countries. Australia, Canada, Netherlands, Sweden and Norway seem in fact to have kept the imbalance between the demand and supply of skills to a relatively constant level over the last two decades.

It is worth noting that the only country where both relative wages and unemployment differentials evolved against the less-skilled is the US (from the early 1980s). This seems to point to a peculiar experience of the US labour market as compared to the other countries. We will keep this in mind when we try to assess the magnitude of the shift in net relative demand towards skilled workers in the next section.

II. Has There Been a Shift in Net Demand?

This section introduces a very simple labour market model that should shed some light on what we mean by a shift in net labour demand and on how we can measure it.

a. Theory

We consider an economy with heterogeneous labour, defined over 2 skill groups, that produce a homogeneous output Y. The technology available to firms is represented by the following Cobb-Douglas production function, involving the 2 labour inputs:

$$(1) \qquad Y = AN_1^{\alpha_1} N_2^{\alpha_2}$$

in which A represents the aggregate state of technology, N is employment and constant returns to scale are imposed so that $a_1 + a_2 = 1$. As a rule, in the rest of the chapter we will denote skilled individuals by the index 1 and unskilled individuals by the index 2. Equation (1) should be thought of as a long run reduced-form production function after one has concentrated out the profit-maximising choice of other inputs so it makes sense to assume that there are constant returns in labour. Under perfect competition in the

[2] See the February 1992 issue of Quarterly Journal of Economics, Davis (1992), Bound and Johnson (1992), Juhn *et al.*(1993), Blanchflower *et al.* (1993), Blau and Kahn (1994), and Gosling *et al.* (1994).

goods market, this gives $W_1=\alpha_1(Y/N_1)$ as the labour demand equation for input 1 - with α_1 denoting its product share – from which the relative labour demand is:

$$(2) \qquad \ln\frac{W_1}{W_2}=\ln\frac{\alpha_1}{\alpha_2}-\ln\frac{N_1}{N_2}=\ln\frac{\alpha_1}{\alpha_2}-\ln\frac{l_1}{l_2}-\ln\frac{1-u_1}{1-u_2},$$

where L denotes total labour force, $l_1\equiv L_1/L$ denotes group 1's labour force share, and $u_1=(L_1-N_1)/L_1$ denotes its unemployment rate.

The technology parameter α_1 represents a relative demand indicator for group 1, and therefore shifts in α_1 can be thought of as being caused - among other factors - by skill-biased change. Similarly, l_1 represents a relative supply indicator for group 1. The same clearly applies to group 2.

Differentiation of (2) gives:

$$(3) \qquad d\ln\frac{W_1}{W_2}=\left(d\ln\frac{\alpha_1}{\alpha_2}-d\ln\frac{l_1}{l_2}\right)-d\ln\frac{1-u_1}{1-u_2},$$

Equation (3) gives the comparative static of our economy. The first term in brackets represents the shift in net relative demand towards group 1, that we identify as the skilled. This term refers to a change in the skill composition of the labour demand (i.e. a change in relative labour demand) which is not perfectly matched by a parallel change in the skill composition of labour supply (i.e. a change in relative labour supply). We refer to this imbalance as skill mismatch.

The mismatch index adopted here, $d\ln(\alpha_1/\alpha_2)$- $d\ln(l_1/l_2)$, displays the property of having the same absolute magnitude and opposite sign for the two groups. If this is the case, sectoral unemployment rates move in opposite directions in the face of a net relative demand shock, as will be shown in the next section. This is one of the main differences between this approach and the one followed in Nickell and Bell (1995) and Manning *et al.* (1996), who focus on an absolute mismatch indicator, $d\ln(\alpha_1/l_1)$.

Another property of our mismatch index - that derives directly from the Cobb-Douglas specification of the production function - is that it weights equally changes in relative wages and changes in relative employment rates. This would not be the case with a CES production technology, in which wage changes carry a higher weight than changes in employment, insofar the elasticity of substitution between labour inputs exceeds one (on this see, among others, Katz and Murphy, 1992). This is another important difference between the present analysis and Nickell and Bell's (1995), who assume a CES production function combining skilled and unskilled labour with an elasticity of substitution greater than one. However, our estimates below show that the elasticity of substitution between skills is not significantly different from one, suggesting that a Cobb-Douglas .production function is possibly a satisfactory representation of technology, making both the algebra and the empirical implementation of our framework more easily tractable.[3]

Suppose now $d\ln(\alpha_1/\alpha_2)-d\ln(l_1/l_2)>0$, implying a positive net relative demand shock for the skilled. Equation (3) says that this requires either a rise in relative wages for the skilled, or a rise in their relative employment rate $d\ln(1-u_2)-d\ln(1-u_1)<0$, or both. The way the total impact is split between employment and wage differentials depends on the curvature and the position of a wage-setting schedule, that will be introduced in the next section. For small enough u_1 and u_2, we can approximate $d\ln(1-u_2)-d\ln(1-u_1)$ as $d(u_1-u_2)$, implying that a demand shock favouring group 1, with $u_1<u_2$, will increase the difference between sectoral unemployment rates. In other words, if the evolution of relative demand and supply is perfectly balanced, there is no need for relative wages to change or for the <u>difference</u> between sectoral unemployment rates to change.

[3] Note that if the elasticity of substitution were above one, then one should give more weight to relative wage changes than to changes in the difference in the unemployment rates. In this sense, this would make any rise in relative demand in the US and UK appear even more pronounced.

b. Evidence

Having set a broad framework for thought, we proceed by exploring the evolution of the demand and supply of skills in our set of OECD countries. The evolution of labour supply can be easily assessed using labour force figures. As in most of the related literature, we treat labour supply as exogenous. With regard to the labour demand indicator, below we estimate a more general specification for aggregate technology than equation (1), and aim at giving possible measures for the evolution of the relative demand for skills. To keep things as general as possible, we proceed by estimating a linear homogeneous CES aggregate production function, involving two labour inputs:

$$(4) \qquad Y = A\left(\alpha_1 N_1^{\rho} + \alpha_2 N_2^{\rho}\right)^{1/\rho}$$

where $\rho=1-1/\sigma<1$, with σ denoting the elasticity of substitution between labour inputs. The α's are, once more, some relative productivity indexes (such that $\alpha_1+\alpha_2=1$), and A represents total factor productivity. Profit maximisation yields the following relative demand for inputs:

$$(5) \qquad \ln\frac{N_1}{N_2} = -\sigma\ln\frac{W_1}{W_2} + \sigma\ln\frac{\alpha_1}{\alpha_2}$$

Due to lack of data on group-specific productivities, we use a linear time trend as a proxy for (log) relative productivities, as in Katz and Murphy (1992). Higher powers of the time trend were included during estimation and found non significant. Moreover, a common elasticity of substitution across countries is imposed between the two labour inputs, to obtain a measure of the "average" elasticity of substitution in OECD countries. The intercept term and the trend coefficient are allowed to differ across countries. Estimation is performed for those six countries on which wages are available.

The regression equation therefore has the form:

$$\text{(6)} \qquad \ln\frac{N_{c1t}}{N_{c2t}} = a_{0c} + a_{1c}t - \sigma \ln\frac{W_{c1t}}{W_{c2t}} + \varepsilon_{ct}$$

where c and t index respectively countries and time and ε is an error term. In order to improve the precision of our estimates, estimation is performed on a system of seemingly-unrelated equations such as (6), with the cross-equation restriction of a common σ. The results are reported in Table 1. The fit of all equations is close to perfect. The estimate of the elasticity of substitution equals 1.059 (s.e. 0.123), and a simple t-test on σ does not lead to a rejection of the null hypothesis $\sigma=1$ at standard significance levels.[4]

This suggests that - over our set of OECD countries - the production function can be legitimately approximated by a Cobb-Douglas specification. This in turn allows to exploit the useful properties of Cobb-Douglas production functions, so that we can measure the growth rate in relative demand by estimating growth rates in wage bill shares.

Table 2 reports estimated annual growth rates of the following variables: relative labour supply L_1/L_2, relative employment N_1/N_2, relative employment rates $(N_1/L_1)/(N_2/L_2)$, relative demand α_1/α_2, relative demand net of relative supply $(\alpha_1/\alpha_2)/(l_1/l_2)$. The estimates for these last two variables are computed only for those countries for which wage data are available. Recall finally that, for small enough unemployment rates, the growth rate in relative employment rates provides an approximation for the change in the difference between the groups' unemployment rates.

A few things are worth mentioning. First, all OECD countries experienced a skill upgrading in the structure of both supply and demand (all of the growth rates in columns 1, 2 and 4 are significantly positive and of comparable magnitude). Second, this tendency towards skill upgrading meant a higher unemployment rate differential between the unskilled and the skilled in France, Germany, Spain and Italy, and, to a lower extent, in the UK, Norway and the US (see column 3). Third, demand for skills grew in any of the countries we have data for. Finally, column 5 shows that there has been a pronounced shift in net relative demand against the unskilled in the US (during the 1980s only) and, but to a more limited extent, in France, Germany and Italy. The UK is somewhat in an intermediate position, with a shift in relative demand about half the one which occurred in the US during the 1980s and about twice the one which occurred (on average) in continental Europe. There is a strong net relative demand shift against the skilled in the Netherlands. This is actually consistent with the fact that the unemployment differential did not really change in this country, while wage differential fell (see also OECD, 1993, 1994b, Table 7.A.1).

Looking more in depth at the US, the magnitude of the shift during the 1980s appears notably higher when compared to any other country (no such distinction between decades is made for other countries, because in no other country is such a change found between the 1970s and the 1980s). A closer look at columns 1 and 4 illustrates that a substantial deceleration in the evolution of the supply of skills - rather than an acceleration in demand - seems responsible for the greater gap between the demand and the supply of skills in the US during the 1980s, a fact pointed out by several other authors (see for example Katz and Murphy, 1992).

This result might be partly due to the different classification used across the set of countries. In particular, if one is willing to assume concavity in the growth of educational attainment in the population, this could imply that a country with higher average skill attainment would tend to experience a less rapid growth in the proportion

[4] Ignoring dynamics in the demand equation, one can use lagged wages as an instrument for current (cont'd on next page)

of skilled workers. But this is not the case for the US. The ratio of skilled to unskilled labour force in the US was 0.65 in 1980, and the average across the whole set of countries was just over two thirds. And sorting countries by this ratio, the US occupies the median position.

In conclusion, we can state that the US experienced a dramatic increase in the gap between the demand and the supply of skills in the 1980s, mainly due to a reduction in the rate of growth of supply. This imbalance is therefore responsible for the peculiar US experience, i.e. widening wage and unemployment differentials during the 1980s.

III. The Impact on Unemployment

The results of the previous section show the occurrence of a net demand shift in the US during the 1980s and - although to a lower extent - in the UK. Continental European countries show evidence of a weak increase.

The next step is to evaluate whether and to what extent these trends in skill mismatch can be held responsible for the increase in unemployment in those countries where a positive demand shift towards the skilled took place. In order to do so, we close the model by combining the labour demand condition presented in section II with a standard wage-setting relationship.

a. Theory

The mechanism at the basis of our model is very simple. It focuses on the idea that wages set by workers and firms are a decreasing convex function of unemployment, being more responsive to unemployment variations when unemployment is low than when it is high. This can be justified on the basis of a bargaining model in which unions

wages. The IV estimates are very similar to ones reported, giving σ=1.036 (s.e. 0.133).

and firms negotiate wages at given unemployment, and firms then chose employment at given agreed wages.

Under the assumption that sectoral wages respond solely to sectoral unemployment, such a convex wage function would imply that an asymmetric labour demand shock, hitting high-unemployment workers and favouring low-unemployment ones, would generate some dispersion in sectoral unemployment rates and therefore increase the average unemployment rate at given average wage.

This can be easily seen from Figure 5, where the WS curve represents the wage-setting schedule as a convex function of the employment rate and LD represents labour demand. Assuming for the moment that the curves WS and LD represent labour market conditions for all types of workers, in the initial position E there is no dispersion in real wages or unemployment rates, and W and u therefore indicate both sectoral and average values. If an asymmetric labour demand shock takes place, this shifts up the labour demand schedule for skilled workers and shifts down that for unskilled workers, therefore introducing some unemployment dispersion in the economy. Average unemployment, being some linear combination of u_1 and u_2, will be situated somewhere on the SU segment. At constant average real wage, determined by average productivity, the aggregate unemployment rate $\bar{u}'$ would be higher than the level associated with no unemployment dispersion $\bar{u}$.

Below we generalise this framework, allowing for initial heterogeneity in sectoral wage functions and labour demand functions and for endogenous changes in the average wage, and we derive the conditions under which such an asymmetric shock can have effects on the aggregate unemployment rate.

Sticking to a well established literature (see inter *alia*, Layard *et al.*, 1991, ch. 6) we adopt a double-logarithmic wage function for each group i, of the form:

$$(7) \qquad \ln W_i = \ln \lambda_i - \gamma \ln u_i, \qquad i = 1,2$$

where λ_i represents group-specific wage pressure factors, and γ represents (the absolute value of) real wage elasticity with respect to own-group unemployment. This last parameter may vary across countries according to how labour market institutions affect the wage-setting process, and may turn out to be a relevant aspect in the comparison of unemployment experiences across the OECD (see chapter 4 for evidence on this).

In equation (7), wage pressure is simply defined as any force that can influence wages at given unemployment. Typically, wage institutions can be thought of entering this term. In the analysis of this chapter we do not concentrate on the identification of these factors, but in chapters 3 and 4 we will briefly discuss the impact of wage institutions on unemployment in continental Europe,

The double-logarithmic specification adopted can be obtained as a log-linear approximation to a first-order condition for wages derived from a bargaining problem (see Manning, 1993), and it is empirically supported by data from a number of countries (see Jackman and Savouri, 1991 and Blanchflower and Oswald, 1994 for regional wage equations and Gregg and Machin, 1994 and Manacorda and Petrongolo, 1996 for skill-specific wage equations).

Based on the labour demand for each input i and the corresponding wage curve we can solve for the equilibrium of the model. If we assume that the only exogenous variation in this economy comes from changes in relative demand and supply of skills, one can show that (see Technical Appendix):

$$(8) \qquad \begin{aligned} du_1 &= -\phi_1 \left(d\ln\frac{\alpha_1}{\alpha_2} - d\ln\frac{l_1}{l_2} \right) \\ du_2 &= \phi_2 \left(d\ln\frac{\alpha_1}{\alpha_2} - d\ln\frac{l_1}{l_2} \right) \end{aligned}$$

where $\phi_1>0$, $\phi_2>0$, $\phi_{1\gamma}<0$, $\phi_{2\gamma}<0$.

A shift in net demand towards the skilled ($d\ln(\alpha_1/\alpha_2)-d\ln(l_1/l_2)>0$) will rise the unemployment rate of the unskilled ($du_2>0$) and lower the unemployment rate of the skilled ($du_1<0$). However, this effect tends to disappear as γ grows. In the case of pure wage flexibility ($\gamma=\infty$), the impact of mismatch on each unemployment rate is zero.

Everything else being equal, perfectly balanced changes in sectoral demand and supply are consistent with constant sectoral unemployment rates and real wages. This result naturally defines a neutrality condition of this model. Neutral changes in relative labour demand and labour supply are such that sectoral unemployment rates and wages are unaffected. This is a stronger condition than the one outlined in section II, where we showed that, along the labour demand schedule, a zero mismatch index implies constant relative wages and unemployment rate differentials between sectors.

Having divided the labour force into two groups, the aggregate unemployment rate is given by $u=u_1l_1+u_2l_2$. Therefore (and ignoring compositional effects):

$$(9) \qquad du = \phi\left(d\ln\frac{\alpha_1}{\alpha_2} - d\ln\frac{l_1}{l_2} \right)$$

where $\phi>0$, $\phi_\gamma<0$ if

$$(10) \qquad \frac{W_1}{W_2} > \frac{u_1/\left(1-u_1\right)}{u_2/\left(1-u_2\right)}.$$

A net relative demand shift favouring the group with better labour market prospects (higher wages and/or lower unemployment) will tend to increase total unemployment. This is a natural prediction of a non-linear model such as the one described. Any increase in dispersion, either in wages or unemployment rates, generated by exactly symmetric shocks for the categories involved, is bound to increase unemployment, due to the convexities in the underlying relationships.

The whole discussion above is based the assumption of homogeneous wage flexibility across skill groups. Some studies find however that the elasticity of pay is higher among low-skill workers (see Gregg and Machin, 1994 and Blanchflower and Oswald, 1994, although Nickell and Bell (1995) find the reverse).

In the Technical Appendix we show that if γ_i denotes the wage elasticity parameter for group i, the impact of mismatch on u_1 is greater in absolute value the higher γ_2 and the lower γ_1, and conversely for u_2. Assuming a positive shift in favour of the skilled ($d\ln(\alpha_1/\alpha_2)-d\ln(l_1/l_2)>0$), having $\gamma_1<\gamma_2$ gives a greater fall in u_1 and a smaller rise in u_2 with respect to the case $\gamma_2=\gamma_1$, therefore producing a smaller rise in aggregate unemployment. If instead $\gamma_1>\gamma_2$, the effect on aggregate unemployment is magnified. One way of reducing the impact of sectoral labour demand and supply shocks on unemployment is therefore to increase wage flexibility for the "losers" and reducing it for the "winners".

b. Evidence

We are now in a position to assess quantitatively the impact of mismatch on sectoral and aggregate unemployment, using equations (8) and (9). In doing so we restrict the analysis to the countries for which we have data on wages and exclude the Netherlands, since clearly no rise in unemployment can be explained there. If anything, the trend in net relative demand for skills is responsible for a decrease in unemployment and some other explanations (that we have generally labelled as wage pressure) must be put forward to account for the increase in the rate of joblessness.

Our set of countries is fairly representative. It includes three European countries, with high and increasing unemployment and no increase in wage differentials, the US, with no significant increase in unemployment and widening wage differentials, and finally the UK, situated somewhere between these two extremes.

The results of this exercise are reported in Tables 3-5, where we estimate the average annual change in skill-specific and aggregate unemployment and the contribution brought about by mismatch. Two alternative values of the parameter γ are used in turn: 0.1 and 0.035. On the basis of the existing evidence, they can be taken as upper and lower bounds for the actual value of real wage flexibility (see Blanchflower and Oswald, 1994 and Manacorda and Petrongolo, 1996).

Tables 3 and 4 report the annual changes in skill-specific unemployment and the contribution of the increased imbalance between the demand and supply of skills. In all of the five countries there is a tendency for mismatch to reduce skilled unemployment and to increase unskilled unemployment. The estimates provided are somehow sensitive to the value of γ, implying a greater contribution of mismatch to the change in unemployment when wages are rigid. In no country except the US is mismatch able to explain all of the rise in the unemployment rate of the poorly educated, and some increase in wage pressure must be invoked to explain this trend. Analogously, since the increase in mismatch implies a reduction in the skilled unemployment rate, some other factors must be blamed for its modest but generalised increase. With the exception of the US, where the rise in aggregate unemployment is negligible, only the UK shows a substantial contribution of mismatch to the increase in unskilled unemployment, accounting for more than 50% of the total rise.

Moving to aggregate unemployment, Table 5 reports the contribution of skill mismatch to the growth in the total rate of joblessness. Mismatch explains no more than 20% of the increase in unemployment in continental European countries, irrespective of real wage flexibility. The relative contribution of mismatch is instead significantly higher in the UK. Our estimates show that the increased imbalance between the demand and the supply of skills may account for as much as 45% of the total rise in unemployment between 1974 and 1992 if wages are relatively rigid. When we allow for further wage flexibility this reduces to 28%, still leaving some rise in unemployment to be explained by the evolution of wage pressure.

Simulations with $\gamma_1 \neq \gamma_2$ (not reported in the table) give pretty similar results to the ones reported for homogeneous γ in France, Germany, Italy and the US, where the change in unemployment explained by mismatch is however fairly small. This change is instead significant in the UK, and it is therefore worthwhile reporting some indicative results for $\gamma_1 \neq \gamma_2$. If $\gamma_1 < \gamma_2$, this gives an impact of mismatch that is 31% of the total rise in unemployment when $\gamma_1=0.035$ and $\gamma_2=0.05$, and 25% when $\gamma_1=0.08$ and $\gamma_2=0.1$. Conversely, if $\gamma_1 > \gamma_2$, the implied contribution of mismatch to the rise in unemployment is 55% when $\gamma_1=0.05$ and % $\gamma_2=0.035$ and 35% when $\gamma_1=0.1$ and $\gamma_2=0.08$.

To summarise, although some shift in net demand towards the skilled can be detected in the five countries considered, only in the UK and the US - where wage and unemployment differentials did widen - is its magnitude significant. In particular, mismatch has the potential to explain between one fourth and one half of the total rise in unemployment in the UK. Overall, the UK stands out as being the only country where the lack of adjustment in the supply of skills has a potential to explain the observed rise in unemployment.

IV. Concluding Remarks

The main concern of this chapter consisted in assessing the role played by the imbalance between the demand and the supply of skills in shaping the evolution of labour market performances across OECD countries over the last two decades. The analysis is guided by a simple theoretical framework where aggregate technology is characterised by a Cobb-Douglas production function involving two inputs (skilled and unskilled labour), and wage-setting is governed by a double-log wage function. Although rather simplified, this model proves rather enlightening in understanding the effect of skill mismatch on aggregate unemployment.

When the relative demand and supply of skills grow in the same proportion, everything else being equal, we expect both relative wages and sectoral unemployment rates to be unaffected. This is therefore the definition of neutrality that stems from our model. When instead demand and supply of skills do not grow in line with each other, we expect that either the wage structure changes or sectoral unemployment rates move in opposite directions, or both.

The first and probably incontrovertible result that stems from our data is that the demand for skills increased steadily in Western countries during the period of observation and probably long before. In continental Europe, this tendency in the evolution of relative demand for skills was essentially matched by an equal increase in the relative supply of skills but this does not seem to have happened in the US (in the 1980s) and - to some extent - in the UK. We come to this conclusion by noticing that the increases in the relative employment rates of skilled workers in continental Europe are of too small a magnitude to suggest that, if wages had been free to vary over the period of analysis, the imbalance between the demand and supply of skills would have generated a change in the structure of wages similar to the one which occurred in the UK and the US over the same period of observation.

At the end of the chapter we try and assess the quantitative importance of skill mismatch on the evolution of unemployment across OECD economies. Skill mismatch was negligible in continental Europe and so this cannot be blamed for the bad aggregate performance of its labour markets during the 1980s. In the UK instead, skill mismatch is theoretically able to explain a substantial part of the nearly 6 percentage points increase in unemployment, between 28% and 45%, across different realistic levels of real wage flexibility. Clearly, if one assumed that wages were perfectly flexible, then the conclusion would be that skill mismatch is solely responsible for the rise in wage inequality in the UK. A similar conclusion applies to the US, where there is no growth in unemployment to be explained. We will make this point more formally in the next chapter.

By ruling out that a shift in relative demand is mainly responsible for changes in the employment structure and the for rise in aggregate unemployment in Europe, our results suggest that one has to look somewhere else in order to explain the different performances of the labour markets on the two sides of the Atlantic. We will try and deal with this issue in chapters 3 and 4.

Data Appendix

Employment, labour force and unemployment:

Australia. Sample: 1979-1993. Source: The Labour Force Attainment, Australia. Selection criteria: males and females, 15-64 years old. Skilled: attended highest level of secondary school available. Unskilled: did not attend highest level of secondary school available.

Canada. Sample: 1979-1993. Source: The Labour Force Statistics, Canada. Selection criteria: males and females, 15 years old and over. Skilled: with some post-secondary education. Unskilled: up to 1983: with 13 years of schooling (some or completed secondary education); from 1984 onwards: with secondary education qualification.

France. Sample: 1978-1994. Source: *La Population Active d'Apres l'Enquete Emploi*, INSEE. Selection criteria: males and females, 15 years old and over. Skilled: with *baccalaureat general* or vocational qualification (CAP or BEP). Unskilled: without either of the above qualifications.

Germany. Sample: 1976, 1978, 1980, 1982, 1985, 1987, 1989. Source: *Mikrozenzus*. Selection criteria: males and females, 15 years old and over. Skilled: with vocational qualifications (*Berufsausbildung*), or higher education (*Fachhochschulqualifikation or Hochschule*). Unskilled: without vocational qualifications.

UK. Sample: 1974-1992. Source: General Household Survey individual record files. Selection criteria: males, 16-64 years old; females, 16-60 years old. Skilled: with A-level (or equivalent), including senior vocational qualification. Unskilled: with O-level (or equivalent), including junior vocational qualification.

Italy. Sample: 1977-1992. Source: *Annuario Statistico Italiano.* Selection criteria: males and females, 14-70 years old. Skilled: with upper secondary qualification (*diploma di* *scuola media superiore*) including vocational qualification. Unskilled: Without secondary school qualification.

Netherlands. Sample: 1979, 1981, 1983, 1985, 1990-1993. Source: 1979-1985: *Arbeid-skrachtetentelling*; 1990-1993: *Enquete Beroepssbevolking*. Selection criteria: males and females, 15 years old and over. Skilled: with senior secondary qualification, including senior vocational training. Unskilled: with junior secondary qualification, including junior vocational training, or below.

Norway. Sample: 1972-1993. Source: *Arbeidmarkedstatistikk* (abs.), Norway. Selection criteria: males and females, 16-74 years old. Skilled: completed secondary school level II (*gymnasiva* II). Unskilled: below secondary school level II.

Spain. Sample: 1977-1993. Source: *Encuesta de Poblacion Activa*, INE. Selection criteria: males and females, 16 years old and over. Skilled: some college. Unskilled: without any college education.

Sweden. Sample: 1971-1993. Source: 1971-1986, Labour Force Survey, February interviews; 1987-1993, all months. Selection criteria: males and females, 16-64 years old. Skilled: with high school qualification (including secondary vocational qualifications). Unskilled: without either of the above qualification.

United States. Sample: 1970-1991. Source: 1979-1989: Handbook of Labor Statistics, 1989; 1990-1991: Statistical Abstract of the US, 1992. Selection criteria: males and females, 25-64 years old. Skilled: with at least some college. Unskilled: with high school qualification or below.

Wages:

(same skill partition as above)

France. Sample: 1984-1994. Source: INSEE, *Enquete sur l'Emploi.* Selection criteria: males and females, 15 years old and over, employees only. Earning concept: gross monthly wages.

Germany. Sample: 1976, 1978, 1980, 1982, 1985, 1987, 1989. Source: *Mikrozenzus.* Selection criteria: males and females, 15 years old and over. Earning concept: net monthly wages.

UK. Sample: 1974-1992. Source: General Household Survey individual record files. Selection criteria: males 16-64 years old, females 16-60 years old. Earning concept: gross weekly earnings.

Italy. Sample: 1977-1984, 1986, 1987, 1989, 1991. Source: *Indagine sui Bilanci delle Famiglie*, Banca d'Italia, individual record files. Selection criteria: males and females, 16-65 years old, employees only. Earning concept: net yearly wages.

Netherlands. Sample: 1975-1993. Source: *Tijdreeksee Arbeidsrekeningen.* Selection criteria: males and females, 15 years old and over. Earning concept: gross monthly wages.

United States. Sample: 1970-1989. Source: Annual demographic files, March Current Population Survey (Outgoing Rotation Group). Selection criteria: wage and salary earners, males and females, 16-69 years old, working at least 40 weeks and earning more than one half the minimum wage on a full time basis. Earning concept: weekly gross wages (annual earnings divided by number of weeks worked). Our thanks to Steve Davis for having provided the data.

Technical Appendix

Consider the labour demand for input 1, deriving from profit maximisation on the part of our representative firm whose technology is described in (1):

$$\text{(A1)}\quad \ln W_1 = \ln A + \ln\alpha_1 - \alpha_2 \ln\frac{1-u_1}{1-u_2} - \alpha_2 \ln\frac{l_1}{l_2}.$$

Differentiation of (A1) assuming that A stays unchanged gives[5]:

$$\text{(A2)}\quad d\ln W_1 = \alpha_2\left(d\ln\frac{\alpha_1}{\alpha_2} - d\ln\frac{l_1}{l_2}\right) + \alpha_2 d\ln\frac{1-u_2}{1-u_1}$$

where we have exploited the fact that $d\ln\alpha_1=\alpha_2\, d\ln(\alpha_1/\alpha_2)$. By differentiating the wage curve (7) (ignoring changes in wage pressure) and interacting it with (A2), it follows:

$$\text{(A3)}\quad du_1 = -\frac{u_1(1-u_1)\alpha_2}{\alpha_2 u_1 + \gamma(1-u_1)}\left[\left(d\ln\frac{\alpha_1}{\alpha_2} - d\ln\frac{l_1}{l_2}\right) - \frac{1}{1-u_2}du_2\right],$$

and similarly for group 2.

The closed-form solutions for du_1 and du_2 is:

$$\text{(A4)}\quad du_1 = -\frac{u_1(1-u_1)(1-u_2)\alpha_2}{\gamma(1-u_1)(1-u_2)+\alpha_1 u_2 + \alpha_2 u_1 - u_1 u_2}\left(d\ln\frac{\alpha_1}{\alpha_2} - d\ln\frac{l_1}{l_2}\right)$$

and

$$\text{(A5)}\quad du_2 = \frac{u_2(1-u_1)(1-u_2)\alpha_1}{\left[\gamma(1-u_1)(1-u_2)+\alpha_1 u_2 + \alpha_2 u_1 - u_1 u_2\right]}\left(d\ln\frac{\alpha_1}{\alpha_2} - d\ln\frac{l_1}{l_2}\right).$$

Now, the denominator of the coefficient on skill mismatch is positive. To see this note that $\gamma(1-u_1)(1-u_2)>0$ and $(\alpha_1 u_2+\alpha_2 u_1-u_1u_2)=(1-\alpha_2)u_2-(u_2-\alpha_2)u_1>0$ if $u_1<u_2$ (and $u_2<1$). Since the numerator in both expressions is positive, than the impact of skill

[5] We have assumed that the term $\ln N_1/N_2 d\alpha_1$ is equal to zero. This picks up a pure income effect.

mismatch is negative (reducing unemployment) for the skilled (A4) and positive (increasing unemployment) for the unskilled (A5). Also, since the derivative of the denominator with respect to γ is positive (and equals $((1-u_1)(1-u_2))$, it is easy to show that the derivative of the coefficient for skill mismatch is negative (in absolute value) for both groups.

To obtain the impact on aggregate unemployment, this is:

(A6)
$$du = l_1 du_1 + l_2 du_2 = \frac{(1-u_1)(1-u_2)}{\left[\gamma(1-u_1)(1-u_2) + \alpha_1 u_2 + \alpha_2 u_1 - u_1 u_2\right]} \left(u_2 l_2 \alpha_1 - u_1 l_1 \alpha_2\right)\left(d\ln\frac{\alpha_1}{\alpha_2} - d\ln\frac{l_1}{l_2}\right)$$

from which (9) follows directly.

When wage flexibility varies across skills, it can be shown that:

(A7)
$$du_1 = -\frac{\alpha_2 u_1 (1-u_1)(1-u_2)}{\gamma_1 (1-u_1)(1-u_2) + (\gamma_1/\gamma_2)\alpha_1 (1-u_1) u_2 + \alpha_2 (1-u_2) u_1} d\left(\ln\frac{\alpha_1}{\alpha_2} - \ln\frac{l_1}{l_2}\right)$$

(A8)
$$du_2 = \frac{\alpha_1 u_2 (1-u_1)(1-u_2)}{\gamma_2 (1-u_1)(1-u_2) + (\gamma_2/\gamma_1)\alpha_2 (1-u_2) u_1 + \alpha_1 (1-u_1) u_2} d\left(\ln\frac{\alpha_1}{\alpha_2} - \ln\frac{l_1}{l_2}\right)$$

References

Bean, C., "European Unemployment: A Survey", *Journal of Economic Literature*, 32, 1994, 573-619.

Berman, E., J. Bound and Z. Griliches, "Changes in the Demand for Skilled Labour within US Manufacturing: Evidence from the Annual Survey of Manufacturers", *Quarterly Journal of Economics*, 109, 1994, 367-397.

Blanchflower, D., G. Loveman and L. Katz, "A Comparison of Changes in the Structure of Wages in Four OECD Countries", *CEP Discussion Paper* No.144, 1993.

Blanchflower, D. and A. Oswald, *The Wage Curve* . Cambridge: The MIT Press, 1994.

Blau, F. and L. Kahn, "International Differences in Male Wage Inequality: Institutions versus Market Forces", *NBER Working Paper* No. 4678, 1994.

Bound, J. and G. Johnson, "Changes in the Structure of Wages in the 1980"s: An Evaluation of Alternative Explanations", *American Economic Review*, 82, 1992, 371-392.

Davis, S., "Cross Country Patterns of Changes in Relative Wages", *NBER Macroeconomic Annuals*, 1992, 239-299. w

DiNardo, J., N. Fortin and T. Lemieux, "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach", *Econometrica*, 64,1996, 1001-1044.

Gosling, A and S. Machin, "Trade Unions and the Dispersion of Earnings in British Establishments", *Oxford Bulletin of Economics and Statistics*, 57, 1995, 167-84.

Gosling, A., S. Machin and C. Meghir, "What has Happened to Men's Wages since the Mid-1960s?", *Fiscal Studies*, 15, 1994, 63-87.

Gregg, P. and S. Machin, "Is the UK Rise in Inequality Different?", in Barrel, R. (ed.), *The UK Labour Market*, 1994, Cambridge: Cambridge University Press.

Juhn, C., K. Murphy and B. Pierce, "Wage Inequality and the Rise in Returns to Skills", *Journal of Political Economy*, 101, 1993, 410-442.

Katz, L. and K. Murphy, "Changes in Relative Wages, 1963-1987: Supply and Demand Factors", *Quarterly Journal of Economics,* 107, 1992, 35-78.

Krugman, P., "Past and Prospective Causes of High Unemployment", in *Reducing Unemployment: Current Issues and Policy Options*, Jackson Hole Conference, WY, 1994.

Layard, R., S. Nickell and R. Jackman, *Unemployment, Macroeconomic Performance and the Labour Market.* Oxford: Oxford University Press, 1991.

Lipsey, R., "The Relation between Unemployment and the Rate of Change of Money Wage Rates in the United Kingdom 1862-1957: A Further Analysis", *Economica*, 27, 1960, 1-31.

Machin, S., "Changes in the Relative Demand for Skills in the UK Labour Market", *CEPR Discussion Paper* No. 952, 1994

Manacorda, M. and B. Petrongolo, "Skill Mismatch and Unemployment in OECD Countries", *CEP Discussion Paper* No. 307, 1996.

Manning, A., "Wage Bargaining and the Phillips Curve: The Identification and Specification of Aggregate Wage Equations", *The Economic Journal*, 103, 1993, 98-118.

Manning, A., J. Wadsworth and D. Wilkinson, "Making Your Mind Up: Skill Mismatch in the UK", London School of Economics, *mimeo*, 1996.

Murphy, K. and F. Welch, "The Structure of Wages", *Quarterly Journal of Economics*, 107, 1992, 285-326. Nickell, S. and B. Bell, "The Collapse in the Demand for Unskilled and Unemployment Across the OECD", *Oxford Review of Economic Policy*, 11, 1995, 40-62.

OECD, *Economic Outlook*, Paris, 1990.

OECD, *Employment Outlook*, Paris, 1993.

OECD, *Economic Outlook*, Paris, 1994 (a).

OECD, *The OECD Jobs Study, Evidence and Explanations, Part II: The Adjustment Potential of the Labour Market*, Paris 1994 (b).

Wood, A., *North-South Trade, Employment and Inequality: Changing Fortunes in a Skill Driven World*. Oxford: Clarendon Press, 1992.

Table 1
The Labour Demand Equation in 6 OECD Countries
Dependent Variable: ln (N_1/N_2)
Constrained Estimation

	Country					
	France	Germany	Italy	Netherlands	UK	US
$\ln(W_1/W_2)$	1.059					
	(1.123)					
constant	-0.728	0.769	-1.691	-0.012	-1.591	-0.523
	(0.049)	(0.079)	(0.075)	(0.076)	(0.068)	(0.052)
t (X 100)	6.57	5.13	6.51	4.15	7.64	5.25
	(0.20)	(0.52)	(0.32)	(0.28)	(0.23)	(0.12)
R^2	0.987	0.937	0.995	0.990	0.975	0.988
sample	84-94	76-89	77-91	79-93	74-92	70-89
No. obs.	11	7	12	8	19	20

Notes. The elasticity of substitution is constrained to be identical across equations. Standard errors in brackets. Source and definitions: see Data Appendix.

Table 2
Annual Growth Rates (X 100) in Supply, Employment and Demand for Skills.

Country	sample (no. obs)	(1) dln L_1/L_2	(2) dln N_1/N_2	(3) dln N_1/N_2-dln L_1/L_2	sample (no. obs)	(4) dln α_1/α_2	(5) dln α_1/α_2-dln L1/L2
Australia	79-93 (15)	5.36	5.43	0.07	-	-	-
Canada	79-93 (14)	5.49	5.46	0.03	-	-	-
France	78-94 (17)	5.80	6.07	0.27	84-94 (11)	6.47	.36
Germany	76-89 (7)	4.54	5.29	0.75	76-89 (7)	5.11	.58
Italy	77-92 (16)	6.46	6.86	0.41	77-91 (12)	6.52	.06
Netherlands	79-93 (8)	5.84	5.83	0.00	79-93 (8)	4.75	-1.08
Norway	72-93 (22)	6.02	6.23	0.21	-	-	-
Spain	77-93 (17)	5.05	5.58	0.53	-	-	-
Sweden	71-93 (21)	6.93	6.94	0.01	-	-	-
UK	74-92 (19)	6.82	7.03	0.21	74-92 (19)	7.55	.73
US	70-91 (22)	4.59	4.74	0.15	70-89 (20)	5.24	.41
US	70-79 (10)	6.77	6.94	0.16	70-79 (10)	5.67	-1.11
US	79-91 (13)	3.21	3.25	0.04	79-89 (11)	4.73	1.48

Notes. The growth rates of relevant variables are the estimated coefficients on a linear time trend (X 100) interpolated trough the series of logarithms. Source and definitions: see Data Appendix.

Table 3

Annual Changes in the Skilled Unemployment Rate and the Impact of Mismatch
(X 100)

Country	Unemployment	Impact of MM	
	u_1	rigid wages	flex wages
France	0.24	-0.07	-0.05
Germany	0.22	-0.03	-0.02
Italy	0.06	-0.15	-0.11
UK	0.18	-0.18	-0.10
US	0.00	-0.07	-0.04

Notes. Changes are computed by interpolating a linear trend on the relevant series. Sample sizes and number of observations are those used in Table 1. Rigid wages: γ =0.035. Flexible wages: γ =0.1.

Table 4
Annual Changes in the Unskilled Unemployment Rate and the Impact of Mismatch
(X 100)

Country	Unemployment	Impact of MM	
	u_2	rigid wages	flex wages
France	0.58	0.18	0.13
Germany	0.88	0.33	0.22
Italy	0.43	0.04	0.03
UK	0.39	0.21	0.13
US	0.14	0.15	0.09

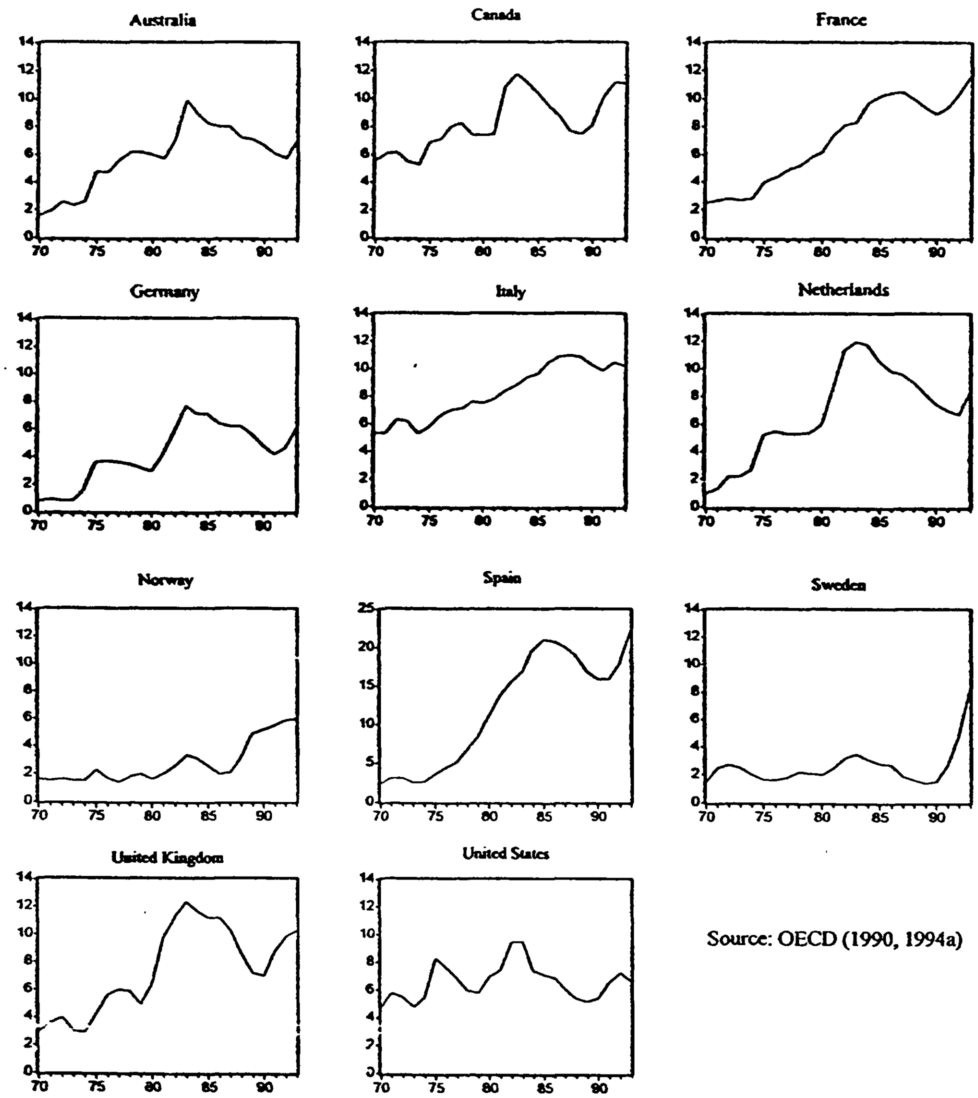
Notes. Changes are computed by interpolating a linear trend on the series. Sample sizes and number of observations are those used in Table 1. Rigid wages: γ =0.035. Flexible wages: γ =0.1.

Table 5
Annual Changes in the Aggregate Unemployment Rate and the Impact of Mismatch
(X 100)

Country	Unemployment	Impact of MM	
	u	rigid wages	flex wages
France	0.36	0.05	0.03
Germany	0.35	0.07	0.05
Italy	0.38	-0.01	-0.01
UK	0.29	0.13	0.08
US	0.05	0.07	0.04

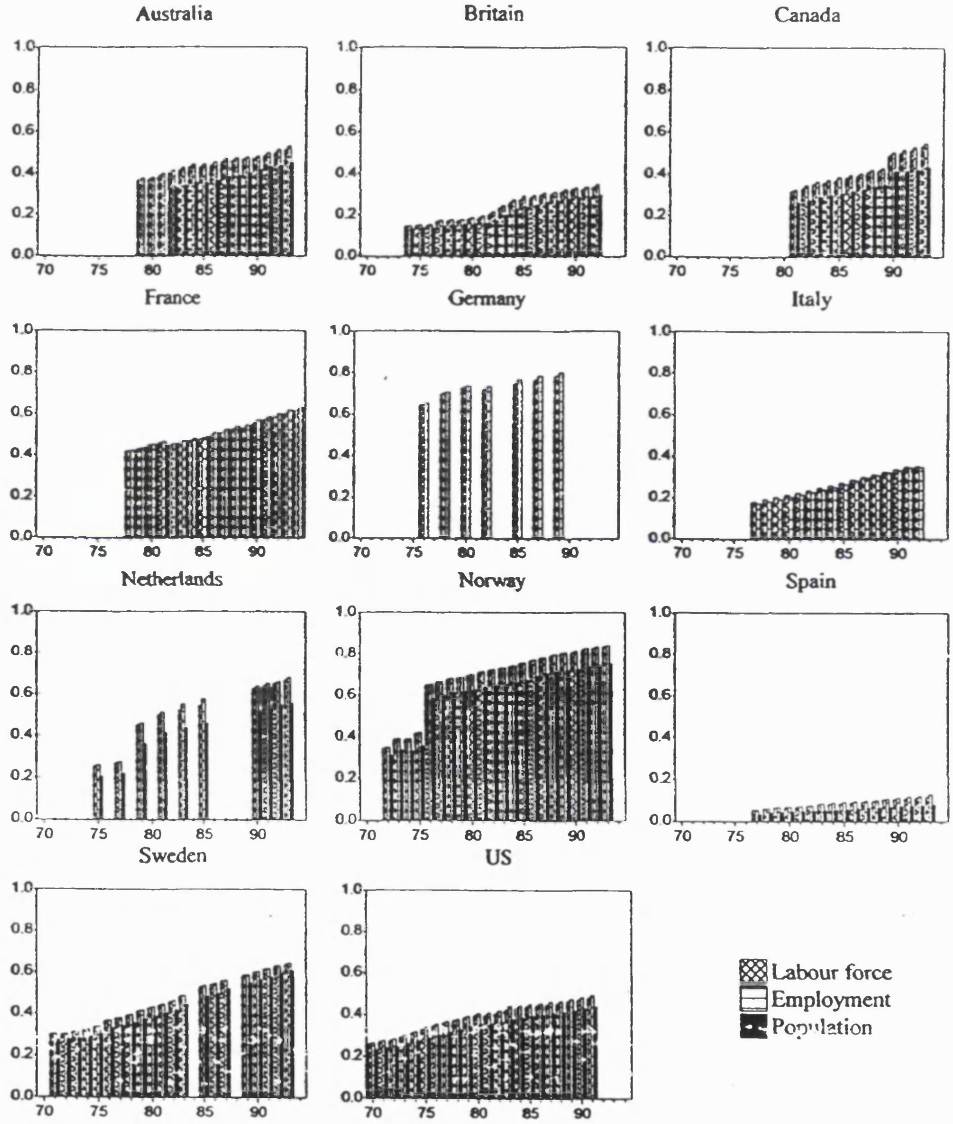
Notes. Changes are computed by interpolating a linear trend on the series. Sample sizes and number of observations are those used in Table 1. Rigid wages: γ =0.035. Flexible wages: γ =0.1.

Figure 1
The Standardised Unemployment Rate in 11 OECD Countries, 1970-1994.



Notes. Source: OECD (1990, 1994a).

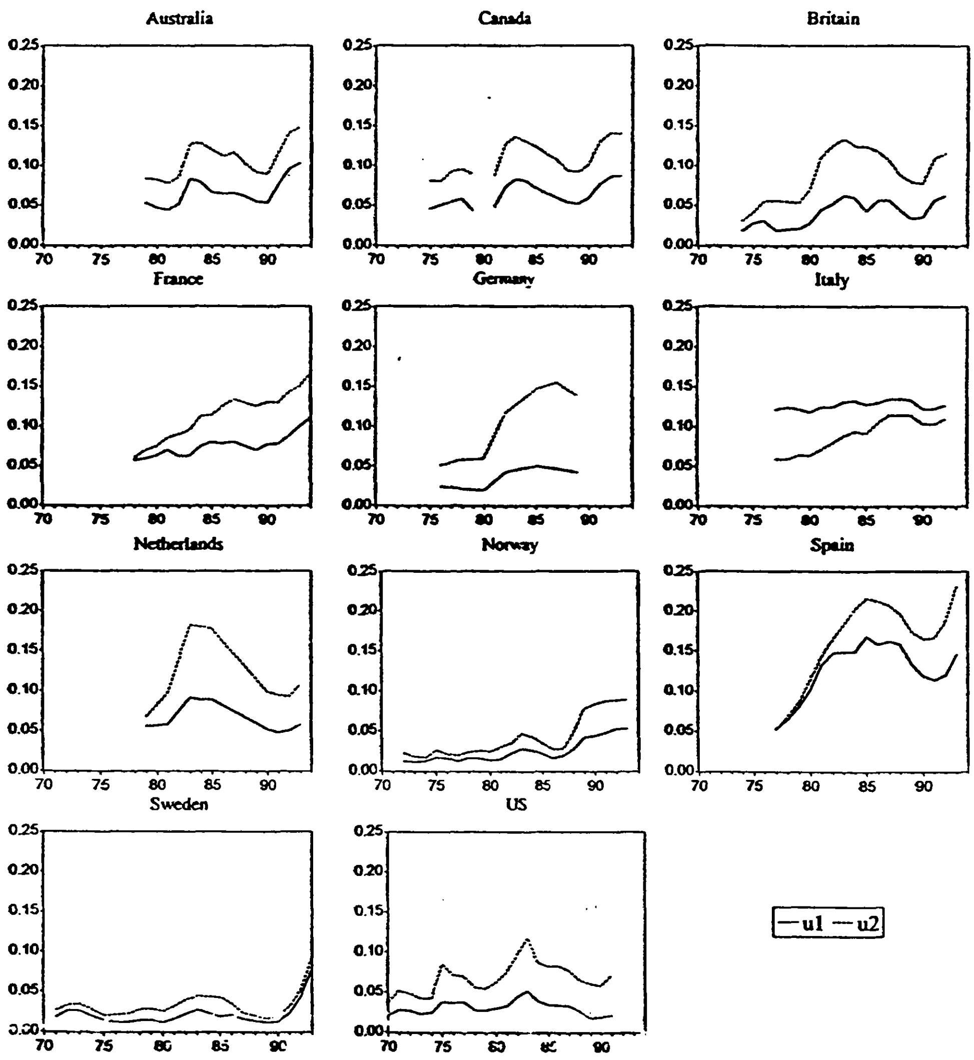
Figure 2
Shares of Skilled Individuals: 1970-1994



Notes. Breaks in the series for Canada in 1990 and Norway in 1976.
Source and definitions: see Data Appendix.

Notes. Source: see Data Appendix. Break in the series in Canada (1990) and Norway (1976).

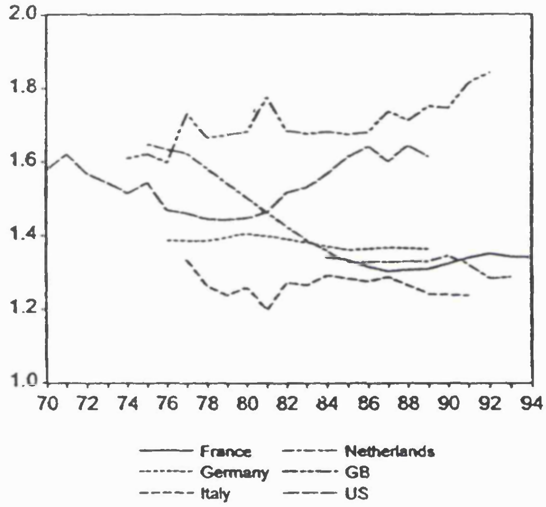
Figure 3
Unemployment Rates by Education: 1970-1994.



Notes. 1=skilled; 2=unskilled. For source and definitions: see Data Appendix.

Notes. Source: see Data Appendix. 1: skilled, 2: unskilled.

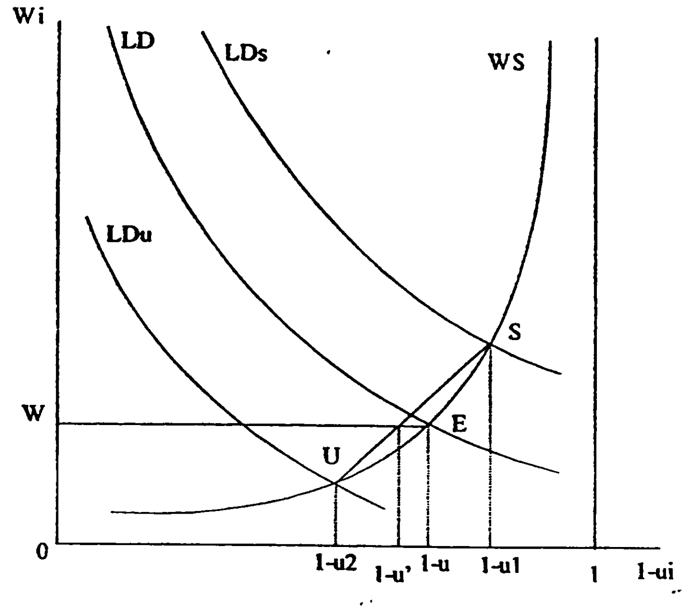
Figure 4
Skilled to Unskilled Wage Ratios: 1970-1994.



Source and definitions: see Data Appendix.

Notes. Source: see Data Appendix.

Figure 5
The Effect of an Asymmetric Labour Demand Shift
on Sectoral and Aggregate Unemployment Rates.



Notes. The picture reports the effect of skill mismatch on unemployment. LD is common labour demand for both skills groups and WS the common wage curve. Equilibrium is initially at E and the aggregate unemployment rate is u. A rise in (net) relative demand shifts the labour demand for the skilled up (LD_s) and the labour demand for the unskilled down (LD_u). At fixed average wage (W), this raises the aggregate unemployment rate ($u' > u$).

Chapter 2

Skill-Biased Change in OECD Countries: Further analysis

As discussed in the previous chapter, it is common in some circles to argue that poor labour market performance in the OECD countries has been caused primarily by shifts in relative demand against the less skilled. However, in chapter 1 we have questioned whether this is really a plausible explanation for the rise in unemployment in continental Europe over the 1980s. In order to get to this conclusion, we have examined the experience of workers with (two) different levels of education in a number of countries. This is an approach common to other studies in the area, although different measures of skills have also been used.[1]

One of the more serious concerns about the analysis in the previous section, as well as many of the other papers in this area (Krugman, 1994; Nickell and Bell, 1995; Manning *et al.*, 1996) is that a lot rests on the assumption that levels of education are comparable both across countries and over time. There is good reason to be sceptical about this. While the OECD has put considerable effort into standardising measures of educational attainment (the ISCED definitions) the fact that these definitions are continually being revised is an indication of the difficulty if not the impossibility of the task. The International Adult Literacy Survey (OECD, 1996) suggests large differences in literacy levels across countries even among individuals with the same ISCED level of education. In addition, the increase in educational attainment in most countries means that a high-school dropout today is likely to be at a rather different position in the ability distribution compared to a dropout 20 years ago. In this chapter we try to achieve comparability across countries and over time by focussing, not on the fortunes of individuals with a given level of education, but on the fortunes of those at a given position in the skills distribution. This has the advantage that it is natural to compare an individual at a given percentile in the skills distribution in one country with someone at the same position in another.

Of course, published statistics do not provide data for individuals at different relative points in the distribution of skills and one of the contributions of the chapter is to show how one can (with certain assumptions) use data on wages, employment and unemployment by levels of education (or for what it matters occupation) to make inferences about changes in the fortunes of those at different points in the skills distribution. The intuition behind this result is that any change in the distribution of human capital in the population will translate into some dispersion of either wages or relative employment across education groups if and to the extent at which human capital is correlated with education.

The plan of the chapter is as follows. In the next section we present the basic data used in the rest of the analysis and introduce some broad evidence on changes in (relative) wages, employment and unemployment by four educational groups education for five OECD countries. Section II introduces a model of the labour market with a continuous distribution of skills and shows how under some parametric assumptions one can derive a simple one-dimensional measure of the gap between the demand for skills and the supply of skills. Section III then shows how this index of skill mismatch can be estimated on the available data and contains empirical evidence on the extent of skill mismatch in the five countries. In section IV we check for the robustness of our results to a variety of assumptions. Finally, section V shows that the measured increase in skill mismatch in the US and the UK is of a magnitude sufficient to explain the rise in wage inequality in these countries.

[1] Nickell and Bell (1995) use occupation (for some countries) while Card et al. (1999) use the wage.

I. Basic Evidence

In this section we show what motivates this study by presenting evidence on changes in the employment, unemployment and wage structures by education for OECD countries. While this evidence is broadly consistent with several other studies in the area (including the evidence in the previous chapter), the point of this section is to show that if one has information on more than two educational groups, it becomes difficult to infer whether a change in the demand for skills has actually occurred and what its magnitude is.

In the rest of the chapter we use data on five countries: France, Italy, the Netherlands, the UK and the US, i.e. a subset of the ones used in chapter 1. This selection was determined by the availability of a partition of the population into (at least) four roughly comparable educational categories (see below). For each country we have data in each year on employment and unemployment (men and women) by education. Details of the data sources and definition of the different educational categories as well as the definitions of wages are provided in the Data Appendix.

In Figure 1 we plot the evolution of the labour force shares for each of these educational groups where level 1 is the lowest level of educational attainment and 4 the highest. As argued in chapter 1, this can be though of as a measure of (relative) labour supply. One can see that, while the definitions of educational attainment are meant to be more or less comparable, the proportions in the different categories vary a great deal across countries. This should make us wary of international comparisons based on allegedly consistent educational definitions. For most of the countries, however, one can see clear evidence of increasing educational attainment.

Figure 2 presents the information on the evolution of the wage bill shares, which under the assumption that the underlying production function is a Cobb-Douglas with

CRTS can be thought as an indicator of relative labour demand. The figure shows once again the increase in the shares of the highly educated groups. Wage bill shares obviously combine information on labour force shares, relative employment rates and relative wages so Figures 3 and 4 present the data for the evolution of employment rates relative to the average employment rate and wages relative to average wages. A closer look at the figures shows some wage decompression in the US and UK during the 1980s (a trend that has been documented elsewhere e.g. Katz and Murphy, 1992; Schmitt, 1995) and a deterioration of the relative employment of the least-skilled in most (though not all) of the European countries.

The trends in Figures 1 to 4 are not particularly easy to see, so Table 1 presents point estimates of the ten-year trend in each of the four series. The point estimates confirm the results of chapter 1, i.e. a deterioration in the relative employment of the least skilled, particularly in some (but not all) European countries whereas it is in relative wages that the trends are most marked in the US and the UK.

An interesting feature of the data is that it is possible for changes in relative wages or employment rates to have the same sign for all education groups. This signals the importance of the changing education composition of the labour force, a fact which is generally ignored in this type of studies.[2] As suggested in the introduction, one of the advantages of our model is that it takes this feature of the data into account.

In the next section we present a model of the labour market based on some continuous measure of skills (human capital) and we derive the implications of this model in terms of employment and wages for those at a given position in the skills distribution. In section III we then show how one can use the evidence presented above in order to estimate the parameters of the model.

[2] To see this, observe that if by W we denote wages and by N employment, it must be the case that $\sum\Delta[(N_e/N)(W_e/W)]=0$, so that keeping fixed the structure of employment (wages), changes in relative wages (employment) are not constrained to sum to zero.

II. A Model of the Labour Market with a Continuous Distribution of Skills

In the following we assume that there is a single index of skill (or human capital) denoted by h. This is continuously distributed in the population at time t with density $\beta(h,t)$. For the time being we assume that h is normal with mean μ_{st} and variance σ^2_h:

$$(1) \qquad \beta(h,t) = \frac{1}{\sigma_h}\phi\left(\frac{h-\mu_{st}}{\sigma_h}\right) = \frac{1}{\sigma_h}\phi(\Phi^{-1}(F(h,t),t)) \equiv \beta(F(h,t),t)$$

where ϕ is the p.d.f. of a standard normal, Φ is the corresponding c.d.f. and, with obvious notation, $F \equiv F(h,t) = \Phi((h-\mu_{st})/\sigma_h)$ is the relative position of an individual with human capital h in the distribution of skills. The function $\beta(h,t)$ defines the supply of skills in the economy. An increase in the average level of skills in the population will be represented in this framework by an increase in μ_{st}. Although any complete model of the economy obviously should model the supply of skills, similarly to chapter 1 we assume that this is exogenously given at each time t. The normality assumption is made for analytical convenience and we investigate the consequence of relaxing this assumption below.

Note that a similar approach is also taken by Juhn, Murphy and Pierce (1993) and Card and Lemieux (1996) though their use of the assumption is very different from ours. These authors take the wage as a measure of human capital. As it will be clear in the following, in a model without unemployment dispersion, one can read off the amount of imbalance between supply and demand at each point of the distribution by looking directly at relative wages. If unemployment is introduced into the model, however, relative wages do not provide an unbiased estimate of the gap between demand and supply. The present work is precisely an attempt to account for differences (and different changes) in relative unemployment across skill groups.

On the demand side, we stick to the analysis of the previous section and we suppose that firms employ this continuous labour input (h, or which is the same, F) using a Cobb-Douglas production function:

(2) $$Y(t) = A(t).\exp\left(\int \alpha(F,t)\log N(F,t)dF\right)$$

where N(F, t) is the employment at date t of those at position F in the population distribution of skills (i.e. with human capital $h=\sigma_h\Phi^{-1}(F)+\mu_s$) and Y(t) is total output. As a convention in the rest of the chapter, variables without the index h (or F) denote aggregate variables. Under CRTS, the restriction on $\alpha(F,t)$ is that the integral with respect to h should sum to one so that density functions are a useful source of possible functions for $\alpha(F,t)$. To keep matters simple let us suppose that this has the following form:

(3) $$\alpha(F(h,t),t)) = \phi(h - \mu_{\alpha t}) = \phi(\sigma_h \Phi^{-1}(F(h,t),t)) - \mu_t) \equiv \alpha(h,t)$$

where again ϕ is the p.d.f. of a standard normal and we have defined $\mu_t \equiv (\mu_{\alpha t}-\mu_{st})$ as the average difference between demand and supply. The assumption that the variance of this distribution is one is simply a normalisation which scales the units of h so σ_h has to be interpreted as the variance in supply relative to the variance in demand. Again, we will discuss the consequences of relaxing the normality assumption below.

This specification implies that at each moment in time there is a 'most desired' level of skills which changes over time if the demand for skills changes. It implies, for example, that the demand for brain surgeons is extremely low when development is low as no-one has the other requisite technology to allow them to do their job but that the demand will rise through time as technology advances and then, if we push further on, will then decay again as their skills become superseded by technology.

Assuming that the labour market is perfectly competitive, (2) then leads to the familiar labour demand curve:

$$\log W(F,t) = \log\alpha(F,t) + \log W(t) - \log N(F,t) + \log N(t) =$$

(4)

$$= \log[\alpha(F,t)/\beta(F,t)] + \log W(t) - \log[(1-u(F,t))] + \log[1-u(t)]$$

where the second equality follows from the fact the relative employment rates can be written as log[1-u(F,t)]-log[u(t)]=log[N(F,t)/N(t)]-log[β(F,t)].

Equation (4) can be thought of as representing a trade-off for workers a position F in the skills distribution between their log relative wage and their log relative employment rate. The slope of this trade-off is -1 (from the Cobb-Douglas assumption) and the term [α(F,t)/β(F,t)] determines the position of this trade-off so can be thought of as an index of relative demand for the person at position F in the skills distribution. Let us denote this index by D(F,t). From equations (1) and (3) it follows:

$$(5) \qquad D(F,t) = \frac{\alpha(F,t)}{\beta(F,t)} = \frac{\phi(\sigma_h \Phi^{-1}(F) - \mu_t)}{\sigma_h \phi(\Phi^{-1}(F))}$$

It is easy to see that this index integrates to one in the population, since:

$$(6) \qquad \int_0^1 D(h(F),t)dF = \int_0^1 \frac{\alpha(h(F,t),t)}{\beta(h(F,t),t)} dF = \int_{-\infty}^{+\infty} \frac{\alpha(h,t)}{\beta(h,t)} \beta(h,t)dh = \int_{-\infty}^{+\infty} \alpha(h,t)dh = 1$$

How this relative demand index varies with F depends on σ_h and μ. The case σ_h=1 is particularly simple and, as we shall see later, also seems to have some empirical relevance.[3] In this case the demand index reduces to:

$$(7) \qquad D(F,t) = \frac{\phi(\Phi^{-1}(F) - \mu_t)}{\phi(\Phi^{-1}(F))} = \exp(\mu_t \Phi^{-1}(F) - \frac{1}{2}\mu_t^2)$$

so that relative demand is increasing (decreasing) in F as $\mu_t \geq (\leq) 0$ which can be interpreted as the demand for skills running ahead or behind the supply of skills. In a situation where relative demand was decreasing in human capital we would expect there to be low or even negative returns to education so that investment would decrease, reducing μ_{st} and bringing us back towards the case where $\mu_t \geq 0$. So, we might expect that the economically relevant case is where $\mu_t \geq 0$ and our estimates below will suggest very strongly that this is the case.

Now consider what is likely to happen if the demand for skills increases faster than the supply so that μ_t increases. By differentiating (7) with respect to μ one can see that such a change will improve the position of the relative demand curve for those at the top of the skills distribution and reduce it for those at the bottom.[4] At fixed unemployment rates, a rise in μ will then increase wage inequality.[5] This discussion suggests using $\mu_t \equiv (\mu_{\alpha t} - \mu_{st})$ as our index of skill mismatch, an index which is particularly simple. So, if we can figure out a way of estimating μ_t then we can examine the way it changes over time to consider whether there have been any changes in skill mismatch: we show how to do this below.

Ideally, in order to derive the equilibrium effect of an increase in relative demand, one would like to close the model with a 'wage curve', as we have done in chapter 1. In order to keep things simple in this chapter we ignore the effect of skill mismatch on unemployment and we set for ourselves the more limited task of assessing the occurrence and the magnitude of skill biased change in a model with a continuous distribution of skills. In chapter 1, however, we have shown that if wages are a convex function of unemployment and if high skilled workers have lower unemployment rates than low skilled workers a shift in relative demand towards skilled workers will rise aggregate unemployment.

So far, the analysis has been entirely theoretical. In the next section we will provide evidence on whether such an increase in skill mismatch has occurred.

[3] The case where $\sigma_h \neq 1$ is more complicated as then the densities for demand and supply do not have the same variance. In this case the relative demand index will not be monotonic in F which makes things intuitively more difficult and also might cause one to wonder about the suitability of the model.
[4]This derivative is $(\Phi^{-1}(F)-\mu)D(F)$.

III. Measuring Skill Mismatch

a. Methodology

In this section we show how one can use the information presented in section I to investigate the occurrence and magnitude of skill mismatch as defined in section II. The theory of the previous sections has all been in terms of human capital (h) or, which is the same, the individual's relative position in the human capital distribution (F). This is a potential source of problems as we do not observe human capital directly. But, we will show below that one can still make progress even if one only has a variable that is imperfectly correlated with human capital. For this chapter we have used education as the appropriate variable as this is what the other papers in the area have most commonly used and it is readily available.

In order to get an estimate of our index of skill mismatch, μ_t, we need to have a model of how human capital is related to education. We will assume that human capital is partly determined by schooling, denoted by s (which we will assume to be a continuous variable), but also by 'ability', denoted by ε so that schooling is not perfectly correlated with skills. Assume that the human capital of individual i at date t is given by:

(8) $$h_{it} = s_{it} + \varepsilon_{it}$$

Assume that s and ε are joint normally distributed with the following distribution:

(9) $$\begin{pmatrix} s_{it} \\ \varepsilon_{it} \end{pmatrix} \sim N\left(\begin{bmatrix} \mu_{st} \\ 0 \end{bmatrix}, \begin{pmatrix} \sigma_s^2 & \rho\sigma_s\sigma_\varepsilon \\ \rho\sigma_s\sigma_\varepsilon & \sigma_\varepsilon^2 \end{pmatrix}\right)$$

The assumption that ability has mean zero is simply a normalisation that can be made without loss of generality. This specification allows for schooling to be correlated with

[5] It is easy to show that $\Delta var(\log(W(h,t)/W(t)) = \Delta\mu_t^2$.

ability (as is sometimes claimed). Equations (8) and (9) obviously lead to (1) with $\sigma^2_h = \sigma^2_s + \sigma^2_\varepsilon + 2\rho\sigma_s\sigma_s$. Notice that assuming that schooling and human capital are perfectly correlated has the implication that the lowest wage for people with a certain level of schooling will be above the highest level of wages for someone with a lower level of schooling, an assumption that is violated in the data. Introducing the ability component ensures that there is some overlap in the human capital distributions for people with different levels of education.

In this model education is a continuous variable but in our data we only have discrete educational categories. We assume that everyone in a particular educational category in our data has a level of schooling between certain limits which remain constant over time. Effectively, we have an ordered probit model for educational attainment.[6]

Now consider how we can use this information to measure skill mismatch. We will show how information on the share of the wage bill going to different education groups can be used to infer something about shifts in demand and supply. Working out the relationship between the share of the wage bill going to the low education group and these trends is not entirely straightforward as the trend in demands is defined relative to h which is only imperfectly correlated with s. But we prove in the Technical Appendix that, given the assumptions made, there is a simple expression for the share of the wage bill going to those with education less than s (which is something we have data on). The share of the wage bill going to individuals with education less than s at date t, A_{st}, is given by:

[6] A similar method is also used by Fortin and Lemiuex (1998), though they only look at the wage distribution.

$$(10) \qquad A_{st} = \Phi\left(\frac{\dfrac{s-\mu_{st}}{\sigma_s} - \dfrac{\rho_{hs}}{\sigma_h}(\mu_{\alpha t}-\mu_{st})}{\sqrt{1-\rho_{hs}^2+\rho_{hs}^2/\sigma_h^2}}\right)$$

where ρ_{hs} is the correlation coefficient between h and s (and of course $\rho_{hs}=(\sigma_s+\rho\sigma_\varepsilon)/\sigma_h$). Although equation (10) might appear intimidating at first sight, this is simply describing the relationship between the c.d.f.'s of two normal variables which are only imperfectly correlated. One can check that for h=s (in which case $\rho_{hs}=1$ and $\sigma_h=\sigma_s$) this expression is nothing but the expression the c.d.f. of a standard normal variable ($A_{st}=\Phi((s-\mu_a)/\sigma_s)$).

Observe now that under the assumption that schooling is normally distributed with mean μ_{st} and standard deviation σ_s, a simple relationship exists between the level of schooling and the fraction of the population below education level s, which we denote by B_{st}:

$$(11) \qquad \frac{s-\mu_{st}}{\sigma_s} = \Phi^{-1}(B_{st})$$

By inverting equation and (10) and using (11) we have that:

$$(12) \qquad \Phi^{-1}(A_{st}) = \frac{1}{\sqrt{1-\rho_{hs}^2+\rho_{hs}^2/\sigma_h^2}}\Phi^{-1}(B_{st}) - \frac{\rho_{hs}/\sigma_h}{\sqrt{1-\rho_{hs}^2+\rho_{hs}^2/\sigma_h^2}}\mu_t$$

So, one can use (12) and data on cumulative wage bill shares and labour force shares accruing to different education groups over time to estimate some linear combination of the demand and supply trends.

Equation (12) shows how one can potentially use a variable like schooling that is not perfectly correlated with human capital to investigate the existence of skill biased demand shocks. This result can obviously also be applied to any other variable that is correlated, albeit imperfectly, with the underlying measure of skill. For example a number of studies (e.g. Berman, Bound and Griliches, 1994; Machin, 1995) investigate changes in the share of the wage bill going to non-production workers. None of these authors believe that white-collar status is the crucial variable for understanding skill-biased technical change: it is simply that this is the best data available and it is plausibly correlated with human capital. A result like the one reported above provides some more formal justification for the procedure used in these papers.

In the case in which $\sigma_h=1$, equation (12) has a particularly simple form:

$$(13) \qquad \Phi^{-1}(A_{st}) = \Phi^{-1}(B_{st}) - \rho_{hs}\mu_t$$

As long as identification is concerned, notice that since the shares in equations (12) and (13) are cumulative ones, no useful information is provided by the top educational group, since by definition the associated shares are invariably equal to one. So, with N educational groups, one can use only the information provided by the bottom N-1 groups. This in turn makes it clear that if one has only a binary partition of the population into two educational groups one cannot identify separately the effect of changes in supply (the coefficient on $\Phi^{-1}(B)$) from changes in the relative demand indicator in equation (12). By the same token, there is no way to test for the goodness of fit of model (12) or (13). So one needs at least three educational groups in order to test if the model fits the data. However, even with more than two educational groups, identification of equations (12) and (13) is somewhat problematic. To keep things simple, suppose that $\sigma_h=1$. It can readily be seen from equation (13) that even under this restriction, one cannot separately identify μ from ρ_{hs}. Any time-series and cross-sectional inference on trends in relative demand based on the estimation of equation (13) requires the assumption that the correlation between education and human capital does not change over time and across countries, respectively. We will go back to the identification of ρ_{hs} in section IV.

Note incidentally (equations (4) and (7)) that if human capital were perfectly correlated with schooling, any rise in μ_t (assuming unemployment rates are given) would only translate into increased wage inequality between educational groups while, if the reverse were true and human capital and education were uncorrelated, any rise in μ_t would only translate into increased wage inequality within educational groups. This suggests that our model is potentially able to account for the simultaneous rise in inequality both between and within educational categories, a fact which is known to have happened in the US (and the UK).

Equations (12) and (13) suggest that one should use data on wage bill and labour force shares to investigate whether skill mismatch has increased or decreased. But, in chapter 1 we arrived to the same conclusion without the need for such a complex model as the one in section II. But, while with only two educational groups (and ρ_{hs}=1) one can easily use the model of chapter 1 to assess the occurrence and magnitude of skill biased change, as soon as one has data on more than two educational groups, this exercise becomes pretty involved. On the other hand, as emphasised above, having more than two educational groups allows to test for the fit of the model and we regard this as an advantage of the analysis of the present section. In section IV we will show how the model of chapter 1 is nested in the model of section II.

To have a sense of the pros and cons of having more than two educational groups, in Table 2 we propose a simple simulation exercise. We have assumed to have four educational groups (1 being the lowest) whose fortunes we observe for 20 years (from 1975 to 1994, say) and, in order to keep things simple, that education and human capital are perfectly correlated (and σ_h=1). Of course, we work under the hypothesis that both demand and supply are normally distributed. Suppose for a start that the low-education group accounted for 25% of the total labour force share (β_1) while the top education group (β_4) accounted for 34%. Suppose now that the wage bill share of the low-skill group (α_1) goes from 20% to 15% at the same time as the wage bill share of the top educational group (α_4) goes from 40% to 48%. Both two intermediate groups see a decline in their relative wage bill share (respectively α_2 and α_3 go from 10% to

9% and from 30% to 28%). In this case one could easily conclude that there has been a rise in skill mismatch and the model derived above would be essentially of no use.[7] But suppose now that the fall in the wage bill share for the less educated coincided with a fall in the labour force share (β_1) from to 25% to 19% while at the same time the labour force share of the highly educated (β_4) had increased to 41%. At the same time group-2 labour force remains unchanged (β_2 remains at 11%) and group-3 share declines (β_3 goes from 30% to 29%). In this case one has to make some judgement about whether relative demand has increased or decreased. This is where a model like the one in section II can provide guidance as, if (13) is the correct model then skill mismatch will actually have stayed unchanged (at 0.17) in this circumstance.

While our model has the potential to account for the unbalanced growth in the demand and supply of a continuously distributed measure of human capital by simply looking at a one-dimensional measure of this gap, one must be careful to check that the theoretical model is an adequate representation of the data. Notice that for our model to be true, we would expect the imbalance between demand and supply, as measured in (12) or (13), to be the same for each educational group. One can easily check that this is true in our simulated data in table 2, but one would like to be reassured that this is also true in the actual data presented in section I. This leads on to a discussion of estimation and goodness-of-fit of the model.

b. Empirical Evidence

In Table 3a we estimate the model (12) for our sample of countries. As, the inverse cumulative shares will, by construction, be heteroskedastic and correlated within years the standard errors must obviously take account of this fact. As we show in the

[7]Indeed one can check that our model suggests a sensible rise in mismatch (from 0.17 to 0.36).

Technical Appendix, we would expect the covariance matrix to be of a particular form and we exploit this in our estimation method, which is feasible GLS.

Recall that the measure of skill mismatch derived from these estimates should be independent of the actual educational categories used so does not rely on educational categories being the same for all countries, and should produce estimates that are comparable across countries and over time.[8]

The coefficient on the inverse of the labour force shares is very close to one for the US and slightly lower for the other European countries. From (12) this implies that $\sigma_h=1$ for the US and that $\sigma_h<1$ for Europe (assuming, as seems reasonable, that $\rho_{hs}>0$). While this could be taken to imply that the distribution of human capital is more compressed in Europe than the US, it would seem that (13) is a reasonable approximation to the data. This is extremely convenient as this case is much easier to understand in intuitive terms and we will use it in what follows. Given this, Table 3b estimates the model imposing this restriction.

All the estimated intercepts in both tables are positive implying that demand is running ahead of supply. This simply says that the share of the wage bill going to high education groups exceeds their share in the labour force because their wages are higher and their unemployment rates are lower than the average. In terms of trends in skill mismatch, the UK and the US show marked increases, France and Italy show a more modest increase in mismatch in the unrestricted model but none in the restricted model, and the Netherlands actually exhibits a decline. Taken together, this suggests that there has been an increase in skill mismatch in the Anglo-Saxon countries but none (or at most a more modest one) in continental Europe.

The different trends in skill mismatch in the US and UK on the one hand and in continental European countries on the other could be caused by a faster rate of increase in the demand for skills or a slower rate of increase in the supply of skills or some combination of the two. We would like some idea of which explanation is more plausible. From (11), we can use the labour force shares to estimate the evolution of the supply of skills. The results of estimating this model are reported in Table 4 where, as suggested by (11), education-specific effects are also included. The increase in the supply of skills seems more marked in the European countries than in the US. The annual change in the year-effects is 3.6% a year in France, 4.5% in the Netherlands, 3.1% in Italy 3.7% in the UK and 2.5% in the US. Unfortunately, these numbers cannot be directly compared with the estimates of the change in skill mismatch obtained from Table 3. In Table 3b, we actually estimate $\rho_{hs}(\mu_{\alpha t}-\mu_{st})$ while, in Table 4, we are actually estimating μ_{st}/σ_s so that the scale of the estimated time-effects will be different.

The results in this section have all been based on estimating a very special model. We would like to have some reassurance that the conclusions drawn are reasonably robust: this is the subject of the next section.

IV. Robustness Checks

In the previous sections we have emphasised that one of the properties of our approach is that it derives a one-dimensional measure of skills mismatch which is (in theory) independent of the partition of the population into different education categories. One would then expect the difference between the inverse cumulative shares $[\Phi^{-1}(A_{st})- \Phi^{-1}(B_{st})]$ to be identical across education categories. Figure 5 presents the evolution of this difference for each country. There are persistent differences across education groups, notably the estimate of mismatch seems highest in the highest education group. As a more formal test we run a LM test for the hypothesis that the residuals are uncorrelated

[8] Though, we would expect that the efficiency of the estimate will be affected by the educational categories used.

over time within each education group. This is simply a Breusch-Pagan test the hypothesis of no random effects. The results of the test are reported in the first two lines of Table 7, respectively for the unrestricted (Table 3a) and unrestricted (Table 3b) ordered probit models. We always reject the null hypothesis. However, this does not mean our model is useless. It is reassuring that the trends in mismatch in Figure 5 seem similar for all education groups and we will see later that our restricted model predicts outcomes very similar to a model that (in most of the cases) passes this specification test. However, the fact that the model does not fit the data perfectly means that there is some potential benefit from investigating the relaxation of certain assumptions of the model.

The model is based on two main assumptions: the distribution of the demand and the supply of skills is normal, and the correlation between education and human capital is unchanged both over time and across countries. These assumptions have been made as much for analytical tractability as for realism: it is hard to relax them without complicating the model enormously. So, we will relax assumptions individually.

Let us first consider the normality assumption. Suppose that, the demand function in (3) is given by $\alpha(F(h,t),t))=f_\alpha(h-\mu_{\alpha t})$ for some function $f_\alpha(.)$ which corresponds to a cumulative density function $F_\alpha(.)$ which is not normal. Suppose also that the supply of skills (1) has a cumulative density $B(s,t)=F_\beta(s-\mu_{st})$. For choices of $F_i(.)$, $i=(\alpha,\beta)$, other than normal one cannot assume that h and s are imperfectly correlated and obtain a result as simple as that in Section III. So, to get some idea of how the results are affected by relaxing the normality assumption, we will assume that $h=s$ (and $\sigma_h=1$). One can then straightforwardly derive the following equivalent of (13):

(14) $$F_\alpha^{-1}(A_{st}) = F_\beta^{-1}(B_{st}) + (\mu_{st} - \mu_{\alpha t}) = F_\beta^{-1}(B_{st}) - \mu_t$$

Given a choice of $F_i(.)$ one can estimate this equation. We assume that:

$$(15) \quad F_i^{-1}(x) = \frac{1}{\lambda_i}\left[\left(\frac{x}{1-x}\right)^{\lambda_i} - 1\right] \quad i = \alpha, \beta$$

so that we have a Box-Cox transformation of the wage bill and labour force shares. One attractive feature of this specification is that if $\lambda_i=0$, (15) implies that the distribution of A and B is logistic which we know is quite close to the normal. So (15) can be thought of as almost nesting our preferred specification.

Interestingly, with only two skills groups, perfect correlation between human capital and education, and $\lambda_i=0$, equation (14) specialises into:

$$\ln\frac{\alpha_t}{1-\alpha_t} - \ln\frac{\beta_t}{1-\beta_t} = \mu_t$$

where α and β are the wage bill share and the labour force share of the top educational group (clearly, it is $A_1=1-\alpha$ and $B_1=1-\beta$). Notice that this is exactly the index used in chapter 1.

Table 6 presents the results of estimating (15). The estimates of λ_α and λ_β are negative which implies that the distribution of both the demand and supply of skills is skewed to the left. However, the conclusions about the evolution of skill mismatch remain the same with the possible exception of France where there is some evidence of an increase in skill mismatch.

For comparison, we report the results of the LM test for the Box-Cox model in the last row of Table 7. Although we still reject the null hypothesis for UK and France, the value of the statistic falls sensibly in all the countries suggesting that this model does quite a good job in fitting the data.

The second check we run in this section regards identification of the parameter ρ_{hs}. We have used estimates like those reported in Table 3b to make comparisons of trends in mismatch over time and across countries. However such comparisons are made difficult by the fact that it is not the mismatch index directly that is being estimated in Table 3b but $\rho_{hs}\mu_t$. Only if ρ_{hs} is constant over time can we use the estimates of Table 3b to make inferences about trends in skill mismatch and only if ρ_{hs} is the same across countries can we use the estimates of Table 3b to make cross-country comparisons. But, nothing that we have done so far allows us to estimate this parameter. This is not a problem unique to our approach as most of the existing literature ignores it by making the convenient but wrong assumption that human capital and schooling are identical so that the correlation between them is perfect.

Let us try to get some idea of the value of ρ_{hs}. Suppose that wages can be represented by a linear function of human capital plus an error term, η, according to the formula:

(16) $$w = \beta_0 + \beta_1 h + \eta$$

where η should be thought of as the measurement error in our estimates of wages plus, more generally, wage differentials that exist in reality that are not related to differences in human capital (e.g. compensating wage differentials might fall into this category). Note that if skills mismatch only translated into wage inequality equation (4) and (7) imply that log wages are a linear function of our measure of human capital. This case is likely to be a good description of the data in the US and possibly the UK, but it is probably less likely to be so in continental Europe, where, as generally argued, wages are exogenously fixed by some labour market institutions.

Suppose we run a regression of log wages on schooling. We can think of the R^2 from this regression as being the fraction of the variance in wages explained by human capital times the fraction of the variance of human capital explained by schooling. This latter variance is given by ρ_{hs}^2 so that we have:

(17) $$R^2 = \frac{\sigma_w^2 - \sigma_\eta^2}{\sigma_w^2}\rho_{hs}^2$$

So, we can use information on the fraction of the variance of wages explained by education plus the fraction of the variance of wages explained by human capital to estimate the correlation between human capital and education. Table 5 presents estimates of the square root of R^2, when an earnings function is estimated using only education as controls.[9] We report two estimates, one based on the four educational categories used in the analysis above and another based on as fine a decomposition as is available in our data sources. For (17) we would like to have education as a continuous variable so the grouping will mean that we are likely to underestimate R to some degree. The extent of the under-estimate is likely to be quite small given that increasing the number of educational categories from the four of our basic analysis to the maximum available does not increase the R^2 by that much. Note that for all countries the fraction of the variance in observed wages that can be explained by education seems to be rising modestly through time. This implies that either the correlation of human capital with schooling is rising through time or the fraction of the variance of wages that can be explained by human capital is rising. This latter hypothesis might be plausible for countries like the UK and the US where we know that the wage distribution is widening (if we thought that measurement error was approximately constant) but it is not particularly plausible for the continental European countries. As argued above, if wages are rigid, as it is sometimes held to be the case in Europe, any increase in skill mismatch (a linear function oh h) will have no effect on wage dispersion. The consequence of assuming that ρ_{hs} is increasing is that the increase in skill mismatch comes to seem even more modest in these countries. This reinforces our earlier conclusion that these countries show no indication of any increase in skill mismatch at all. As cross-country comparisons are concerned, on the whole the fraction of the variance in earnings that can be explained by schooling is remarkably similar in all countries. This would be

[9] Note that we positively do not want other variables in these regressions.

consistent with the view that ρ_{hs} is similar in all countries and differences in the estimates of Table 3b can be ascribed to differences in skill mismatch suggesting that the problem is worse in the UK and US than in the other European countries.

In this section we have argued that our basic conclusions are robust to a variety of alternative assumptions. For countries other than the UK and the US there is obviously little point in assessing formally whether skill mismatch can be held responsible for their labour market performance, for the simple reason that our estimates do not suggest that there has been any sensible rise in skill mismatch. But, for the UK and the US we can try to get some idea as to the size of the problems likely to be caused by the estimated increase in skill mismatch: this is the aim of the next section. Of course, others have looked at the effect of changes in demand and supply and skills on the wage distribution in the US and the UK and have concluded that the data are consistent with an acceleration in demand for skills over supply over the 1980s. The point of this last section is rather to show of our one-dimensional measure of relative demand is able to account for the rise in wage inequality in these two countries over the 1980s. In this sense, this can be thought of as an internal consistency check for our model.

V. Can Skill Mismatch Be Responsible for the Rise in Wage Inequality?

In this section we try to obtain a quantitative estimate of the impact of increased mismatch in the US and UK. We use both the Box-Cox model of Table 6 and the restricted model of Table 3b to see how much difference the model specification makes.

As it is common practice in the empirical work for the US (again, see for all Katz and Murphy, 1992), we assume that relative employment rates were constant i.e. all the increases in mismatch went into increased wage inequality. So we can use (4) to get some idea of the likely impact of the estimated changes in μ_t on the dispersion of wages. Suppose that between t-1 and t μ changed by $\Delta\mu_t = \mu_t - \mu_{t-1}$. Then we can use this to compare the change in wages at two positions in the wage distribution F_0 and F_1. From (14):

$$(18) \quad \Delta \log(W(F_1,t)/W(F_0,t)) = \log f_\alpha(F_\beta^{-1}(F_1) - \mu_t) - \log f_\alpha(F_\beta^{-1}(F_1) - \mu_{t-1}) - \log f_\alpha(F_\beta^{-1}(F_0) - \mu_t) + \log f_\alpha(F_\beta^{-1}(F_0) - \mu_{t-1})$$

In the special case in which both the supply and the demand for skills are normal, (18) takes the simple form:

$$(19) \quad \Delta \log(W(F_1,t)/W(F_0,t)) = [\Phi^{-1}(F_1) - \Phi^{-1}(F_0)]\Delta\mu_t$$

Figure 6a plots the actual change in wages relative to the median in the US over the period 1978-90 against the predicted change assuming that all the rise in skill mismatch went into a rise in wage inequality and relative employment rates were constant and letting F_0=0.5. We do this exercise both for the estimates in Table 3b and Table 6. Figure 6b does the same for the UK.

From Figure 6 the general impression for both the US and the UK is that the actual and predicted changes are quite close though there is some deviation at the extremes of the distribution particularly for the results based on the normal distribution.[10] The estimates based on the Box-Cox transformation are very similar to those based on the normal distribution except in the lower tail where it does not predict such dramatic changes in relative wages. Using the normal distribution leads to the

[10] Some notes of caution here. First, the observed wage distribution includes the bit due to measurement error that is not taken account of in these computations: this is likely to be small. Second, the predicted wage distribution relates to the distribution among all individuals, the actual data to that among workers in employment. If, as seems likely, employment rates rise as we move up the skills distribution, a given percentile in the employed wage distribution will be a higher percentile in the skills distribution of the population as a whole. However there is no guidance about the direction of the impact of this effect on the change in wages relative to the median. The problem however is likely to be more serious in the UK and the evidence in Figure 6b shows that this seems to be the case.

correct conclusion, namely that the increase in skill mismatch is a potential explanation of the rise in wage inequality in both countries.

VI. Conclusions

In this chapter we have proposed a conceptual framework for thinking about the labour market consequences of changes in relative demand and skills of different skills. We have proposed comparing the fortunes of individuals at different positions in the skills distribution arguing that this cuts through the problem of assuming comparability of educational classifications across countries and over time. We have shown how one can use data on changes in labour force shares, employment rates and relative wages by education to provide a measure of the extent of skill mismatch in the economy which is comparable across countries with different measures and levels of educational attainment. Using this technique we found an increase in skill mismatch in the US and the UK but not in the other European countries. Our evidence suggests that the increase in skill mismatch as we have measured it is of a magnitude sufficient to explain the rise in wage inequality in the US and the UK.

Interestingly, the results of this chapter are in line with those in chapter 1, suggesting implicitly that accounting for differences in the definition of education across countries and the generalised increase on the educational attainment of the population over time is likely to affect only marginally our conclusions.

References

Berman, E., J. Bound and Z. Griliches, "Changes in the Demand for Skilled Labor within US Manufacturing Industries: Evidence from the Annual Survey of Manufacturing", *Quarterly Journal of Economics*, 109, 1994, 367-398.

Blanchflower, D. And A. Oswald , *The Wage Curve*, Cambridge, MIT Press, 1994.

Card, D., F. Kramarz and T. Lemieux, "Changes in the Relative Structure of Wages and Employment: A Comparison of the United States, Canada and France", *Canadian Journal of Economics*, 1999, forthcoming.

Card, D. and A. Krueger, *Myth and Measurement: The New Economics of the Minimum Wage*, Princeton, Princeton University Press, 1995.

Card, D. And T. Lemieux (1996) "Wage Dispersion, Returns to Skill, and Black-White Wage Differentials", *Journal of Econometrics* , 74, 319-61.

DiNardo, J, N. Fortin and T. Lemieux, "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach", *Econometrica*, 64, 1996, 1001-44.

Goldin, C. and L. Katz, "The Origins of Technology-Skill Complementarity", NBER Working Paper No. 5657, 1996.

Gregg, P. and A. Manning, "Skill-Biased Change, Unemployment and Wage Inequality", *European Economic Review*, 41, 1997, 1173-120.

Juhn, C., K. Murphy and B. Pierce, "Wage Inequality and the Rise in Returns to Skill", *Journal of Political Economy*, 101 , 1993, 410-42.

Juhn, C., K. Murphy and R. Topel, "Why Has the Natural Rate of Unemployment Increased Over Time? ", *Brooking Papers on Economic Activity*, 1991, 75-126.

Katz, L. and D. Autor, "Changes in the Wage structure and Earnings Inequality", in *Handbook of Labour Economics*, Ashenfelter O. and D. Card (eds.), North Holland, 1999.

Katz, L. and K. Murphy, "Changes in Relative Wages, 1963-1987: Supply and Demand Factors", *Quarterly Journal of Economics*, 57, 1992, 35-78.

Krugman, P., "Past and Prospective Causes of High Unemployment", unpublished paper, Stanford University, 1994 .

Layard, R., S. Nickell and R. Jackman , *Unemployment: Macroeconomic Performance and the Labour Market*, Oxford University Press, Oxford, 1991.

Machin, S., "Changes in the Relative Demand for Skills in the UK Labour Market", in A. Booth and D. Snower (eds.) *Acquiring Skills: Market Failures, Their Symptoms and Policy Responses*, Cambridge University Press, Cambridge, 1995.

Machin, S., "Wage Inequality in the UK", *Oxford Review of Economic Policy*, 12, 1996, 47-64.

Nickell, S. and B. Bell, "The Collapse in the Demand for the Unskilled and Unemployment Across the OECD", *Oxford Review of Economic Policy*, 11, 1994, 40-62

OECD, *OECD Jobs Study*, Paris, 1994.

OECD, *Literacy, Economy and Society*, Paris, 1995.

OECD, *Job Study*, Paris, 1996.

Schmitt, J., "The Changing Structure of Male Earnings in Britain, 1974-88" in R. Freeman (ed.) *Differences and Changes in Wage Structures*, University of Chicago Press, Chicago.

Technical Appendix

A. Equation (10)

Let us denote by $\alpha_s(s)$ the share of the wage bill going to workers with schooling s. These workers will have different levels of h: we know that the share of the wage bill going to workers with human capital h is given by $\alpha(h)$. Of these workers a fraction $f(s|h)$ have education s where $f(s|h)$ is the density of s conditional on h. So, we must have:

$$\text{(A1)} \quad \alpha_s(s) = \int \alpha(h) f(s \mid h) dh$$

From (8) and (9) we have that:

$$\text{(A2)} \quad s \mid h \sim N\left(\mu_s + \frac{\rho_{hs}\sigma_s}{\sigma_h}(h-\mu_s), \sigma_s^2(1-\rho_{hs}^2)\right)$$

where $\rho_{hs} \equiv \mathrm{Corr}(h,s) \equiv \frac{\sigma_s + \rho\sigma_\varepsilon}{\sigma_h}$. Putting (3) and (A1) in (A2) we have that:

$$\text{(A3)} \quad \alpha_s(s) = \frac{1}{2\pi\sigma_s\sqrt{1-\rho_{hs}^2}} \int e^{-0.5(h-\mu_\alpha)^2} e^{-0.5\left(\frac{s-\mu_s-\frac{\rho_{hs}\sigma_s}{\sigma_h}(h-\mu_s)}{\sigma_s\sqrt{1-\rho_{hs}^2}}\right)^2} dh$$

Let us collect the exponential terms and try to find coefficients $(\delta_0,\delta_1,\delta_2)$ so that:

$$\text{(A4)} \quad (h-\mu_\alpha)^2 + \left(\frac{s-\mu_s-\frac{\rho_{hs}\sigma_s}{\sigma_h}(h-\mu_s)}{\sigma_s\sqrt{1-\rho_{hs}^2}}\right)^2 = (\delta_0 h - \delta_1)^2 + \delta_2$$

Equating coefficients we have that:

$$\text{(A5)} \quad \delta_0^2 = 1 + \frac{\rho_{hs}^2}{\sigma_h^2(1-\rho_{hs}^2)}$$

$$(A6)\quad \delta_0\delta_1 = \mu_\alpha + \frac{\frac{\rho_{hs}\sigma_s}{\sigma_h}\left(s-\mu_s\left(1-\frac{\rho_{hs}\sigma_s}{\sigma_h}\right)\right)}{\sigma_s^2(1-\rho_{hs}^2)}$$

$$(A7)\quad \delta_2+\delta_1^2 = \mu_\alpha^2 + \frac{\left(s-\mu_s\left(1-\frac{\rho_{hs}\sigma_s}{\sigma_h}\right)\right)^2}{\sigma_s^2(1-\rho_{hs}^2)}$$

Now:

$$\delta_2 = \mu_\alpha^2 + \frac{\left(s-\mu_s\left(1-\frac{\rho_{hs}\sigma_s}{\sigma_h}\right)\right)^2}{\sigma_s^2(1-\rho_{hs}^2)} +$$

$$-\frac{\sigma_h^2(1-\rho_{hs}^2)}{\sigma_h^2(1-\rho_{hs}^2)+\rho_{hs}^2}\left(\mu_\alpha + \frac{\frac{\rho_{hs}\sigma_s}{\sigma_h}\left(s-\mu_s\left(1-\frac{\rho_{hs}\sigma_s}{\sigma_h}\right)\right)}{\sigma_s^2(1-\rho_{hs}^2)}\right)^2 =$$

$$= \frac{\rho_{hs}^2}{\sigma_h^2(1-\rho_{hs}^2)+\rho_{hs}^2}\mu_\alpha^2 + \frac{\sigma_h^2}{\sigma_s^2(\sigma_h^2(1-\rho_{hs}^2)+\rho_{hs}^2)}\left(s-\mu_s\left(1-\frac{\rho_{hs}\sigma_s}{\sigma_h}\right)\right)^2 +$$

$$-2\frac{\sigma_h\rho_{hs}}{\sigma_s(\sigma_h^2(1-\rho_{hs}^2)+\rho_{hs}^2)}\left(s-\mu_s\left(1-\frac{\rho_{hs}\sigma_s}{\sigma_h}\right)\right)\mu_\alpha =$$

$$= \left(\frac{\rho_{hs}}{\sqrt{\sigma_h^2(1-\rho_{hs}^2)+\rho_{hs}^2}}\mu_\alpha - \frac{\sigma_h}{\sigma_s\sqrt{(\sigma_h^2(1-\rho_{hs}^2)+\rho_{hs}^2)}}\left(s-\mu_s\left(1-\frac{\rho_{hs}\sigma_s}{\sigma_h}\right)\right)\right)^2 =$$

$$= \left(\frac{s-\mu_s+\frac{\rho_{hs}\sigma_s}{\sigma_h}(\mu_s-\mu_\alpha)}{\sigma_s\sqrt{1-\rho_{hs}^2+\frac{\rho_{hs}^2}{\sigma_h^2}}}\right)^2$$

Putting these equations into (A4), we have that:

$$\alpha_s(s) = \frac{1}{2\pi\sigma_s\sqrt{1-\rho_{hs}^2}\cdot\delta_0} e^{-0.5\delta_2}\int\delta_0 e^{-0.5(\delta_0 h-\delta_1)^2}dh =$$

$$= \frac{1}{\sqrt{2\pi}\sigma_s\sqrt{1-\rho_{hs}^2}\cdot\delta_0} e^{-0.5\delta_2} = \frac{1}{\sqrt{2\pi}\sigma_s\sqrt{1-\rho_{hs}^2+\frac{\rho_{hs}^2}{\sigma_h^2}}} e^{-0.5\left(\frac{s-\mu_s+\frac{\rho_{hs}\sigma_s}{\sigma_h}(\mu_s-\mu_\alpha)}{\sigma_s\sqrt{1-\rho_{hs}^2+\frac{\rho_{hs}^2}{\sigma_h^2}}}\right)^2}$$

where the second line follows from the integral of a standard normal random variable. The final expression is the expression for the density function of a normal random variable given in (10).

b. The GLS Procedure

In the estimation of a regression like (12) or (13) there are good reasons to believe that the individual observations will be both heteroskedastic and correlated across observations within individual years. We deal with this problem by assuming that, within time periods, the covariance matrix of $[\Phi^{-1}(\underline{A})-\gamma\Phi^{-1}(\underline{B})]$ is of the form $\sigma^2\Omega$ where γ is the slope coefficient in equation (12) and Ω is derived below. We assume that the covariances between periods are all zero. Our estimation method is to use feasible GLS where our estimate of γ in Table 2a is first derived from OLS. To derive Ω we obviously need the covariance matrices of A and B and the covariance between them.

By definition, and ignoring the time subscript for simplicity

$$\sigma^2\Omega = \mathrm{var}[\Phi^{-1}(\hat{\underline{A}})-\gamma\Phi^{-1}(\hat{\underline{B}})] = \mathrm{var}[\Phi^{-1}(\hat{\underline{A}})]+\gamma^2\mathrm{var}[\Phi^{-1}(\hat{\underline{B}})]+$$

$$-\gamma\mathrm{cov}[\Phi^{-1}(\hat{\underline{A}}),\Phi^{-1}(\hat{\underline{B}})]-\gamma\mathrm{cov}[\Phi^{-1}(\hat{\underline{B}}),\Phi^{-1}(\hat{\underline{A}})] =$$

where underlined letters denote vectors and we use hats to denote sample estimates.

Let us define :

$$D\hat{A} = \mathrm{diag}(\phi(\hat{A}_s))^{-1}$$
$$D\hat{B} = \mathrm{diag}(\phi(\hat{B}_s))^{-1}$$

By the delta method:

$$\begin{aligned}
\mathrm{var}[\Phi^{-1}(\hat{A})] &= D\hat{A}\,\mathrm{var}(\hat{A})\,D\hat{A} \\
\mathrm{var}[\Phi^{-1}(\hat{B})] &= D\hat{B}\,\mathrm{var}(\hat{B})\,D\hat{B} \\
\mathrm{cov}[\Phi^{-1}(\hat{A}),\Phi^{-1}(\hat{B})] &= D\hat{A}\,\mathrm{cov}(\hat{A},\hat{B})\,D\hat{B} \\
\mathrm{cov}[\Phi^{-1}(\hat{B}),\Phi^{-1}(\hat{A})] &= D\hat{B}\,\mathrm{cov}(\hat{B},\hat{A})\,D\hat{A}
\end{aligned}$$

Let d_{ij} be an indicator variable which takes value one if the educational level of individual i is less than j. Then:

$$d_{ij} = \begin{matrix} 1 & \text{with probability} & B_j \\ 0 & \text{with probability} & 1 - B_j \end{matrix}$$

so that:

$$E[d_{ij}] = B_j$$

$$\mathrm{var}[d_{ij}] = E[d_{ij}^2] - E[d_{ij}]^2 = E[d_{ij}] - B_j^2 = B_j(1 - B_j)$$

$$\mathrm{cov}[d_{ij}d_{ik}] = E[d_{ij}d_{ik}] - E[d_{ij}]E[d_{ik}] = E[d_{ij}] - E[d_{ij}]E[d_{ik}] = B_j(1 - B_k) \qquad j < k$$

Using hats on variables to denote sample estimates, this implies that:

$$E(\hat{B}_j) = E(\Sigma_i \frac{d_{ij}}{L}) = B_j$$

where L is labour force. Under the assumption of independence of the d_{ij}=s across individuals, it follows that:

$$\mathrm{var}(\hat{B}_j) = \mathrm{var}(\Sigma_i \frac{d_{ij}}{L}) = \Sigma_i(\mathrm{var}(\frac{d_{ij}}{L})) = \frac{B_j(1 - B_j)}{L}$$

$$\mathrm{cov}(\hat{B}_j, \hat{B}_k) = \mathrm{cov}(\Sigma_i \frac{d_{ij}}{L}, \Sigma_s \frac{d_{sk}}{L}) = \frac{1}{L^2}\Sigma_i \Sigma_s \mathrm{cov}(d_{ij}, d_{sk}) =$$
$$= \frac{1}{L^2}\Sigma_i \mathrm{cov}(d_{ij}, d_{ik}) = \frac{B_j(1 - B_k)}{L} \qquad j < k$$

Let α_{ij} be the share of the total wage bill of those with education less than j that is earned by individual i. We have that:

$$\alpha_{ij} = \frac{w_j(F_i)}{wN} \quad \text{with probability} (1-u_j)B_j$$
$$0 \quad \text{with probability} 1-(1-u_j)B_j$$

where F_i is the position of individual i in the earnings distribution of those with education less than j and $w_j(F_i)$ is the wage associated with position i among those with education less than j. Note α_{ij} will be zero if individual i has education more than j. Then:

$$E[\alpha_{ij} \mid d_{ij}=1] = (1-u_j)\int \frac{w_j(F_i)}{wN} dF_i = \frac{w_j N_j}{wN}\frac{1}{L_j} = \frac{A_j}{L_j}$$

$$\text{var}[\alpha_{ij} \mid d_{ij}=1] = E[\alpha_{ij}^2 \mid d_{ij}=1] - E[\alpha_{ij} \mid d_{ij}=1]^2 =$$
$$= (1-u_j)\int \left(\frac{w_j(F_i)}{wN}\right)^2 dF_i - \left(\frac{A_j}{L_j}\right)^2 = \frac{(1-u_j)}{(wN)^2}\text{var}(w_j) + \left(\frac{A_j}{L_j}\right)^2\left(\frac{u_j}{1-u_j}\right)$$

Now our estimate of A_j can be written as:

$$\hat{A}_j = \Sigma_i \alpha_{ij} d_{ij}$$

Using the previous results we have that:

$$E(\hat{A}_j) = E(\Sigma_i \alpha_{ij} d_{ij}) = \Sigma_i E(\alpha_{ij} d_{ij}) =$$
$$= \Sigma_i E(\alpha_{ij} \mid d_{ij}=1)\Pr(d_{ij}=1) = \Sigma_i \frac{A_j}{L_j} B_j = A_j$$

$$\text{var}[\hat{A}_j] = \text{var}(\Sigma_i d_{ij}\alpha_{ij}) = \Sigma_i \text{var}(\alpha_{ij} d_{ij}) = \Sigma_i E(\alpha_{ij}^2 d_{ij}^2) - \Sigma_i [E(\alpha_{ij} d_{ij})]^2 =$$
$$= L\, E(\alpha_{ij}^2 d_{ij}) - L[E(\alpha_{ij} d_{ij})]^2 =$$
$$= L\, E(\alpha_{ij}^2 \mid d_{ij}=1)\Pr(d_{ij}=1) - L[E(\alpha_{ij} \mid d_{ij}=1)\Pr(d_{ij}=1)]^2 =$$
$$= \frac{L(1-u_j)B_j}{(wN)^2}\text{var}(w_j) + \frac{A_j^2}{L_j(1-u_j)} - \frac{A_j^2}{L} = \frac{L_j(1-u_j)}{(wN)^2}\text{var}(w_j) + A_j^2\left(\frac{1}{N_j} - \frac{1}{L}\right)$$

$$\mathrm{cov}[\hat{A}_j,\hat{A}_k] = \mathrm{cov}(\Sigma_i d_{ij}\alpha_{ij},\Sigma_s d_{sk}\alpha_{sk}) = \Sigma_i \mathrm{cov}(\alpha_{ij}d_{ij},\alpha_{ik}d_{ik}) =$$

$$= \Sigma_i E(\alpha_{ij}d_{ij}\alpha_{ik}d_{ik}) - \Sigma_i[E(\alpha_{ij}d_{ij})][E(\alpha_{ik}d_{ik})] =$$

$$= L\,E(\alpha_{ij}^2 d_{ij}) - L\frac{A_j}{L}\frac{A_k}{L} =$$

$$= \frac{L(1-u_j)B_j}{(wN)^2}\mathrm{var}(w_j) + \frac{A_j^2}{L_j(1-u_j)} - \frac{A_jA_k}{L} = \frac{L_j(1-u_j)}{(wN)^2}\mathrm{var}(w_j) + A_j\left(\frac{A_j}{N_j} - \frac{A_k}{L}\right)$$

$$\mathrm{cov}(\hat{A}_j,\hat{B}_j) = \mathrm{cov}(\Sigma_i\alpha_{ij}d_{ij},\Sigma_i\frac{d_{ij}}{L}) = L\,E(\alpha_{ij}\frac{d_{ij}}{L}) - L\,E(\alpha_{ij}d_{ij})E(\frac{d_{ij}}{L}) =$$

$$= \frac{A_j}{L} - \frac{A_j}{L}B_j = \frac{A_j}{L}(1-B_j)$$

$$\mathrm{cov}(\hat{A}_j,\hat{B}_k) = \Sigma_i \mathrm{cov}(\alpha_{ij}d_{ij},\frac{d_{ik}}{L}) = L\,E(\alpha_{ij}d_{ij}\frac{d_{ik}}{L}) - L\,E(\alpha_{ij}d_{ij})E(\frac{d_{ik}}{L}) =$$

$$= E(\alpha_{ij}d_{ij}) - A_jB_k = \frac{A_j}{L}(1-B_k) \qquad j<k$$

$$\mathrm{cov}(\hat{A}_k,\hat{B}_j) = \Sigma_i \mathrm{cov}(\alpha_{ik}d_{ik},\frac{d_{ij}}{L}) = L\,E(\alpha_{ik}d_{ik}\frac{d_{ij}}{L}) - L\,E(\alpha_{ik}d_{ik})E(\frac{d_{ij}}{L}) =$$

$$= E(\alpha_{ik}d_{ij}) - A_kB_j = E(\alpha_{ij}d_{ij}) - A_kB_j = \frac{A_j}{L} - \frac{A_kB_j}{L} \qquad j<k$$

We are now in a position to estimate the variance of the estimator.

Data Appendix

For each country we divide the labour force into four education groups. For each of these groups we collected data on the share of the labour force in each group, the unemployment rate and wages. Sources and definitions are listed for each country.

France. Data come from *Enquete Emploi*, 1982-1993. The four groups are: up to primary school (*cep, be, beps*), junior high school (*cap, bep*), high school (*bac* or equivalent), university education.

Italy. Data on wages come from the Bank of Italy Survey of Household Income and Wealth for the years 1977-1984,1986,1987,1989,1991. Data on employment and unemployment come from the *Annuario statistico italiano*, ISTAT, various issues. The four groups are: up to primary school, junior high school, high school and university degree or above. Wages are defined as take home annual pay. Wage data presented are weighted by the population weights.

Netherlands. Employment data come from *Arbeidskrachtetentelling* for the period 1979-1985 and from *Enquete Beroepssbevolking* for the period 1990-1993. Wage data come from *Tijdreeksee Arbeidsrekeningen*. The four groups are: up to primary school, junior high school, high school and university degree or above. Earning concept: gross monthly wages.

UK. Data come from the General Household Survey for 1974-92. The four groups are: those with no qualifications, those with O-levels or equivalent qualification, those with A-levels or equivalent qualification and university graduates. The wage variable is weekly earnings.

US. Data come from the Current Population Survey. Data for the period 1972-1977 are derived from the May Annual Files, while data for the period 1978-1990 come from the Outgoing Rotation Group. The four groups are high-school dropouts, high school graduates, those with 2 years of college and those with 4 or more years of college. The wage variable is weekly earnings. Since data on earnings are top coded in the CPS we estimate a tobit model of log earnings on experience, experience square, four education dummies, a sex dummy, a race dummy, 50 state dummies, a part-time dummy, a dummy for married individuals. Based on the estimated standard deviation of residuals from this tobit regression we then construct an uncensored normal distribution and impute wages for top coded observations on the assumption of a log normal distribution of wages. Wage data are weighted by the earning weights.

Table 1
Trends in Relative Employment and Wages by Education

	Education Category			
	Ed=1	Ed=2	Ed=3	Ed=4
I. Relative Employment Rate				
France	-.024	.010	.006	.022
Italy	.008	.006	.031	.056
Netherlands	-.017	-.010	-.020	.026
UK	-.023	-.001	.003	.017
US	-.023	-.005	.005	-.001
II. Relative Wages				
France	-.048	-.027	-.112	-.088
Italy	-.020	-.052	-.055	-.075
Netherlands	.009	.016	-.102	-.119
UK	-.089	-.085	-.104	.013
US	-.113	-.079	-.048	.033

Notes. The numbers are the estimated 10-year trends in the relevant variables. The relative employment rate is the employment rate of the particular education group relative to the aggregate employment rate and the relative wage is the wage of the particular education group relative to the average wage. Level 1 is the lowest level of educational attainment, level 4 the highest. Sources and definition: Data Appendix.

Table 2
Simulated Changes in the Demand and Supply of Skills

	Initial distribution			Final distribution		
	Shares	Cumulative shares	Inverse c.d.f.	Shares	Cumulative shares	Inverse c.d.f.
I. Wage bill share	α	A	$\Phi^{1}(A)$	α	A	$\Phi^{1}(A)$
Ed=1	.20	.20	-.84	.15	.15	-1.03
Ed=2	.10	.30	-.52	.09	.24	-.71
Ed=3	.30	.60	.25	.28	.52	.06
Ed=4	.40	1		.48	1	
II. Labour force share	β	B	$\Phi^{1}(B)$	β	B	$\Phi^{1}(B)$
Ed=1	.25	.25	-.67	.19	.19	-.86
Ed=2	.11	.36	-35.	.11	.30	-.54
Ed=3	.30	.66	.42	.29	.59	.23
Ed=4	.34	1		.41	1	
μ=-(Φ^{-1}(A)- Φ^{-1}(B))			.17			.17

Notes. The table reports the results of a simulation of changes in the distribution of supply and demand on our measure of relative demand. For both the initial and the final distribution, we report the shares accruing to each educational group, the cumulative shares and the associated inverse c.d.f. , which allow to calculate the relative demand index μ, reported at the bottom of the table. The simulated numbers are obtained assuming that both demand and supply are normally distributed, with variance 1 and that the correlation between human capital and education is perfect.

Table 3a

Estimates of Shifts in Demand Relative to Supply: Unrestricted Model

	France	Italy	Netherlands	UK	US
$\Phi^{-1}(B)$	.894	.933	.970	.912	1.001
	(.005)	(.003)	(.008)	(.011)	(.004)
1972					.226
					(.027)
1973					.227
					(.027)
1974				.191	.259
				(.019)	(.028)
1975				.189	.247
				(.017)	(.028)
1976				.207	.241
				(.017)	(.026)
1977		.050		.223	.246
		(.002)		(.016)	(.026)
1978		.072		.207	.229
		(.003)		(.017)	(.014)
1979		051	.270	.210	.237
		(.003)	(.024)	(.017)	(.013)
1980		.073		.230	.247
		(.003)		(.020)	(.014)
1981		.061	.262	.264	.278
		(.002)	(.024)	(.019)	(.014)
1982		.066		.233	.286
		(.002)		(.021)	(.014)
1983		.064	.276	.278	.285
		(.002)	(.025)	(.021)	(.014)
1984	.203	.084		.300	.300
	(.002)	(.002)		(.023)	(.014)
1985	.198		.251	.308	.309
	(.002)		(.026)	(.027)	(.013)
1986	.204	.091		.315	.314
	(.002)	(.002)		(.022)	(.013)
1987	.206	.093		.327	.311
	(.002)	(.002)		(.022)	(.014)
1988	.212			.329	.310
	(.002)			(.022)	(.013)
1989	.215	.089		.350	.323
	(.002)	(.002)		(.022)	(.013)
1990	.227		.220	.356	.329
	(.002)		(.026)	(.023)	(.013)
1991	.237	.093	.215	.359	
	(.002)	(.002)	(.026)	(.022)	
1992	.248		.197	.347	
	(.003)		(.026)	(.023)	
1993	.245		.207		
	(.003)		(.027)		
1994	.254				
	(.003)				
R^2	.9999	.9999	.9988	.9980	.9994
No. of obs.	33	36	24	57	57

Notes. The table reports the estimates in mismatch using equation (12). Estimation method: FGLS. For the standard errors (in brackets) see Technical Appendix. See also notes to Table 1.

Table 3b
Estimates of Shifts in Demand Relative to Supply: Restricted Model

	France	Italy	Netherlands	UK	US
$\Phi^{-1}(B)$	1.000	1.000	1.000	1.000	1.000
1972					.226
					(.026)
1973					.228
					(.027)
1974				.206	.260
				(.030)	(.027)
1975				.198	.247
				(027)	(.027)
1976				.213	.242
				(.027)	(.026)
1977		.059		.225	.246
		(.019)		(.026)	(.026)
1978		.076		.205	.230
		(.015)		(.027)	(.014)
1979		.051	.261	.208	.238
		(.016)	(.033)	(.028)	(.013)
1980		.069		.224	.248
		(.012)		(.032)	(.013)
1981		.053	.251	.256	.279
		(.010)	(.033)	(.030)	(.014)
1982		.054		.222	.286
		(.014)		(.031)	(.014)
1983		.049	.264	.257	.285
		(.014)	(.035)	(.033)	(.014)
1984	.211	.065		.273	.301
	(.010)	(.013)		(.033)	(.013)
1985	.204		.238	.289	.309
	(.010)		(.035)	(043)	(.013)
1986	.205	.065		.279	.314
	(.010)	(.011)		(.034)	(.013)
1987	.202	.062		.294	.311
	(.011)	(.012)		(.035)	(.013)
1988	.205			.293	.310
	(.010)			(.035)	(.013)
1989	.207	.052		.312	.324
	(.011)	(.011)		(.035)	(.013)
1990	.212		.208	.317	.330
	(.012)		(.035)	(.037)	(.013)
1991	.217	.048	.200	.319	
	(.012)	(.011)	(.035)	(.034)	
1992	.225		.181	.303	
	(.013)		(.035)	(.036)	
1993	.217		.191		
	(.014)		(.036)		
1994	.223				
	(.013)				
R^2	.9988	.9995	.9975	.9948	.9826
No. of obs.	33	36	24	57	57

Notes. The table reports the estimates in mismatch using equation (13) (σ_h=1). Estimation method: FGLS. For the standard errors (in brackets) see Technical Appendix. See also notes to Table 1.

Table 4
Estimates of Shifts in Supply

	France	Italy	Netherlands	UK	US
Ed=1	.052	.083	-.792	.141	-.529
	(.022)	(.072)	(.042)	(.058)	(.043)
Ed=2	.787	.979	.062	.747	.588
	(.022)	(.074)	(.041)	(.059)	(.043)
Ed=3	1.174	1.921	1.140	1.701	1.164
	(.022)	(.079)	(.043)	(.061)	(.043)
1973					.047
					(.061)
1974					.086
					(.061)
1975				.061	.114
				(.079)	(.061)
1976				.075	.146
				(.080)	(.061)
1977				.138	.169
				(.079)	(.058)
1978		.056		.179	.215
		(.101)		(.080)	(.058)
1979		.107		.166	.246
		(.100)		(.080)	(.048)
1980		.161		.221	.267
		(.099)		(.080)	(.048)
1981		.209	.093	.235	.297
		(.099)	(.056)	(.079)	(.048)
1982		.262		.274	.332
		(.098)		(.084)	(.048)
1983		.310	.154	.362	.355
		(.098)	(.056)	(.083)	(.048)
1984		.353		.440	.379
		(.098)		(.083)	(.048)
1985	.015		.235	.471	.400
	(.030)		(.056)	(.082)	(.048)
1986	.048	.443		.528	.415
	(.030)	(.097)		(.081)	(.048)
1987	.082	.487		.526	.429
	(.030)	(.097)		(.081)	(.048)
1988	.115			.551	.452
	(.030)			(.082)	(.048)
1989	.125	.566		.583	.471
	(.030)	(.096)		(.081)	(.048)
1990	.182		.378	.610	.491
	(.030)		(.055)	(.083)	(.048)
1991	.220	.647	.402	.605	
	(.030)	(.096)	(.055)	(.082)	
1992	.255		.437	.666	
	(.030)		(.055)	(.083)	
1993	.303		.473		
	(.030)		(.054)		
1994	.330				
	(.030)				
R^2	.999	.992	.998	.993	.999
No. of obs.	33	36	24	57	57

Notes. The table reports the estimates of shifts in supply using equation (11). Estimation method: FGLS. For the standard errors (in brackets), see Technical Appendix. See also notes to Table 1.

Table 5
R from a Regression of Log Wages on Education

	Italy		UK		US	
1972						.34
1973					.32	.35
1974			.30	.35	.33	.36
1975			.30	.34	.34	.36
1976			.32	.36	.34	.35
1977	.28	.29	.36	.40	.32	.36
1978	.25	.26	.35	.40	.34	.34
1979	.25	.26	.35	.39	.32	.35
1980	.26	.28	.35	.39	.33	.35
1981	.21	.22	.37	.41	.33	.36
1982	.26	.26	.38	.42	.34	.37
1983	.29	.30	.35	.39	.35	.35
1984	.31	.31	.36	.40	.33	.36
1985			.35	.41	.34	.36
1986	.31	.32	.36	.41	.35	.37
1987	.31	.31	.39	.42	.36	.37
1988			.35	.40	.35	.41
1989	.33	.34	.37	.42	.40	.41
1990			.38	.42	.40	.41
1991	.31	.31	.39	.42	.40	
1992			.39	.43		
1993	.32	.33				
1994						

Notes. These numbers are the square root of the R^2 from a regression of log wages on a set of dummy variables for educational attainment alone. The first column for each country just uses the four educational dummies from our basic analysis while the second use the maximum available (5 for Italy, 14 for the UK, and 18 for the US).There are no results for France or the Netherlands because we do not have access to micro data for these countries. See also notes to Table 1.

Table 6
Box -Cox Estimates of Shifts in Demand Relative to Supply: Restricted Model

country	France	Italy	Netherlands	UK	US
λ_β	-.297 (.012)	-.492 (.013)	-.083 (.019)	-.159 (.014)	-.162 (.006)
λ_α	-.228 (.022)	-.505 (.014)	-.059 (.016)	-.171 (.016)	-.048 (.004)
1972					.355 (.008)
1973					.354 (.010)
1974				.322 (.021)	.408 (.009)
1975				.315 (.020)	.383 (.011)
1976				.342 (.020)	.371 (.010)
1977		.089 (.005)		.368 (.018)	.376 (.009)
1978		.118 (.004)		.339 (.021)	.346 (.007)
1979		.085 (.005)		.345 (.022)	.360 (.006)
1980		.118 (.004)		.379 (.026)	.374 (.007)
1981		.096 (.005)	.449 (.033)	.440 (.025)	.428 (.007)
1982		.106 (.005)		.385 (.027)	.441 (.007)
1983		.101 (.005)	.433 (.030)	.46 (.027)	.438 (.007)
1984	.340 (.003)	.137 (.005)		.504 (.029)	.466 (.007)
1985	.331 (.005)		.449 (.032)	.521 (.039)	.480 (.007)
1986	.339 (.006)	.153 (.005)		.536 (.028)	.490 (.007)
1987	.340 (.005)	.153 (.005)		.562 (.029)	.485 (.007)
1988	.349 (.006)			.559 (.028)	.483 (.007)
1989	.354 (.005)	.146 (.005)	.400 (.033)	.600 (.029)	.509 (.006)
1990	.371 (.006)		.361 (.033)	.610 (.029)	.517 (.007)
1991	.387 (.007)	.152 (.006)	.345 (.034)	.629 (.029)	
1992	.406 (.008)		.313 (.033)	.604 (.032)	
1993	.398 (.010)		.331 (.035)		
1994	.413 (.010)				

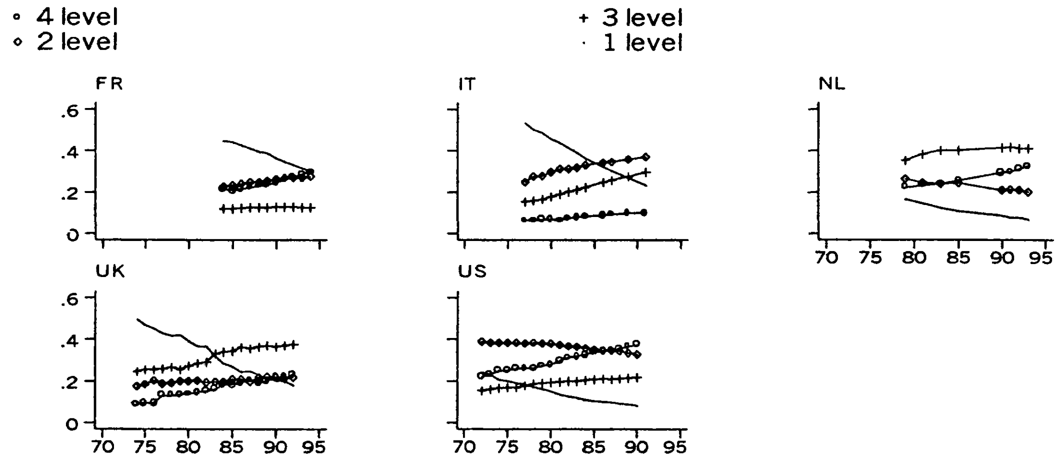
Notes. The table reporters the estimates in mismatch using equation (14). Estimation method: FGLS. For the standard errors (in brackets) see Technical Appendix. See also notes to Table 1.

Table 7
Breusch-Pagan test

	France	Italy	Netherlands	UK	US
Unrestricted Probit	10.04	1.09	0.11	281.1	493.2
(Table 3a)	(0.00)	(0.30)	(0.74)	(0.00)	(0.00)
Restricted Probit	161.32	178.51	8.90	436.31	492.64
(Table 3b)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Restricted Box-Cox	85.92	0.77	0.47	17.97	2.73
(Table 6)	(0.00)	(0.41)	(0.50)	(0.00)	(0.10)

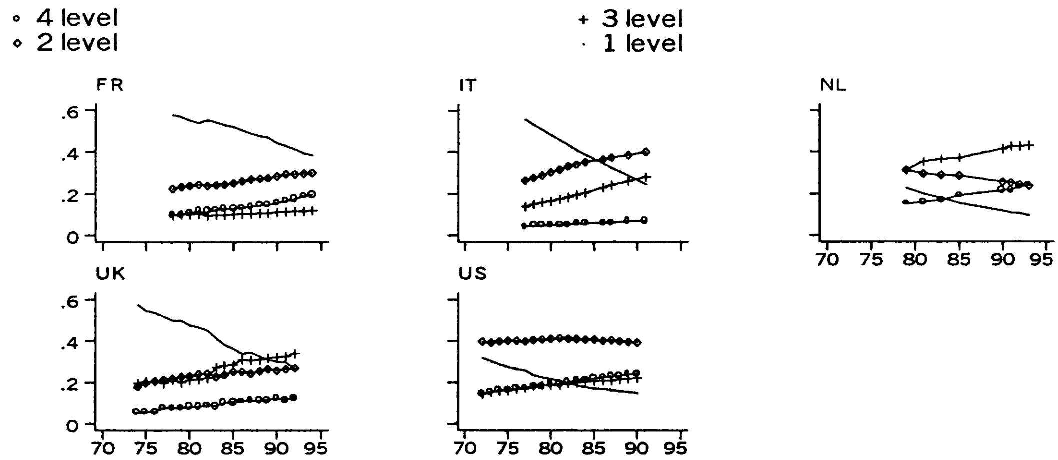
Notes. The table reports the results of a LM test for the hypothesis of no auto-correlation of the disturbances within education groups. The statistics are asymptotically distributed as $\chi^2(1)$. P-value in brackets

Figure 1
Labour Force Shares by Education



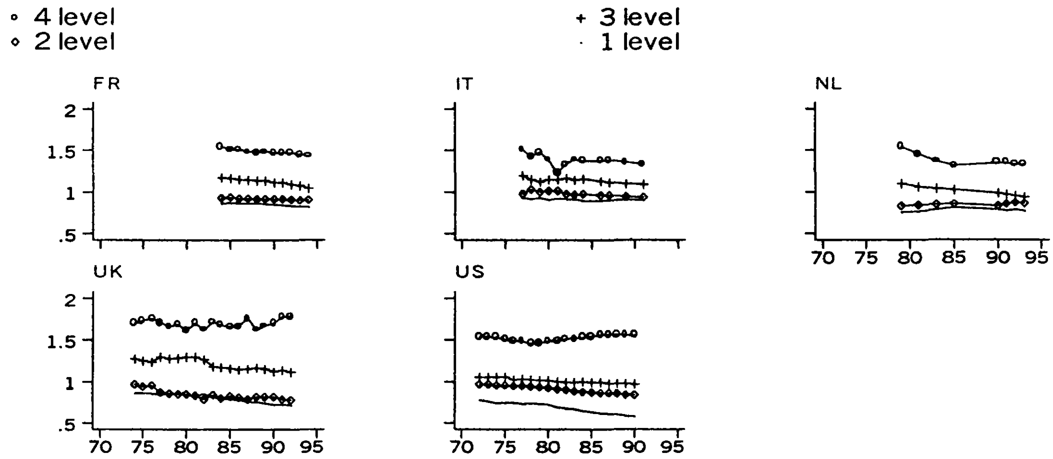
Notes. The figure reports the evolution of the labour force share for 4 educational groups in 5 OECD countries: France, Netherlands, and Italy. Level 1 is the lowest level of educational attainment, level 4 the highest. For sources and definition: see Data Appendix.

Figure 2
Wage Bill Shares by Education



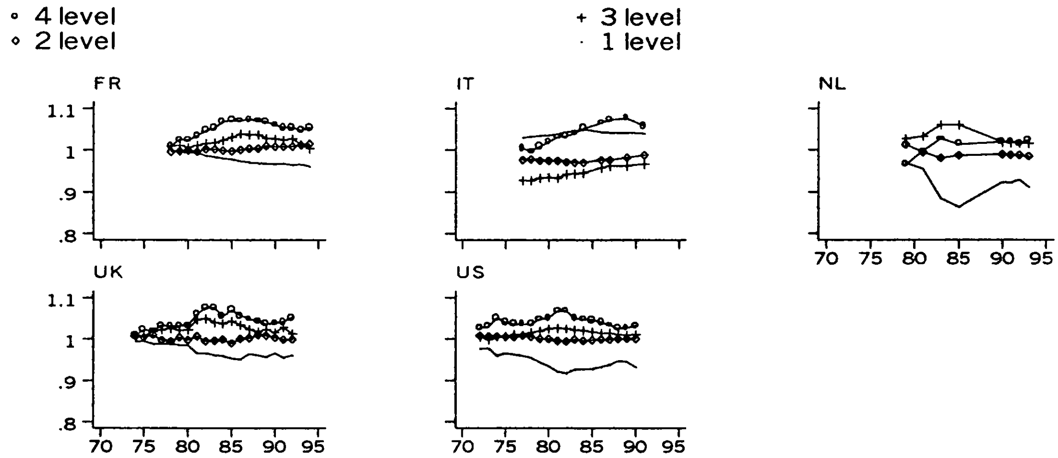
Notes. The figure reports the evolution of the wage bill share for 4 educational groups in 5 OECD countries. See also notes to Figure 1.

Figure 3
Relative Employment Rates by Education



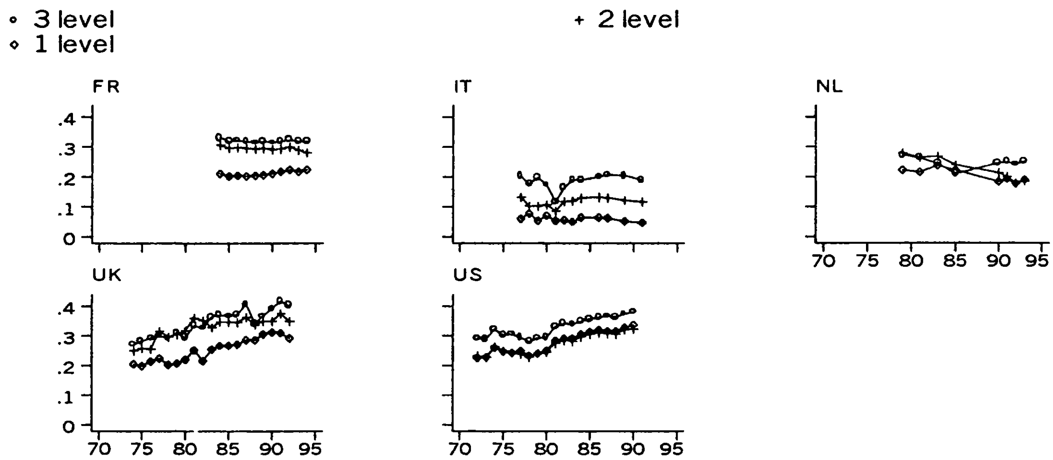
Notes. The figure reports the evolution of the wage bill share for 4 educational groups in 5 OECD countries. The relative employment rate is the employment rate of the education group divided by the aggregate employment rate. See also notes to Figure 1.

Figure 4
Relative Wages by Education



Notes. The figure reports the evolution of the wage bill share for 4 educational groups in 5 OECD countries. The relative wage is the average wage of the education group divided by the aggregate average wage. See also note to Figure 1.

Figure 5
Estimates of Skill Mismatch by Education Group.



Notes. The figure reports the evolution of our estimated measure of skills mismatch for in 5 OECD countries. The series are obtained by plotting $[\Phi^{-1}(A_{st})- \Phi^{-1}(B_{st})]$ over time for each education group. See also notes to Figure 1.

Figure 6a
Predicted and Actual Rises in Wage Inequality

United States

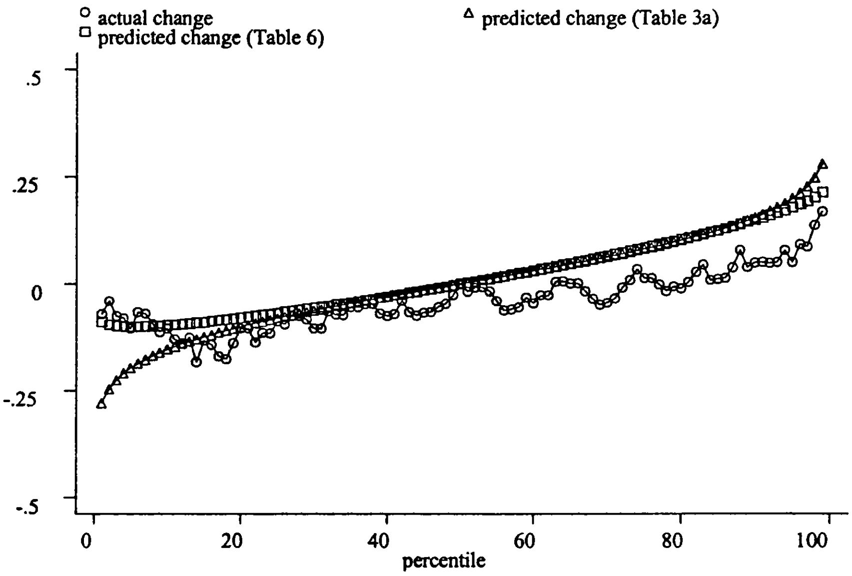
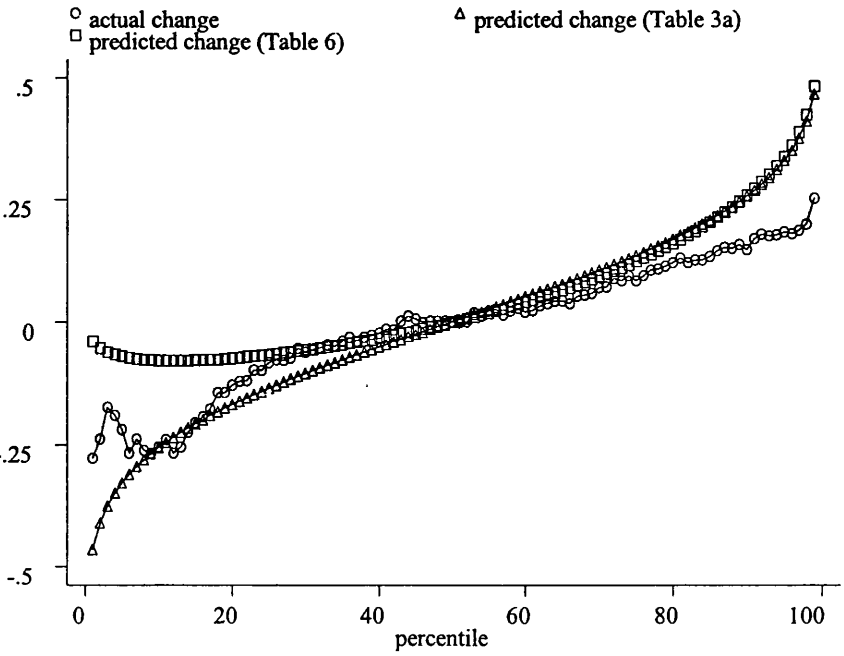


Figure 6b
United Kingdom



Notes. The figure reports the actual change in inequality over the period 1978-90 for the US and 1979-92 for the UK and the predicted change. The predicted change is what would be obtained using the formula in equation (18) the estimates from table 3b and table 6, respectively under the normality assumption and using the Box-Cox approximation. See text for details. All series are standardised to changes at the median.

Chapter 3

Changes in Earnings Inequality in Italy in the 1980s and the Effect of Institutions

It is well known that during the 1980s the US experienced a dramatic increase in the dispersion of wages while wage inequality 'failed' to increase in most of continental Europe (for all, Katz and Autor, 1999; OECD, 1993 and 1996). The analyses in chapters 1 and 2, where we have examined the changes in the wage structure by education in a variety of OECD countries, is consistent with these findings: returns to education increased dramatically in the UK and the US but stayed constant or possibly decreased in many continental European countries. We have also shown that changes in the supply and demand for skills are consistent with changes in the wage structures in the UK and US during the 1980s.

A natural question that arises is why continental European countries have apparently been spared by this trend in wage inequality. Freeman and Katz (1995) suggest that differences and different changes in institutions and market forces (supply and demand) can explain the different trends in the wage structure on the two sides of the Atlantic in the 1970s and 1980s. Indeed, the evidence in chapters 1 and 2 shows that that the imbalance between the demand and supply of skills has increased more in the UK and US than in continental Europe.

In this chapter we evaluate how important these different changes are in a typical European country.

The aim of this chapter is double. The first goal is to document the evolution of earnings inequality in Italy from 1977 to 1993 using the individual records of the Bank of Italy Survey of Household's Income and Wealth (SHIW). The second aim is to assess the role played by the evolution of the Scala Mobile in shaping this trend. The Scala Mobile –literally escalator– was a wage indexation mechanism granting the <u>same</u>

absolute wage increase to all employees as prices rose, thereby potentially compressing the wage distribution.

Figure 1 shows what motivates this study. In the top left-hand panel we plot the evolution of the 9-1 log decile gap (the difference in log wages at the ninth and first deciles) of the earnings distribution in Italy, for men and women together, at five points in time between 1977 and 1993. The series is standardised to its value in 1993, so it only provides information on changes in wage inequality, and controls for changes in the age and education composition of the sample. Between 1977 and 1980 the earnings gap declines by almost 15 log points, it then stays essentially unchanged and it increases by a similar amount between 1989 and 1993. In the top right-hand panel we plot the evolution of earnings inequality in the US over the same period. Inequality in the US rises almost monotonically over the period of observation, by approximately 20 log points. In the bottom left-hand panel we plot the predicted evolution of the 9-1 gap in Italy assuming that the Scala Mobile was the only source of wage change over this period, which is obtained by cumulating contingent (on prices) wage changes due to this institution from one period to the other (what we call later the ex-ante effect of the escalator). One can see that the Scala Mobile has a potential to compress differentials throughout the period of observation but its potential declines over time as the series of predicted differentials flattens out. In 1991 the Scala Mobile is abolished, and in the last period the curve is essentially horizontal. Between 1977 and 1993 the Scala Mobile implies an (ex-ante) reduction in inequality of approximately 60 log points. In the right-hand panel, we plot the residual evolution of the 9-1 log decile gap (denoted by NSM), simply obtained as the difference between the actual trend in the gap and the estimated ex-ante effect of the Scala Mobile (SM). This is essentially the share of wage growth that is bargained over between unions and firms at the national level or awarded by firms to their workers at the local level. At this stage, it is useful to think of this series as the evolution of inequality had the Scala Mobile been inoperative over the period of observation. One can see that this series is monotonically rising throughout the period: between 1977 and 1993 changes in this residual inequality are in the order of almost 60 log points, so that the level of inequality in 1993 is essentially the same as in 1977. Based on this evidence, one might be tempted to conclude that latent inequality (i.e. the one which would have been observed in the absence of indexation, but on which we do not have data) was rising throughout the period. At the beginning the Scala Mobile counteracted this rise and observed inequality fell but, as the escalator was curbed, observed inequality rose.

Erickson and Ichino (1995) have offered this as one of the possible explanations for the decline in inequality in Italy between the late 1970 and the late 1980s. To make their point they provide some suggestive evidence based on different sets of data (including the SHIW between 1978 and 1987) pointing to the existence of a time-series correlation between the Scala Mobile and wage inequality. However, they do not draw any definitive conclusion on how much weight to attach to this explanation relative to explanations relying on changes in market forces. Implicitly, they recognise that using the time-series variation in the structure of earnings to identify the effect of the Scala Mobile raises the suspicion that one is attributing to the Scala Mobile the effect of other aggregate factors.

One difficulty with concluding that the Scala Mobile is responsible for the observed fall and subsequent rise in inequality in Italy is that one might argue that the Scala Mobile had no effect on the structure of earnings and, in its absence, wage differentials would have evolved as they in fact did. This would be the case if the latent distribution of earnings happened to move as the actual distribution, so that the Scala Mobile just predated some early compression in the differentials. In terms of Figure 1, this is equivalent to assuming that residual wage inequality (NSM) increased as a reaction to the equalising effect of the Scala Mobile, and, had the Scala Mobile been inoperative, this would have evolved differently or possibly exactly as the observed series in the top part of the panel. The main aim of this chapter is then to estimate whether and to what extent the observed evolution of the wage structure can be attributed to the effect of the indexation mechanism, once one has controlled for any offsetting effect due to other sources of wage changes (what we call later the ex-post effect of the Scala Mobile).

One way to obtain a consistent estimate of the ex-post effect of the Scala Mobile is to identify a source of variation in contingent payments that is arguably exogenous to changes in the latent structure of wages. The difficulty here is that the Scala Mobile affected all employees and in this sense it was intrinsically a macro-economic institution. So one does not have a natural control group to estimate a counterfactual distribution of wages. However, one can exploit the differential effect of the Scala Mobile across different groups of workers together with some parametric assumptions about latent wage growth to uncover its effect on the distribution of wage changes.

By granting the same absolute wage increase all over the wage distribution, the equalising potential effect of the escalator was more pronounced at the bottom. In this sense, the Scala Mobile was a system of transfers that disproportionately benefited low-wage earners. Since female workers were typically concentrated in the bottom tail of the wage distribution (of men and women together), one can use this feature of the data to estimate the effect of the Scala Mobile on wage growth. In this chapter we assume that in the absence of the Scala Mobile inequality would have evolved similarly for men and women and we attribute any deviation around this (assumed) common growth path to the effect of the Scala Mobile. In Figure 2 we plot evolution of the 9-1 log decile gap separately for men and women. Between 1977 and 1980 the female earnings gap declines by almost 30 log points, it decreases by approximately 10 log points during the

1980s and it increases again by approximately 30 log points between 1989 and 1993. Changes for men are about a third as much and the level of inequality in 1993 is similar to the one in 1977. In the bottom panel of the figure, we plot the ex-ante effect of the escalator. A remarkable feature of this figure is that not only does the escalator predict the early compression in wage differentials for both gender groups, but it also predicts the faster compression for women. For example, between 1977 and 1980, changes in the 9-1 log decile gap due to the indexation are in the order of more than 40 points for women and about half as much for men. Between 1989 and 1993, when inequality rises, the Scala Mobile implies a reduction in the gap of only 4 points for women and 3 points for men. One can see that the series of residual inequality (ex-ante NSM) is monotonically rising throughout the period for both men and women. Over the whole period of observation, changes in residual inequality are about 50 log points for men and more than 70 log points for women. Using differences between gender groups to identify the effect of the Scala Mobile is equivalent to asking what fraction of contingent wage payments should have translated into actual wage growth (the ex-post effect Scala Mobile) in order for whatever residual (latent) inequality is left to display a similar trend for men and women. Based on these estimates, we can then assess the ex-post effect of the Scala Mobile and, by the same token, reconstruct a counterfactual distribution of wage changes, i.e. the one that would have been observed in the absence of indexation, which gives an indication of the latent trend in inequality.

A way to rephrase the identifying assumption is to say that (possibly for a differential average growth) a man and a woman at the same relative position in their respective wage distributions would have experienced the same wage growth in the absence of indexation. The rest of the chapter is devoted to assess how plausible this identifying assumption is and how sensitive our results are to departures from it. Although this assumption is ultimately untestable on our data, one way to assess its validity it to examine the evolution of inequality within gender groups in the US over the same period. Implicitly, if inequality changed similarly for men and women in the US over this same period, this can be thought as lending some support to our identification strategy.

An alternative avenue consists in relaxing the hypothesis of uniform latent wage growth within gender groups. We do so by imposing a variety of parametric restrictions on the evolution of the wage structure in the absence of indexation. As a first avenue, we postulate that latent changes in the wage structure in Italy over this period were the same as the ones observed in the US. The question then becomes: what fraction of Scala Mobile payment should have translated into actual wage growth for Italy to experience an underlying change in latent inequality as the one observed in the US? A second avenue consists in assuming that in the absence of indexation a man and a woman with the same wage levels (as opposed to a man and a woman at the same relative position in their respective wage distributions) would have experienced the same wage growth. As a third strategy, we postulate a fairly unrestricted model in which we let latent wage growth to vary differently (but parametrically) within gender groups. A comparison between these different estimates works as an internal consistency check for our identifying assumption.

A related issue that we deal with in this chapter is that the observed evolution of wage inequality might mask some endogenous compositional effects. If the Scala Mobile exogenously altered the structure of market wages by compressing differentials, one would expect this compression to induce firms to substitute skilled workers for unskilled ones. A corollary to this assertion is that relative employment losses among the unskilled would further alter the observed distribution of wages, essentially shifting part of the mass from the bottom tail to the top tail. The question then becomes: was the Scala Mobile (partly) responsible for the observed trend in wage inequality via its indirect employment effects rather than via changes in the wage schedule? In order to address this issue we construct a counterfactual wage distribution, where the composition of employment is endogenously determined by the exogenous changes in the wage structure due to the Scala Mobile, and, based on this, we estimate the indirect effect of the escalator on the trend in wage inequality.

The plan of the chapter is as follows. Section I briefly describes the institutional features of the system of wage determination in Italy. Section II illustrates the data used in the rest of the analysis and provides some descriptive evidence for the changes in the distribution of earnings and the ex-ante effect of the Scala Mobile on these changes. In section III we present the regression results for the ex-post effect of the Scala Mobile on the wage structure and discuss the possible sources and directions of biases in the OLS estimates. Based on our identifying assumption, we present results from 2SLS. In the same section we experiment with different specifications of the model. Finally, we present estimates for the distribution of latent wage changes, based on our most conservative estimate for the effect of the escalator. Section IV extends the results of the previous analysis by allowing for endogenous changes in the observed distribution of earnings as exogenous variations in the wage structure due to the Scala Mobile affect the composition of the sample. Section V concludes and states the main findings.

I. Institutional Background

Wages of Italian workers are determined through a strongly centralised system whose mainstay is the national agreement between the confederations of trade unions and the association of entrepreneurs.[1] This agreement sets minimum wages for employees at different skill levels in each industry that extend to both unionised and non-unionised

[1] This section and the Data Appendix are based on Treu (1991), various issues of the Industrial and Labor Relations Review and references therein.

workers. Wage conditions more favourable to the worker can be negotiated at the firm level or set unilaterally by the firm for an individual worker or a group of workers. Until 1991, all wage levels were also automatically adjusted by the Scala Mobile that ensured automatic rises in wages in the face of inflation.[2] Like many North-American Cost of Living Allowances (COLAs, see Card, 1983, and references therein), in its original formulation the escalator implied a flat increase in nominal wages (Scala Mobile point) for each point increase in a special quarterly consumer price index (*indice sindacale*). We denote nominal wages by W, the level of prices by P and the Scala Mobile point by α. Then the increase in nominal wage levels between period t-1 and period t determined by the Scala Mobile formula was:

$$(1) \qquad \Delta SM_t = \alpha_t \left(\frac{\Delta P_t}{P_0} \right) \text{x } 100$$

where the term in brackets is the change in prices from t-1 to t divided by the price level at some reference date 0.[3] Note that the Scala Mobile increase was the same for every individual.

Over time the Scala Mobile (SM hereafter) underwent a number of reforms. In 1983 the value of the SM point was lowered by approximately 15%. In 1986 a major reform established a semi-proportional adjustment of wages to changes in prices, which further reduced the potential equalising effect of the escalator. In 1991 the SM was finally abolished. These reforms and their exact timing are summarised in the Data Appendix.

Since, at least in its original formulation, the SM awarded the same absolute wage increase (as opposed to the same proportional wage increase) to both high- and low-wage workers, this had a <u>potential</u> to compress wage differentials. To illustrate this

[2] In 1994 a new system of wage indexation entered in force, which linked contingent wage changes to expected inflation. This is the reason why in the empirical analysis we restrict to the data until 1993.

point and to provide an idea of the magnitudes involved, in Table 1 we report the changes in wages due to the SM in the first quarter of 1978 for two individuals approximately at the top and bottom deciles of the earnings distribution. Their monthly wage in December 1977 (t-1) was respectively 461,000 and 192,000 lit., so that the relative wage was 2.40. From January to April the price index rose by 5 points (167-162) triggering a rise in everybody's wages of approximately 12,000 lit (with α=2,400, this is 5 X 2,400) and reducing the 9-1 log decile gap to 2.32. Because of the SM the relative wage would have decreased by 3% in only three months.

Over this period, however, wages might have changed because of collective bargaining or firm-level increases. Consider an individual i at the starting time t-1 with wage W_{it-1}, whose wage (including any Scala Mobile increase between t-1 and t) is W_{it} in the ending period t and let W_{is} be the sum of the initial wage plus the escalated wage increase between t-1 and t, where s stands for the Scala Mobile:

$$W_{is} = W_{it-1} + \Delta SM_t$$

If lower case letters denote logarithms (ln(W)=w), then the proportional change in i's wage from t-1 to t can be decomposed into a contingent component (Δsm_{it}) and a not contingent component (Δv_{it}):

$$\Delta w_{it} \equiv \Delta v_{it} + \Delta sm_{it} \tag{2}$$

where:

$$\Delta v_{it} \equiv w_{it} - w_{is}$$

$$\Delta sm_{it} \equiv w_{is} - w_{it-1}.$$

A useful expression for the proportional contingent increase is:

$$\Delta sm_{it} \approx e_{it} \frac{\Delta P_t}{P_{t-1}} \tag{3}$$

[3] In 1983 the base period for the price index was renegotiated, implicitly reducing the value of the SM point.

where:

$$(4) \qquad e_{it} = \frac{\alpha_t P_{t-1}}{W_{it-1} P_0} x100$$

is the elasticity of nominal wages with respect to inflation. A value of e_{it} above (below) one implies that, everything else being equal, i's real wages will rise (fall) with inflation. Equations (2) and (3) illustrate that, if the non-contingent component of wage growth (Δv_{it}) does not offset the SM (Δsm_{it}), high inflation will tend to raise the relative wages of low-wage workers leading to a compression of wage differentials. Clearly, however, the effect of the SM depends on the extent to which non-contingent wage increases work to offset the SM.

II. Data and Descriptive Evidence

a. Data

Ideally, in order to estimate the impact of the SM on the distribution of wage changes, and therefore on changes in the wage structure, one would like to use repeated observations on the same individuals. Unfortunately, these data are not available for Italy for such a long period of time. In this chapter we use micro data from the Bank of Italy Survey of Household's Income and Wealth (SHIW), a repeated cross-sectional survey collecting some labour market information on the individuals in the sample, and we estimate for each person in the SHIW sample the component of their pay that is attributable to the SM payments accrued over the previous period. We restrict attention to full-year employees, aged 18-65, over five approximately equally spaced waves (1977, 1980, 1984, 1989 and 1993),[4] which gives a sample of 19,349 individuals over

[4] The survey is available from 1977 and has been run on a yearly basis until 1987 (with the exception of 1985) and every other year since then. Although starting in 1987 a small component of rotated panel is introduced in the survey, we ignore this feature of the data in the present analysis. By taking approximately equally-spaced points in time at least three years apart, we allow for at least one contract (cont'd on next page)

five waves.[5] Yearly labour income, which is the earnings variable used in this study, is defined net of taxes and social security contributions and inclusive of bonuses and overtime payments. In the following we will refer to this variable indifferently as earnings or wages but one has to bear in mind that this is in reality take-home annual pay from labour.

In Table 2 we report some descriptive statistics for our sample at five points in time (1977, 1980, 1984, 1989, 1993) and on average over these years. Similar to other OECD countries, in the last two decades Italy witnessed an increase in the share of highly educated workers: the share of male employees with post compulsory school qualification (thirteen years of education or more) increased from about 24% in the late 1970s to around 39% in the early 1990s, while for females this proportion grew from 36% to 60%. The share of young workers declined among both male and female workers. Apart from the secular trends, there is evidence that the distribution of employment was sensitive to the state of the business cycle. In 1984, when the economy was booming, we can see a relatively high proportion of workers aged 31-40. This suggests that the observed changes probably confound compositional effects of varying attributes of the labour force (say because of a generalised increase in educational attainment) together with the increase in unemployment among the less educated and the younger workers. Real earnings grew both for men and women, with an average reduction of the male-female earnings gap of approximately 1% a year.

To compute the SM payments for each individual in the sample, we integrate the SHIW data with data on the SM point (α_t) and the series of prices (P_t), both of which

renewal between two consecutive points in time. In turn, this rules out the possibility that in the rest of the analysis we are picking up short-term responses of wages to the indexation (see Card, 1990).

5 We take both full-time time part-time workers because in the early years no information on hours of work is available. This is likely not to be a serious problem in our data: between 1989 and 1993, when this information is available, part-time workers account for less than 6% of the female sample and less then 1% of the male one. We also eliminate managers from our sample because the indexation system worked somewhat differently for them and we do not have complete information on the parameters of (cont'd on next page)

are published in ISTAT (various issues) and reported in the Data Appendix. It must be emphasised that the earnings data in the SHIW have several important limitations for this exercise. First, earnings are measured over the entire previous year, while the SM payments were triggered every three or six months, depending upon the period of observation. Second, earnings in the SHIW are net of taxes and social security contributions, while the parameters of the SM were defined relative to gross monthly income from labour. To cope with this problem we use information on tax brackets and social security contributions at each decile of the wage distribution (as obtained on the 1989 SHIW). Third, starting from 1986, SM payments were made dependant on contractual minimum wages rather than actual wages that are available in our data. In order to estimate the impact of the SM on the distribution of wages we need therefore to make some assumptions on the way contractual wages relate to actual ones. We discuss these assumptions in the Data Appendix.

b. Decomposing Changes in the Wage Structure: Notation and Methodology

In this section we decompose changes in wages at each percentile of the distribution into a component due to the Scala Mobile and a residual component due to non-contingent wage changes. As already suggested in the introduction, this evidence is purely descriptive and cannot be used to make any direct inference about the evolution of wage inequality in the absence of indexation. This will be the object of the next section where we use the decomposition of this section to derive an estimate of the correlation between contingent and non-contingent wage changes.

To characterise changes in the distribution of wages over time, we compare each quantile of the distribution of log wages between period t-1 and period t. Suppose we have J groups and let us denote by $f_{jt}(w)= f_j(w|t)$ the density of log wages at time t for an

the indexation mechanism. Overall, they account for about 3% of the male sample and 0.5% of the (cont'd on next page) individual in group j (j=1,...J) and by $F_{jt}(w)$ the corresponding c.d.f. Let $w^q_{jt} = F_{jt}^{-1}(q)$ be the q-th percentile of the (conditional) distribution of log wages. Analogously, let $F_{js}(w)$ be the (conditional) distribution of log lagged wages plus escalated wage increases and $w^q_{js} = F_{js}^{-1}(q)$ the corresponding quantile. In our analysis j can only take two values: males (denoted by m) and females (denoted by f). Then one can decompose wage changes at each percentile (for each group) into the effect of the SM and the effect of non-contingent wage changes, analogously to the decomposition in (2):

(5) $$\Delta w^q_{jt} \equiv w^q_{jt} - w^q_{js} + w^q_{js} - w^q_{jt-1} \equiv \Delta v^q_{jt} + \Delta sm^q_{jt}.$$

Equation (5) is a simple accounting identity. In section III we will argue how, under some assumptions, this equation can be interpreted as the growth in wages experienced by an individual at position q in his reference group's wage distribution at time t-1. Let us refer to the second term on the right hand side as the <u>ex-ante</u> contingent wage change, i.e. the effect of the SM in the absence of any correlation between contingent and non-contingent wage changes. Analogously, let the first term on the right hand side be the <u>ex-ante</u> non-contingent wage change.

Up to now, we 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, which we denote by z. Let $f_{jt,t-1}(w) \equiv f_j(w|t_w=t, t_z=t-1)$ be the distribution of wages which one would have observed if individuals at time t-1 had been paid according to the wage schedule at time t. By definition, $f_{jt,t}(w) \equiv f_{jt}(w)$. One can therefore add an extra element to the decomposition in (5) and write:

female sample.

$$\Delta w_{jt}^{q} \equiv \left(w_{jt}^{q} - w_{js,t}^{q}\right) + \left(w_{js,t}^{q} - w_{js,t-1}^{q}\right) + \left(w_{js,t-1}^{q} - w_{jt-1}^{q}\right) \equiv$$

$$(6) \qquad \equiv \Delta v_{jt,t}^{q} + \Delta z_{jt,t-1}^{q} + \Delta sm_{jt,t-1}^{q}$$

where $w_{js,t-1}^{q}$ is the q-th quantile of the distribution of wages which one would have observed if individuals at time t-1 had only been awarded contingent wage increases triggered between t-1 and t. By the same token, $w_{js,t}^{q}$ can be thought of as the q-th quantile of the distribution of wages which one would have observed if individuals at time t had only been awarded contingent wage increase between t-1 and t, or, which is the same, if they had been deprived of the non-contingent wage changes triggered between t-1 and t.

Then one can decompose observed changes in the earnings distribution into three terms: the ex-ante effect of the Scala Mobile, conditional on a set of attributes, at their time t-1 value $\left(\Delta sm_{jt,t-1}^{q}\right)$; the effect of varying attributes $\left(\Delta z_{jt,t-1}^{q}\right)$; the ex-ante effect of non-contingent wage changes, conditional on a set of attributes, at their time t value $\left(\Delta v_{jt,t}^{q}\right)$.

In order to characterise the changes in the distribution of earnings over time we have estimated the earnings densities using standard kernel estimation methods. This has a double advantage. On the one hand, since we have relatively small samples, smoothing the distribution of wages might help eliminate the effect of measurement error. On the other hand, one can estimate the effect of changes in the sample composition using the procedure suggested by DiNardo, Fortin and Lemieux (1996) (DFL in the following). The idea is that one can construct a counterfactual distribution of wages at time t-1 assuming that the distribution of observable attributes were the one prevailing at time t by reweighting each observation at time t-1 by the probability of occurrence of his observed characteristics at time t. We provide details of how the DFL procedure applies to this case in the Technical Appendix a. In the rest of the analysis we restrict our attention to changes in the age and education composition of the sample (the vector z).

c. Decomposition Results

In Table 3 we document the changes in the wage structure over the period of observation, separately for men and women, by examining different percentiles of the nominal earnings distribution based on these smoothed densities. Alongside, we report the annualised changes over each sub-period (1978-1980, 1980-1984, 1984-1989, 1989-1993) as well as the average annualised change over the whole period of observation (1977-1993). It is easy to see that at each decile the female distribution is always on the left of the male distribution. Yet, over time, the two distributions tend to converge. In 1977, the bottom decile of the distribution of women's wages differs from the corresponding decile of men's wages by 60 log points, while at the top the difference is in the order of 25 log points. In the mid-1980s the gender earnings gap at the bottom is about 30 log points and approximately 25 log points at the top. Similar values of the gap are observed in 1993.

In the bottom part of the table we report different measures of earnings inequality and the corresponding annualised changes. Independent of the particular measure of inequality used, it appears that wage differentials decrease in the late 1970s and continue to narrow slightly over the first half of the 1980s. The level of inequality is higher for females than for males at the beginning of the period. In 1977 the 9-1 decile gap is approximately 35 log points higher for females then for males. By the mid-1980s, the gap reduces to 5 log point, to increase only slightly in the last years of observation. In 1993 the level of inequality for men is 5 log points higher than in 1977 and for women is about 20 log points lower. Part of this compression of women's wages, as we will see, is due to compositional changes.

In Table 4 we report the contribution of each source of wage change to changes in different measures of inequality using the decomposition in (6). The men's 9-1 log decile gap declines by about 2.4 points a year between 1977 and 1980, at a substantially lower rate than the change implied by the SM alone, which contributes to a reduction of almost 7 points a year. For women, the changes are even more pronounced: the gap falls by more than 10 points a year during the first three years of observation. The Scala Mobile alone would have implied a reduction of more than 14 points a year. It is evident that most of the differences between men and women are due to changes at the bottom of the distribution. In the fist period, the 1-5 log decile gap increases by 0.4 points for men and by about 8.5 points for women, so that their differential reduces by about 8 points. The SM alone would have implied a reduction of more than 6 points. At the top of the distribution the observed changes in inequality are of a similar magnitude across gender groups and the difference in the growth rates implied by the SM is about 1 point. The fact that female workers experience a somewhat bigger impact of the SM depends on the circumstance that their wages are on average lower than those of men and far more dispersed. Over time, we see that the effect of the SM decreases for both men and women. This reflects both a reduction in the SM elasticity and the reduction in inflation. The decline in the elasticity is due both to the circumstance that real wages increase over time, so that, everything else being equal, the protection offered by the indexation system declines (see equation (3)), and the circumstance documented in the Data Appendix that the SM point, i.e. the absolute increase in wages triggered by a one percent rise in the consumer price index, decreases over time. Finally, starting in 1986, the length of wage adjustment increases and the system becomes semi-proportional. By switching from a flat adjustment to a semi-proportional one the SM potential for compressing wage differential is further reduced. At the bottom of Table 3 we report the annualised inflation rate over the four sub-periods: this decreases from around 14% between 1977 and 1980 to about 6% between 1989 to 1993. Also note that that magnitude of contingent wage changes at each decile tends gradually to become similar for men and women, this in turn being due to the gradual reduction in the gender earnings gap, especially at the bottom of the distribution. One can also see how the non-escalated wage changes tend 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 is relatively ineffective. Another interesting feature of the data is that, maybe with the exception of the last period, non-contingent wage changes show similar patterns between men and women. We will go back to this in section III.

As far as changes in the composition of the sample by age and education are concerned, it is interesting to note that these changes are sometimes sizeable and can have opposite effects on the distribution of male and female wages. In principle, an increase in the proportion of highly educated workers, as documented in Table 2, has an ambiguous effect on the distribution of wages, depending on the initial distribution of wages. In the first period of observation, for example, since women's wages are far more dispersed at the bottom, the generalised increase in educational attainment tends to further compress their distribution, while, by increasing the mass in the upper tail of the distribution of male workers, whose wages are relatively more dispersed at the top, this trend tends to have the opposite sign. Note that between 1977 and 1980, compositional changes account for a decline of more than 1 point a year in 9-1 log decile gap for female workers, i.e. almost 10% of the total observed decline. Over the whole period of observation, compositional changes account for a rise in the dispersion of men's wages of about 1.6 points (16 X 0.1) while they account for a reduction in women's inequality of about 10 points (16 X 0.6), which is about half of the actual decline in the gap between 1977 and 1993.

To get a visual impression of changes in the wage structure, in Figure 3 we plot the annualised wage change at each percentile of the wage distribution separately for men and women. All series are standardised to the change at the median and control for changes in the sample composition. As detailed in Table 4, wage inequality for men decreases in the late 1970s, tends to be stable afterwards and increases in the second half of the 1980s. The same story is true for women but the reversion in inequality takes place somewhat later and changes are more pronounced. In Figure 4 we have decomposed the wage changes of Figure 3 into the two sources of wage changes: contingent and non-contingent. One can see how the SM tends to compress wages dramatically in the first period of observation but its equalising effect vanishes over time. Most important, there is a clear sign of non-contingent wage changes offsetting the SM: the two series appear strongly negatively correlated.

III. The Effect of the Scala Mobile on Changes in the Earnings Structure

In the previous section we have established that earnings inequality decreased in the late 1970s, then stayed basically unchanged, to increase again afterwards. The evidence suggests that the SM might have played a role in shaping this trend. However, some formal analysis of this correlation is required. In this section we estimate the distribution of wage changes conditional on the SM, and address issues of potential endogeneity of contingent wage changes with respect to observed changes in the wage structure.

a. Econometric Specification and Identification: OLS estimates

In order to model the effect of the Scala Mobile on wage changes, we postulate a very simple model of wage determination in which individual wage growth is some linear combination of latent growth and the effect of the SM. Let us denote by Δw^* latent wage growth, i.e. the growth in wages which one would observe in the absence of indexation, and assume that Scala Mobile payments translate into actual wage changes through a coefficient η:

$$(7) \qquad \Delta w_{it} = \Delta w_{it}^* + \eta \Delta sm_{it}.$$

A value of η=0 implies that contingent wage changes are completely counteracted by other sources of wage changes and the SM has no effect. A value of η=1 implies that contingent wage changes fully translate into total wage changes and one can simply subtract contingent wage changes from actual ones to infer what the distribution of wage changes would have been in the absence of indexation. In this model, the term $\eta \Delta sm_{it}$ can then be interpreted as the wage change attributable to the SM, once one has controlled for the counteracting effect of non escalated wage changes. We will refer to this as the ex-post effect of the SM. Analogously, one can think of Δw_{it}^* as the ex-post effect of non-escalated wage changes.[6]

In order to estimate model (7) on our data, we need to derive an expression in terms of the percentiles of the distribution of wages, which are our basic observations. In the following we assume that the wage change between time t-1 and time t (including any contingent wage increase) for an individual i initially at quantile q in the (within-gender) distribution of wages is the wage change at the q-th quantile over this period:

$$(8) \qquad E\left(\Delta w_{it} \mid w_{jt-1}^q\right) = w_{jt}^q - w_{jt-1}^q \equiv \Delta w_{jt}^q.$$

In the rest of this section we abstract from changes in observable characteristics within each period and examine wage changes assuming Δz in equation (6) is fixed. Equation (8) is equivalent to postulating that current wages are a rank-preserving transformation

[6] One could think of more complicated models of wage determination. For example, the equalising effect of the SM could come from employers being unable to impose pay cuts on their workers. Such a form (cont'd on next page)

of past wages. Others (explicitly or implicitly) have used this hypothesis to characterise changes in the wage structure in the US.[7] We show in the Technical Appendix b how one can derive this expression from joint normality of lagged and current log wages when the correlation coefficient between the two is equal to one (which warrants rank invariance as time passes). We also show that under normality equation (8) implies that wage growth varies monotonically in the relative position of one individual in the initial wage distribution. Figure 3 shows that there is indeed some evidence for this to be the case. To account for the fact that this assumption is not literally true in our data, in the following we attribute any deviation around this assumed monotonic growth path to measurement and labour market errors.

Note now that, since the SM granted the <u>same</u> absolute wage increase to any individual, this can also be thought of a rank-preserving transformation of starting wages. Thus $E\left(w_{is} \mid w_{jt-1}^{q}\right) = w_{js}^{q}$, from which:

$$(9) \qquad E\left(\Delta sm_{it} \mid w_{jt-1}^{q}\right) = w_{js}^{q} - w_{jt-1}^{q} \equiv \Delta sm_{jt}^{q}.$$

This equation illustrates that the expected contingent increase for an individual at position q in the distribution of lagged wages is nothing but the difference in the q-th quantiles of the two distributions: initial plus escalated, and initial.

To estimate model (7), finally denote the expected latent wage growth for an individual i at position q in the conditional (i.e. by gender) distribution of wages by:

$$(10) \qquad \Delta w_{jt}^{*q} \equiv E\left(\Delta w_{it}^{*} \mid w_{jt-1}^{q} \right) \quad .$$

Note that, under assumption (8) and based on equation (9), one can interpret the decomposition in (5) (or (6)) as describing the ex-ante wage change for an individual at

of wage rigidity implies that one would expect non-contingent wage changes to be censored. The evidence in the previous section, however, does not show shows any sign of censoring.

[7] This model is very close in spirit to Card's and Lemieux's (1996). Based on US data, they cannot reject the hypothesis that wage growth leaves the individual position in the distribution of wages unchanged.

position q in the distribution of initial wages. Then one can simply look at the correlation between contingent and non-contingent wage changes at each quantile of the distribution to infer the presence of any correlation between the two components at the individual level. These series are plotted in Figure 4.

Based on equations (8) to (10), equation (7) rewrites:

(11) $\Delta w_{jt}^{q} = \Delta w_{jt}^{*q} + \eta \Delta sm_{jt}^{q}$.

Since identification of η requires some exclusion restrictions on Δw_{jt}^{*q}, in the rest of this section we assume that – except possibly for some group specific location parameter – wage growth is the same for two individuals at the same relative position in their respective wage distributions, i.e. potentially with different wage levels:

(12) $\Delta w_{jt}^{*q} = \Delta w_{jt}^{*} + \Delta w_{t}^{*q}$

where Δw_{jt}^{*} is a group-specific shift parameter which is common across the wage distribution and Δw_{t}^{*q} is a function only of the position of one individual in his/her gender group's wage distribution which, in the following, we denote by $q_{jt} = F_{jt}^{-1}\left(w_{jt}^{q}\right)$. Later on we will provide some evidence for this assumption and we will discuss different identification strategies for the case in which this assumption does not hold in the data.

Incidentally note that a similar assumption is used by Lee (1999), although in a very different setting, to identify latent changes in the wage structure in the US. His identifying assumption being that, in the absence of the minimum wage, each percentile of the conditional distribution of wages (for men and women together) within each US state would have evolved at the same rate (relative to the some central measure of tendency within that state).

Since we do not have data on either 'true' wage changes or contingent wage changes, it is convenient to rewrite our sample estimates (denoted by a hat) in terms of 'true' population values and sampling errors. Let:

(13) $$\hat{\Delta}w_{jt}^{q} = \hat{w}_{jt}^{q} - \hat{w}_{jt-1}^{q} = \Delta w_{jt}^{q} + d_{qjt} - d_{qjt-1}$$

be the sample counterpart of wage growth at the q-th quantile, where with obvious notation $d_{qjt} = \hat{w}_{jt}^{q} - w_{jt}^{q}$ is the sampling or labour market error in log wages at time t. We assume that, conditional on q_{jt} and q_{jt}^{2}, the sampling error has zero mean, variance s_{qjt}^{2} and is uncorrelated over time and across individuals.

Finally, in the absence of any prior on the shape of Δw_{t}^{*q}, we assume that this can be approximated by a quadratic function of the individual's relative position in the reference group. Combining equations (8) to (13), this yields:

(14) $$\hat{\Delta}w_{jt}^{q} = \beta_{0jt} + \beta_{1t}q_{jt} + \beta_{2t}q_{jt}^{2} + \eta\Delta sm_{jt}^{q} + u_{qt} + d_{qjt} - d_{qjt-1}$$

which relates wage changes at percentile q of group j between t-1 and t to some function of q_{jt} and the contingent wage change at that percentile. u_{qt} is an error term induced by the quadratic approximation and we assume that this is uncorrelated with measurement error in the dependent variable. By assumption u_{qt} is group-invariant (an assumption that we remove later). Note that while there is no need for this function to be quadratic, we assume this for convenience. Later on we discuss what are the likely implications of this hypothesis.

One way to investigate the validity of model (12) (and therefore model (14)) is to consider its implications in terms of the wage growth differential between a man and a woman at position q in their own gender group's wage distributions. The model suggests that, apart from an error term, this differential should simply be a fraction η of the differential SM growth. It also suggests that if women's wages are below men's wages at any percentile (see Table 3), one should see some reduction in the gender earnings gap at each percentile. However, the difference should be more pronounced for low values of q_{jt}, where contingent wage changes are relatively higher and the difference in wages and therefore contingent wage changes between men and women more pronounced.

In Figure 5 we report the estimated change in relative wages between men and women due to the SM at each percentile of the wage distribution (standardised to the change at each group's median). It is apparent that most of the compression takes place in the late 1970s: female workers are disproportionately concentrated in the bottom tail of the unconditional wage distribution and the SM has a powerful effect in reducing their pay gap relative to comparable men. By the beginning of the 1980s the two distributions are similar and after that the SM has little impact on the differentials. In the picture we superimpose to the set of contingent changes the actual changes in the male-female wage gap at each percentile. One can see that actual wage changes track the changes predicted by the SM very clearly.

In order to assess how much of the observed trend in wage growth can be ascribed to the SM, in Table 5 we report the results of the estimation of model (14) using OLS, based on pooled data for men and women. Our data are the observations from the 5^{th} through the 95^{th} percentile of the conditional distributions (by sex) of wages. Overall we have 360 observations (4 time periods x 90 percentiles) for each gender group, i.e. a total of 720 observations. The dependent variable is the estimated total wage change at each percentile of the wage distribution. The regressor is the estimated contingent payment at each quantile. Variables are annualised and are calculated at fixed sample composition. The standard errors are computed based on the theoretical variance of the error term. The exact formula is provided in the Technical Appendix c.

In column 1 we report the results of the estimation of model (14) using OLS. The estimated coefficient on the Scala Mobile is 0.647 (s.e. 0.105), suggesting that approximately 35% of contingent wage growth is 'undone' by other sources of wage changes.[8]

b. Potential Biases of OLS Estimates and 2SLS Estimates

A problem with the OLS estimate of the coefficient η is that this estimate might be biased by the correlation of the regressors with the error term. One source of potential bias stems from having assumed that latent changes in the wage structure can be well approximated by a quadratic function in q_{jt}. Any omitted component of latent wage growth that is correlated with contingent wage changes is going to bias the OLS estimates. This is equivalent to assuming that the correlation between Δsm^q_{jt} and u_{qt} in equation (14) is non zero, once one has conditioned for q_{jt} and q^2_{jt}. In principle, it is not clear which direction the bias goes. As long as the latent distribution of wage changes tends to <u>offset</u> the effect of the SM, however, one might suspect that omission of higher order terms in q_{jt} in equation (14) tends to <u>underestimate</u> the effect of the SM by spuriously removing some of its equalising effect and attributing it to latent changes in the wage structure.[9]

A second source of potential bias comes from measurement error. This error stems from the circumstance that the measure of contingent wage changes used in this

[8] If we restrict wage growth to be the same within gender groups but for changes at the median (the same as in Figure 9), the estimated coefficient is 0.693 (s.e. 0.100).

[9] A regression of total wage changes on contingent wage changes and the interaction of a gender dummy with year dummies with no controls in q_{jt} leads to an estimate for η of 0.463. The point estimates increase to 0.564, 0.730 and 0.740 and 0.750, respectively for the case in which we control for a polynomial of order 1, 3,4 and 5 in q_{jt}.

study is an estimated one. To see this, observe that the estimated contingent wage changes at the q-th quantile is:

$$(15) \qquad \hat{\Delta sm}^{q}_{jt} = \hat{w}^{q}_{js} - \hat{w}^{q}_{jt-1} = \Delta sm^{q}_{jt} + d_{qjs} - d_{qjt-1}$$

where $d_{qjs} = \hat{w}^{q}_{js} - w^{q}_{js}$ is the measurement error in the estimated contingent payment, which again we assume with zero mean, variance $s_{qjs}{}^{2}$ and uncorrelated over time. By construction this is correlated with the error term in lagged log wages and we denote by $s_{qjs,t-1}$ the covariance between these two terms.

To evaluate the impact of measurement error in the OLS estimates of η, note that classical measurement error (i.e. uncorrelated with the true population value and the error term in equation (14)) would yield downward biased OLS estimates of η (assuming this is positive). However the issue is here further complicated by the mechanical correlation between the dependent variable and the regressor Δsm. To see this, observe that by the definition of contingent wage growth $\left(\Delta sm^{q}_{jt} = w^{q}_{js} - w^{q}_{jt-1}\right)$ and total wage growth $\left(\Delta w^{q}_{jt} = w^{q}_{jt} - w^{q}_{jt-1}\right)$, any bias in the estimation of w^{q}_{jt-1} will induce some correlation between the error term and the regressor, as long as the polynomial in q_{jt} leaves part of the variation in lagged log wages unexplained. The covariance between the error term in equation (14) and the measurement error in the estimated contingent payments is $s_{qjt-1}{}^{2}$- $s_{qjs,t-1}$. This covariance is positive, so that any mechanical correlation between the error term and the estimated regressor will arguably tend to overestimate the impact of the SM.[10]

To conclude, the sources and direction of potential bias in the OLS estimates of model (14) are multiple and their overall effect ambiguous. Ideally, one would like to have different instruments to control for the different sources of bias and assess their

[10] See Technical Appendix c.

individual impact on the OLS estimates. Since we are not able to find separate instruments for the different sources of potential bias, our strategy in the following is to try and find some lower bound for the effect of the SM on changes in the wage structure.

Observe that under the maintained assumption that changes in the wage structure are similar across groups (in the sense defined above), and conditional on q_{jt} and q_{jt}^2, one can use interactions of q_{jt} and q_{jt}^2 with the gender dummy at any time to uncover the effect of the SM. This is a way to control for the potential correlation between the error term and the lagged dependent variable stemming from having omitted a cubic (or higher) term in q_{jt}. Identification is warranted by the circumstance that while contingent wage payments are a function of the initial level of wages and therefore the position in the unconditional (men plus women) wage distribution, we have assumed that latent wage growth is only a function of the position in the conditional (by gender) wage distribution q_{jt}.

As far as measurement error is concerned, under the assumption that this does not affect the ranking of individuals in the lagged wage distribution (but only their value), a polynomial in q_{jt} is a also legitimate instrument for this source of potential bias in the OLS estimates. This is because, by definition, the variable q_{jt} only picks up the variation in the relative position of one individual in the wage distribution rather than the actual wage level.

Whether our 2SLS estimates are above or below the OLS estimates will depend on the net effect of pure classical measurement error versus the combined effect of the endogeneity of contingent payments and the mechanic correlation between the measurement error in estimated contingent wage payments and the error term in the estimated wage changes. As long as measurement error is negligible, we have argued that the OSL estimates will tend to underestimate the true population parameter. In column (2) we have estimated the same model as in column (1) using 2SLS, where the instrument is given by the interaction of a quadratic term in q_{jt} with a gender dummy at any time. The estimated coefficient is 0.712 (s.e. 0.129), above the corresponding OLS estimate but not statistically different from it, as confirmed by the Hausman test at the bottom of the table.

c. Alternative Models of Changes in the Latent Earnings Structure

The crucial assumption in the above discussion and the derivation of the results is that latent wage growth within each group is independent of that group, but for some average group change. Although the validity of this identifying assumption is ultimately untestable with our data, an examination of the behaviours of the series of actual and contingent wage changes at the top of the distribution seems to lend to some support to it. Intuitively, one might argue that if the early compression in the gender earnings gap was due to reasons other that the SM one would expect wage differentials to compress at a similar rate all over the distribution, which does not happen in our data.

An alternative avenue to assess the validity of this assumption is to examine the behaviour of the gender earnings gap in the US. In Figure 6 we have plotted the growth differential in earnings between a man and a woman at each quantile q of their respective wage distributions using March CPS data. We restrict to full year-employees with at least 30 hours of work a week in the previous year and the series are calculated at fixed age and education composition of the sample.[11] Earnings are defined as the total

[11] To do so, we have used the DFL procedure within each sub-period where individuals are classified based on 5 age categories (the same as in Italy) and 4 education groups (same as in Katz and Murphy, 1992: less than 12, 12, 13-15 and 16 or more years of schooling). For comparison, in Table A7 in the appendix we report data on the level and changes in inequality based on CPS data. It is worth observing that because of the definition of earnings used in this study (sum of annual wages and salaries as (cont'd on next page)

sum of wages and salaries in the previous year. The series are obtained at fixed sample composition and are standardised to changes at the median. One can see that in the US the gender earnings gap at different points of the distribution remains remarkably stable as time goes on. The circumstance that, in a period of almost unprecedented changes in the wage structure in the US, the change in the gender earning gap was uniform across percentiles again lends some support to our main identifying assumption.

Despite both these two pieces of evidence speak in favour of the identifying assumption used in the previous section, it is worth emphasising that others have postulated different models of latent wage growth. An alternative model of latent wage growth would be for example one where a man and a woman with the same wage level experience the same wage change. This is similar to the assumption used, among others, by Blau and Kahn (1997) who assume that one can estimate the effect on a woman's wage of changes in the (residual) wage structure, based on her initial position in the men's (residual) wage distribution and the change in the dispersion of men's (residual) wages over the period of interest. Their model relies on the implicit assumption that a man and woman with the same (residual) wages have similar levels of skills and they are therefore perfect substitutes. In doing so, however, their model ignores the existence of discrimination in the labour market. As a matter of fact, if part of the differences between men's and women's wages reflect discrimination, a model like the one in the previous section where a man and woman at the same relative position in their own gender group's wage distribution (and potentially with different wage levels) are assumed to be comparable, is arguably more successful in describing the data.[12] Evaluating which one is the correct model of wage determination is ultimately an empirical matter. Our strategy in the following is to show that abandoning the

opposed to hourly or weekly wages) and because of the sample selection criteria (full year, full time workers), these figures are not directly comparable to the ones generally presented to document changes in the wage structure in the US.

hypothesis of uniform wage growth within gender groups (12) makes little difference to our results. Since in order to identify the effect of the SM we need to impose some exclusion restrictions on Δw^{*q}_{jt}, we do so by experiencing with alternative parametric assumptions about the latent evolution of the wage structure.

A first way to relax the model of the previous section is to constrain latent wage growth in Italy to be the same as in the US, but for a location parameter. This is equivalent to postulating that:

$$(16) \qquad \Delta w^{*q}_{jt} = \Delta w^{*}_{jt} + \Delta w^{USq}_{jt}$$

where the second term on the right-hand side is the growth in wages at each (conditional) percentile of the wage distribution in the US. Equation (11) then rewrites:

$$(17) \qquad \hat{\Delta w}^{q}_{jt} = \beta'_{0jt} + \Delta w^{USq}_{jt} + \eta \Delta sm^{q}_{jt} + d'_{qjt} - d'_{qjt-1}.$$

One implicit advantage of this estimation strategy is that, under the assumption that the latent wage structure in Italy indeed evolved at it did in the US, this offers a way to control for both the potential endogeneity of contingent wage payments due to omitted terms in q_{jt} of order higher than 2 and the effect of differential changes in the wage structure across gender groups. The point estimate for this model is reported in column (3): this is 0.631 (s.e. 0.060) and statistically indistinguishable from the point estimate in column (1).[13] This can be thought of as the proportion of contingent payments which should have translated into actual wage changes for Italy to experience a latent change in the wage structure similar to the actual change which occurred in the US over the same period. This estimate is still likely to be affected by both classical measurement error and the bias stemming from the mechanical-correlation between the error term and

[12] For some discussion on this point see Juhn, Murphy and Pierce (1991).

[13] An alternative strategy is estimate a model: $\Delta w^{*q}_{jt} = \Delta w^{*}_{jt} + \gamma \Delta w^{USq}_{jt}$. The OLS estimates of η and γ are respectively 0.611 (s.e. 0.060) and 0.873 (s.e. 0.088).

the regressor. In column (4) we report the 2SLS estimates using the same instrument as in column (1): the bias is negative but again statistically insignificant.

A second strategy we pursue is to postulate a model in the same spirit as Blau's and Kahn's (1997). Let:

$$(18) \qquad q_{mjt} = F_{mt}\left(F_{jt}^{-1}\left(q_{jt}\right)\right)$$

be the relative position in the men's wage distribution of an individual – man or woman – at position q in his/her reference group's j wage distribution,[14] and let latent wage growth be a function of q_{mjt}:

$$(19) \qquad \Delta w_{jt}^{*q} = \Delta w_{jt}^{*} + \Delta w_{mjt}^{*q}.$$

Model (19) assumes that, possibly for a location parameter, wage growth is the same for two individuals with the same wage level and therefore at the same relative position in the men's wage distributions. Using again a quadratic approximation, model (11) now rewrites:

$$(20) \qquad \hat{\Delta w}_{jt}^{q} = \beta_{0jt}'' + \beta_{1t}'' q_{mjt} + \beta_{2t}'' q_{mjt}^{2} + \eta \Delta sm_{jt}^{q} + u_{qjt}'' + d_{qjt}'' - d_{qjt-1}''$$

where the error term u_{qjt}'' not only contains higher order terms in q which we have omitted from the regression, but it now depends on j, as well as on t.

Before discussing the estimation of model (20), it is worth underlining the difference between this model and model (14). If the distribution of women's wages is more dispersed from the left than the distribution of men's wages, as it appears to be the case (see Table 3), and if model (19) is the correct model of latent wage growth, it is arguable that estimation of model (14) yields an upward-biased estimate for the effect of the SM. To see this assume that the men's latent wage distribution is uniformly compressing (decompressing) and consider the growth in wages experienced by a man and a woman at the same relative position q in their own wage distributions, where q is somewhat low (i.e. below the percentile corresponding to each group's average wage growth). Then one would expect the wage change for a woman at position q in her group's wage distribution to be above (below) the change experienced by a man at the same relative position q in the men's wage distribution. For example, if between 1977 and 1980 – when unskilled women gained substantially relative to unskilled men – the latent distribution of men's wages was uniformly compressing, one does not have necessarily to invoke the SM to explain this feature of the data. Unskilled women might have gained substantially simply because they were concentrated at the very bottom of the men's wage distribution and, as the latter was uniformly compressing, they might have experienced high wage increases. In column (5) we report the OLS estimate for model (20): this is 0.637 (s.e. 0.085), which is below the point estimates in column (1) but statistically indistinguishable from it.[15] Implicitly, this result suggests that if latent wage growth is indeed some smooth function of the level of initial wages, there is no way to replicate the curvature in wage growth at the bottom of the distribution of women's wages (Figure 5) by extrapolating the behaviour of changes in women's wages from changes in men's wages.

The last strategy we pursue in this chapter is to estimates of a model where we free up the coefficients on the quadratic polynomial in q_{jt}, by allowing them to differ (within each time period) between men and women:

$$(21) \qquad \hat{\Delta w}^q_{jt} = \beta'''_{0jt} + \beta'''_{1jt} q_{jt} + \beta'''_{2jt} q^2_{jt} + \eta \Delta sm^q_{jt} + u'''_{qjt} + d'''_{qjt} - d'''_{qjt-1}$$

where the error term is now $u'''_{qjt} = \Delta w^{*q}_{jt} - \left(\beta'''_{0jt} + \beta'''_{1jt} q_{jt} + \beta'''_{2jt} q^2_{jt}\right)$. This is a rather flexible model, in which we allow latent wage growth to vary differently (up to a

[14] The average position of a woman in the men's wage distribution is 31[st] percentile.

[15] Fortin and Lemieux (1998) argue that the 'right' counterfactual is the unconditional (i.e. men's and women's) distribution of wages, rather than the distribution of men's wages. If we condition on a quadratic in the individual position in the unconditional wage distribution, the OLS estimate of η turns out to be 0.665 (0.094).

quadratic term in q_{jt}) between gender groups. Identification then stems essentially from the behaviour of actual wage growth at the top of the distribution within each gender group (where the value of contingent wage payments is negligible). The coefficient, reported in column (6) decreases to 0.520 (s.e. 0.113), suggesting that part of the stronger compression in women's wages in the early years has to be attributed to more pronounced changes in women's latent wage structure. Again, however, this stronger compression is not sufficient to wash out the effect of the SM. This estimate might still be biased both because of the correlation with the error term due to omission of terms in q_{jt} higher than 2 and because of potential measurement error. However, given our previous discussion, the first source of bias is likely to imply that the OLS estimates are downward biased because one is ignoring a part of non-contingent wage changes that is arguably negatively correlated with the SM payments.[16] A comparison with column (3) reinforces this point. If changes in the wage structure in the US are a consistent estimate of latent changes in the wage structure in Italy, the only difference between the estimate in column (3) and that in column (6) is that the latter will be affected by omission of higher order terms in q_{jt} and this suggests that their omission induces a downward bias in the OLS estimates. As far as measurement error is concerned, we know that its effect is theoretically ambiguous. Under the maintained assumption that the growth in wages at each conditional percentile can be legitimately approximated by a quadratic function of the variable q_{jt}, however, one can use higher order terms in q_{jt} to control for this source of potential bias. Implicitly, one is exploiting the circumstance that the SM is

[16] The evidence here is less clear-cut than in section a. A regression of total wage changes on contingent wage changes, the interaction of a gender dummy with year dummies and the interaction of a polynomial in q_{jt} with the gender and year dummies leads to the following estimates for η: 0.490, 0.500 and 0.436 and 0.680, respectively for the case in which we control for a polynomial of order 1, 3,4 and 5 in q_{jt}.

highly non-linear in the variable q_{jt} to uncover any effect of measurement error. The condition for this to be a valid instrument, under the maintained assumption that a quadratic in polynomial in q_{jt} approximates wage growth sufficiently well, is again that measurement error only affects the level of the estimated contingent payments but not their ranking. In column (7) we estimate equation (21) where we use a polynomial of the third order in q_{jt} interacted with a gender dummy at any time as an instrument. The 2SLS estimate of model (21) is basically indistinguishable from the OLS one, suggesting at least that the two sources of bias tend to offset each other.

The conclusion from this exercise is that the estimates of model (21) seem to provide a lower bound for the effect of the SM on changes in the wage structure. Omission of higher order terms in q_{jt} in equation (21) will imply, if anything, that the OLS estimate (or, for what it matters, the 2SLS estimate) is downward biased, while measurement error does not appear to affect sensibly our estimates.

d. Estimated Changes in the Latent Structure of Earnings

In Table 6 we decompose the changes in wage inequality into ex-post contingent and non-contingent wage changes. We use the estimated coefficient from column (7), Table 5, which, as argued, is a lower bound for the effect of the SM, to derive its ex-post effect and the predicted value of the quadratic polynomial in q_{jt} to estimate latent wage changes. The corresponding decomposition for changes in nominal earnings is reported in table A8 in the Appendix.

One can see that in the first period of observation ex-post non-escalated wage increases tend to compress the distribution of wages. Our estimates suggest that even in the absence of the indexation mechanism, between 1977 and 1980 wage inequality would have decreased. The data show that the 9-1 log decile gap would have decreased by more than 1 point a year for women and only 0.15 points for men. In the second period latent wage inequality tends to increase by approximately 2 points for both groups. Some differences emerge between 1984 and 1989 where latent inequality increases for men but not for women, but the latter seem to catch up in the last period with a very pronounced growth in inequality. Over the entire sample period, we estimate that latent inequality would have risen by approximately 25 points for men and by almost 30 points for women.

To get a visual impression of the effect of the SM, in Figure 7 we plot the actual evolution of 9-1 log decile gap alongside the estimated evolution of the latent trend in wage inequality, obtained as the cumulative sum of the changes from one period to the other, separately for men and women. Both series are constructed at a fixed distribution of observable characteristics and are standardised to zero in 1993. The difference between these two series is the estimated impact of the SM, which is pictured in the bottom panel. One can clearly see the equalising effect of the SM in the early years, especially for women. A comparison with Figure 2, however, makes it clear that one cannot simply subtract contingent wage changes from the actual distribution of wage changes to infer what the evolution of wages would have been in the absence of indexation. While ex-ante one would have expected the SM to reduce inequality by approximately 80 log points for women and almost 50 log points for men, ex-post one finds that the SM was responsible for a reduction of approximately half as much: about 40 log points for women and about 25 log points for men. By the same token, if ex-ante one would have estimated non-contingent wage changes to increase inequality by approximately 70 log points for women and 50 log points for men, our estimates show that once one controls for the share of non-contingent wage growth which was meant to offset contingent wage increases, this numbers reduce to approximately 30 and 25 log points respectively.

In Figure 8 we replicate the same exercise as in Figure 1: here we plot both the actual evolution of the earnings gap for males and females together in Italy and in the US. In the bottom panel we report the estimated effect of the SM on wage inequality as well as the latent trend in the gap. Again all series are standardised to their value in 1993 so the graph only provides information on changes. One can see that the series of latent inequality in Italy and the series of inequality in the US show similar trends. Latent inequality in Italy rises by approximately 26 log points in 17 years while inequality in the US rises in the same period by 20 log points.

IV. Accounting for Employment Effects

Until now we have assumed that density of observable characteristics is independent of the wage schedule. Firms, however, might react to changes in relative wages by substituting workers whose relative wage has decreased for workers whose relative wage has increased. One natural question that arises is then whether the observed trend in the wage distribution can itself be partly ascribed to the endogenous compositional effects of the SM via (exogenous) changes in the wage structure. If we are able to predict the relative employment changes induced by the SM, we can then use these changes to estimate what the composition of our sample (by age and education) would have been at time t if the SM had been the only source of wage changes between t-1 and t, and we can then reweight the individual observations using the DFL procedure using these new weights. This makes it possible to estimate a counterfactual wage distribution for the case in which the only variation in the composition of the sample is the one implied by the SM. By comparing the actual distribution of wages with this counterfactual, we can then evaluate the indirect effect of the SM on the observed changes in the wage structure.

To model the effect of wage changes on the composition of employment, we assume that firms face an infinitely elastic labour supply at given wages and employment is determined along a relative labour demand curve once wages have been set.[17] Wages are determined based on the SM and on some bargaining process. Changes in relative employment will be due to either exogenous changes in relative wages (shifts along the labour demand curve, identified by movements of the labour supply curve) or changes in relative demand (movements of the demand curve along the flat labour supply). In order to account for the employment effects of the SM, we need to separately identify these two effects and attribute to the SM only the movements of the labour supply along a fixed labour demand. Since movements in relative labour supply can either be due to the effect of contingent wage changes (which reduce the relative wages of high-wage workers and push firms to substitute these workers for low wage-ones) and the effect of non contingent wage changes (which act in the opposite direction for most of the period of analysis) one has to derive an expression that relates changes in relative employment to changes in relative wages due to the (ex-post) effect of the SM.

To evaluate the impact of the Scala Mobile on employment changes, we follow Katz and Murphy (1992) in assuming that firms produce an output Y using a CES production function in two (equivalent) educational labour inputs with elasticity of substitution σ:

[17] To keep things simple we have assumed that the "wage curve" in chapters 1 and 2 if flat, i.e. that the elasticity of wages with respect to unemployment is zero. In chapter 4 we provide some indirect evidence on this point.

$$Y_t = \left(\alpha_{1t} N_{1t}^{\frac{\sigma-1}{\sigma}} + \alpha_{2t} N_{2t}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}.$$

The α's are measures of relative productivity for the two inputs which shift their relative labour demand curve. For σ=1, this is the production function used in chapters 1 and 2. Under perfect competition in the labour market and assuming that factor specific productivities stay unchanged, it follows that relative employment for group 1 changes with wages according to the following equation:

$$\Delta\left(n_{1t} - n_t\right) = -\sigma\Delta\left(w_{1t} - w_t\right)$$

where lower case letters denote logarithms, w is the average (log) wage in the economy and l is (log) aggregate employment. The same expression holds for group 2. Based on this expression, we can then compute the implied changes in relative employment due to the SM based on the following expression:

$$\Delta\left(n_{1t} - n_t\right)^{SM} = -\sigma\eta\Delta\left(sm_{1t} - sm_t\right)$$

where Δsm_t is the proportional contingent wage change at w_t, and we can then compute the new weights and finally reweight each individual observation depending on whether this belongs to group 1 or group 2.

In our application we classify individuals as either college (1) or 5th grade (2) equivalents,[18] and we treat individuals in different age groups for any given level of education as perfect substitutes. The details of the derivations and the estimation of the weights are presented in the Technical Appendix, d and e. The results of our exercise are reported in Table 7, where we provide the employment effect of the SM over different measures of inequality for three values of the elasticity of substitution between educated and uneducated labour: 0.5, 1.41, and 4. These can be thought of covering the range of all plausible values of σ, with 1.41 being the consensus estimate for the elasticity of substitution between college graduates and non-college graduates in the US. For brevity, we report only the annualised changes over the whole period for different measures of inequality and, for comparison, we also report the actual compositional changes as presented in Table 4.

The first observation is that the estimated employment changes grow in absolute value as the elasticity of substitution increases, which is what one would expect. Second, the sign of the predicted changes is in line with the actual changes, and in particular with the fact that these are positive (raising inequality) for men and negative (reducing inequality) for women. For a value of σ equal to 4, actual and estimated changes for men are remarkably similar. A simple way to reconcile these results is to postulate that, as relative demand for male college graduates increased, latent wage growth seconded this rise, so that in the absence of the SM the structure of employment for men would have remained unchanged. However, the SM, by acting in the opposite direction, tended to induce some substitution away from college graduates and that explains the compositional changes documented in Table 2.

As far as women are concerned, the predicted changes account for at most one fourth of the actual changes: the model is unable to pick up the pronounced rise in the relative employment of female college graduates. Within the stylised framework adopted here this suggests that demand for female college graduates (relative to women with only a 5-th grade) must have shifted more than demand for male college graduates (relative to men with a 5-th grade).

The main conclusion from this exercise, however, is that allowing for endogenous employment changes is not likely to sensibly affect the estimated impact of the SM on the distribution of wages. Endogenous employment changes, even with the

[18] We treat those with 13[th] grade as college equivalents and everybody else as a 5-th grade equivalent.

highest elasticity of substitution, would have implied a rise in the 9-1 log decile gap for men of about 1 point over the entire period of observation and a decline of about twice as much for women. An interesting side result is that the estimates for men suggest that the SM could be held responsible for all of the observed changes in the structure of employment over the period of observation. It remains a puzzle why the same is not true for women.

V. Conclusions

It is often heard that wage inequality failed to increase in continental Europe in the 1980s, while it rose substantially in the US. In this chapter we have used individual earnings data for Italy to document the trends in wage inequality between 1977 and 1993 and to assess the role that the Scala Mobile played in shaping these trends. First, we have shown that, after a marked compression in the late 1970s, beginning in the mid 1980s wage inequality in Italy started to increase. In 1993 the level of inequality was comparable to the level in 1977. Second, we have shown that the Scala Mobile had a considerable equalising effect. We estimate that between one half and three fourths of the wage changes implied by the indexation mechanism translated into actual wage changes. We conclude that this institution did matter: market forces did not completely undo the effect of the SM. Finally, we show that beginning in the early 1980s latent wage inequality started to increase in Italy. As the SM was curbed, observed wage inequality tended to increase too. An interesting result of our analysis is that in the absence of indexation wage inequality in Italy would have risen throughout the 1980s and early 1990s at a rate comparable to the one observed in the US.

To come to this conclusion we have assumed that in the absence of the SM inequality would have changed similarly for men and women. Although the hypothesis is untestable with our data, we show that US data lend some support to it. In addition, we have shown that our results are essentially unchanged if one relaxes the assumption of uniform changes in the wage structure within gender groups and extends the model in a variety of directions.

We have also shown that the trends in observed wage inequality were substantially unaffected by changes in the composition of employment. While the SM might have had some non-negligible employment effects the impact of these compositional changes on the trend in inequality does not seem to be of much importance.

Our results suggest that the pressure towards higher inequality of earnings in the 1980s was not a phenomenon unique to the US. Rather, they seem to point in the direction that this trend was a general one. Consistently with the findings in chapters 1 and 2, in chapter 4 we will argue that this trend was the result of some global shift in labour demand toward skilled workers. In contrast to the US, however, it appears that in continental Europe institutions were relatively effective in opposing –at least for some time– the latent tendency towards wage decompression. If anything, changes in relative demand translated into relative employment changes.

References

Blau, F. and L. Kahn, "International Differences in Male Wage Inequality: Institutions versus Market Forces", *Journal of Political Economy*, 104, 1996, 791-837.

Blau, F. and L. Kahn, "Swimming Upstream: Trends in the Gender Wage Differential in 1980s", *Journal of Labor Economics*, 15, 1997, 1-42.

Bound, J. and J. Johnson, "Changes in the Structure of Wages in the 1980"s: An Evaluation of Alternative Explanations", *American Economic Review*, 82, 1992, 371-92.

Card, D. "Cost of Living Escalators in Major Union Contracts", *Industrial and Labor Relations Review*, 37, 1983, 34-48.

Card, D. "Unexpected Inflation, Real Wages and Employment Determination in Union Contracts", *American Economic Review*, 80, 4, 1990, 669-688.

Card, D. and T. Lemieux, "Wage Dispersion, Returns to Skill, and Black-White Wage Differentials", *Journal of Econometrics*, 74 , 1996, 319-61.

Card, D. and T. Lemieux, "Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis," *Working Paper #13, Center for Labor Economics*, University of California at Berkeley, 1999.

Di Biase, R. and M. Di Marco "The Redistributive Effects of the Tax Wedge in Italy", *Labour*, 9, 1995, 377-401.

DiNardo, J., N. Fortin, and T. Lemieux, "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach", *Econometrica*, 64, 1996, 1001-1044.

Erickson, C. and A. Ichino, "Wage Differentials in Italy: Market Forces, Institutions, and Inflation", in *Differences and Changes in The wage Structure*, Freeman, R. and L. Katz (eds.), The University of Chicago Press, 1995.

Fortin, N. and T. Lemieux, "Rank Regressions, Wage Distributions, and the Gender Gap", *Journal of Human Resources*, 33, 1998, 610-43.

Freeman, R. and L. Katz, "Differences and Changes in Wage Structures: Introduction and Summary", in *Differences and Changes in The wage Structure*, Freeman, R. and L. Katz (eds.) NBER Comparative Labor Markets Series. Chicago and London: University of Chicago Press, 1995.

ISTAT, *Annuario Statistico Italiano*, Rome.

Juhn, C., K. Murphy and B. Pierce, "Accounting for the Slowdown in Black-White Wage Convergence", in Kosters, M. (ed.) *Workers and their wages: Changing patterns in the United States*, AEI Studies, no. 520, Washington, D.C, 1991.

Juhn, C., K. Murphy and B. Pierce, "Wage Inequality and the Rise in Returns to Skills", *Journal of Political Economy*, 101, 1993, 410-442.

Katz, L. and K. Murphy, "Changes in Relative Wages, 1963-1987: Supply and Demand Factors", *Quarterly Journal of Economics*, 107, 1992, 35-78.

Katz, L. and D. Autor, "Changes in the Wage structure and Earnings Inequality", in *Handbook of Labor Economics*, Ashenfelter O. and D. Card (eds.), North Holland, 1995.

Lee, D. "Wage inequality in the US during the 1980s: Rising dispersion or falling minimum wage?", *Quarterly Journal of Economics*, 114, 1999, 997-1023.

Machin, S. (1995) "Changes in the Relative Demand for Skills in the UK Labour Market", in A. Booth and D. Snower (eds.) *Acquiring Skills: Market Failures, Their Symptoms and Policy Responses*, Cambridge University Press: Cambridge.

OECD, *Employment Outlook*, Paris, 1993.

OECD, *Job study*, Paris, 1996.

Silverman, B. *Density estimation for statistics and data analysis*, Chapman and Hall, London, New York, 1986.

Treu, T. (ed.) *European Employment and Industrial Relations Glossary: Italy*, Sweet and Maxwell Luxembourg, 1991.

Technical Appendix

a. Kernel density estimation

Estimation of the empirical quantiles is obtained based on kernel density estimates of the wage distributions at selected points in time. In the following we ignore the subscript j to simplify the notation. A kernel density estimate of the wage distribution at time t can be obtained as:

$$\text{(A1)} \quad \hat{f}_t(w) = \sum_{i \in S_t} \frac{\theta_i}{h} K\left(\frac{w - w_i}{h}\right)$$

where S_t is the sample of individuals at time t, w are the individuals (log) wages used as a support for the kernel, h is the bandwidth and K(.) is a kernel function which integrates to one. The θ_i's are the SHIW sampling weights, standardised to sum to one. An estimate of the distribution which would have prevailed (ex-ante) if the SM had been the only source of wage increases, $f_{s,t-1}(w) \equiv f(w|t_w=s, t_z=t-1)$, can be obtained by the following expression:

$$\text{(A2)} \quad \hat{f}(w \mid t_w = s, t_z = t-1) = \sum_{i \in S_{t-1}} \frac{\theta_i}{h} K\left(\frac{w - w_{is}}{h}\right)$$

where w_{is} is the individual (log) lagged wages plus the contingent payments between t-1 and t. Finally, in order to allow for changes in observable characteristics, we use the DFL reweighting procedure. Observe that:

$$\text{(A3)} \quad f(w \mid t_w = s, t_z = t) = \int f(w \mid t_w = s, t_z = t, z)\, dF(z \mid t_w = s, t_z = t).$$

Under the assumption that the mapping of individual characteristics into wages (the wage schedule) does not depend on the distribution of attributes,[19] this expression simplifies to

[19] A sufficient condition for this to be the case is that labour supply is perfectly elastic.

$$\text{(A4)}\quad \begin{aligned} f(w \mid t_w = s, t_z = t) &= \int f(w \mid t_w = s, z)\, dF(z \mid t_z = t) = \\ &= \int f(w \mid t_w = s, z)\, \lambda(z)\, dF(z \mid t_z = t-1) \end{aligned}$$

where:

$$\text{(A5)}\quad \lambda(z) = \frac{dF(z \mid t_z = t)}{dF(z \mid t_z = t-1)}.$$

Equation (A4) implies that one can recover the desired wage distribution simply re-weighting the distribution at time t-1. If z varies over some discrete support, by Bayes' rule the re-weighting function can be written as:

$$\text{(A6)}\quad \lambda(z) = \frac{\Pr(t_z = t \mid z)}{\Pr(t_z = t-1 \mid z)} \frac{\Pr(t_z = t-1)}{\Pr(t_z = t)}$$

and one can easily obtain estimates of these weights by pooling observations at time t-1 and t 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 we do in this chapter, 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. A kernel density estimate of distribution (A4) is therefore:

$$\text{(A7)}\quad \hat{f}(w \mid t_w = s, t_z = t) = \sum_{i \in S_{t-1}} \frac{\theta_i}{h} \hat{\lambda}_i K\left(\frac{w - w_{is}}{h}\right).$$

Estimation of kernel densities is performed using a Gaussian smoother, with optimal bandwidth under the hypothesis that the underlying distribution is normal (Silverman, 1986).

<u>b. A model of wage growth</u>

Suppose w_{it} and w_{it-1} are jointly normal distributed with:

$$\begin{pmatrix} w_{it-1} \\ w_{it} \end{pmatrix} \sim N\begin{pmatrix} \mu_{t-1} & \sigma_{t-1}^2 & \rho\sigma_{t-1}\sigma_t \\ \mu_t & \rho\sigma_{t-1}\sigma_t & \sigma_t^2 \end{pmatrix}.$$

Assume now that wage growth leaves the ranking of individual wages unchanged i.e.

$\rho=1$.

Under this hypothesis:

$$E\left(w_{it} \mid w_{it-1}\right) = \left(\mu_t - \frac{\sigma_t}{\sigma_{t-1}}\mu_{t-1}\right) + \frac{\sigma_t}{\sigma_{t-1}} w_{it-1}.$$

It follows:

$$E\left(w_{it} \mid w_{t-1}^q\right) = \mu_t + \sigma_t z^q = w_t^q.$$

Note that in this model the q-th quantile of the distribution of wages at time t is a linear transformation of the q-th quantile of the distribution of wages at time t-1:

$$w_t^q = \left(\mu_t - \frac{\sigma_t}{\sigma_{t-1}}\mu_{t-1}\right) + \frac{\sigma_t}{\sigma_{t-1}} w_{t-1}^q.$$

Wage inequality uniformly increases (decreases) if $\sigma_t > \sigma_{t-1}$ ($\sigma_t < \sigma_{t-1}$). In terms of wage growth

$$\Delta w_t^q = \left(\mu_t - \frac{\sigma_t}{\sigma_{t-1}}\mu_{t-1}\right) + \frac{\sigma_t - \sigma_{t-1}}{\sigma_{t-1}} F_{t-1}^{-1}(q).$$

Wage changes at each percentile of the distribution of wages are a monotonically increasing (decreasing) transformation of q if $\sigma_t > \sigma_{t-1}$ ($\sigma_t < \sigma_{t-1}$).

c. Standard Errors

In order to estimate the standard errors of the vector of OLS coefficients ($\hat{\beta}_{OLS}$), we use the standard formula for the variance-covariance matrix of the estimators when the variance-covariance of the error term Ω is non-diagonal:

$$\operatorname{var}\left(\hat{\beta}_{OLS}\right) = s^2 (X'X)^{-1} X'\Omega X (X'X)^{-1}$$

where X is the matrix of the regressors. The formula for the 2SLS estimator is analogous. To derive an estimate of Ω, we use the expression for the theoretical variance of the quantiles of a distribution. We allow for a non zero cross-correlation in each year within each gender group and, since the dependent variable is in first differences, we also allow for autocorrelation at lag one. The expressions for the elements of the variance-covariance matrix are:

$$\operatorname{cov}\left(\frac{w_{jt}^{q} - w_{jt-k}^{q}}{k}, \frac{w_{jt}^{p} - w_{jt-k}^{p}}{k}\right) =$$

$$= \frac{1}{k^2}\left[\operatorname{cov}\left(w_{jt}^{q}, w_{jt}^{p}\right) + \operatorname{cov}\left(w_{jt-k}^{q}, w_{jt-k}^{p}\right)\right] =$$

$$= \frac{1}{k^2}\left[\frac{q(1-p)}{f_{jt}\left(w_{jt}^{q}\right) f_{jt}\left(w_{jt}^{p}\right)} + \frac{q(1-p)}{f_{jt-k}\left(w_{jt-k}^{q}\right) f_{jt-k}\left(w_{jt-k}^{p}\right)}\right] \qquad q \le p$$

$$\operatorname{cov}\left(\frac{w_{jt}^{q}-w_{jt-k_1}^{q}}{k_1},\frac{w_{jt-k_1}^{p}-w_{jt-k_1-k_2}^{p}}{k_2}\right)=$$

$$=-\frac{1}{k_1 k_2}\operatorname{cov}\left(w_{jt-k_1}^{q},w_{jt-k_1}^{p}\right)=$$

$$=-\frac{1}{k_1 k_2}\left[\frac{q(1-p)}{f_{jt-k_1}\left(w_{jt-k_1}^{q}\right)f_{jt-k_1}\left(w_{jt-k_1}^{p}\right)}\right] \qquad q \le p$$

Analogously, to compute the variance-covariance matrix of the coefficients in the first-stage regression for 2SLS, we need to derive an expression for the variance-covariance matrix of the contingent wage changes:

$$\operatorname{cov}\left(\frac{w_{js}^{q}-w_{jt-k}^{q}}{t-(t-k)},\frac{w_{js}^{p}-w_{jt-k}^{p}}{t-(t-k)}\right)=$$

$$=\frac{1}{k^2}\left[\operatorname{cov}\left(w_{js}^{q},w_{js}^{p}\right)+\operatorname{cov}\left(w_{jt-k}^{q},w_{jt-k}^{p}\right)-2\operatorname{cov}\left(w_{js}^{q},w_{jt-k}^{p}\right)\right]$$

where:

$$\operatorname{cov}\left(w_{js}^{q},w_{js}^{p}\right)=\frac{1}{W_{js}^{q}}\frac{1}{W_{js}^{p}}\operatorname{cov}\left(W_{js}^{q},W_{js}^{p}\right)=$$

$$=\left(\frac{1}{W_{js}^{q}}\frac{1}{W_{js}^{p}}\right)\operatorname{cov}\left(W_{jt-k}^{q}+\Delta SM_{t},W_{jt-k}^{p}+\Delta SM_{t}\right)=$$

$$=\left(\frac{W_{jt-k}^{q}}{W_{js}^{q}}\frac{W_{jt-k}^{p}}{W_{js}^{p}}\right)\operatorname{cov}\left(w_{jt-k}^{q},w_{jt-k}^{p}\right) \qquad q \le p$$

$$\operatorname{cov}\left(w^{q}_{js}, w^{p}_{jt-k}\right)=\frac{1}{W^{q}_{js}}\frac{1}{W^{p}_{jt-k}}\operatorname{cov}\left(W^{q}_{js}, W^{p}_{jt-k}\right)=\frac{1}{W^{q}_{js}}\frac{1}{W^{p}_{jt-k}}\operatorname{cov}\left(W^{q}_{jt-k}, W^{p}_{jt-k}\right)=$$

$$=\left(\frac{W^{q}_{jt-k}}{W^{q}_{js}}\right)\operatorname{cov}\left(w^{q}_{jt-k}, w^{p}_{jt-k}\right) \qquad q \leq p$$

from which:

$$\operatorname{cov}\left(\frac{w^{q}_{js}-w^{q}_{jt-k}}{t-(t-k)}, \frac{w^{p}_{js}-w^{p}_{jt-k}}{t-(t-k)}\right)=\frac{1}{k^{2}}\frac{W^{p}_{js}-W^{q}_{jt-k}}{W^{q}_{js}W^{p}_{js}}\Delta SM_{t}\operatorname{cov}\left(w^{q}_{jt-k}, w^{p}_{jt-k}\right)=$$

$$=\frac{1}{k^{2}}\left[\frac{q(1-p)}{\left[f_{jt-k}\left(w^{q}_{jt-k}\right)\right]\left[f_{jt-k}\left(w^{p}_{jt-k}\right)\right]}\right]\left[\frac{W^{p}_{js}-W^{q}_{jt-k}}{W^{q}_{js}W^{p}_{js}}\Delta SM_{t}\right] \qquad q \leq p$$

d. Reweighting Procedure with Endogenous Weights

In a model where employment is determined by a flat labour supply and a downward sloping labour demand, as the one we postulated in section IV, one can think of the distribution of wages as depending on three elements: the mapping of characteristics into wages, the distribution of characteristics and the distribution of the demand shifters (factor specific productivities). Then:

(A8) $\quad f_{s,t,r}(w) \equiv f\left(w \mid t_{w}=s, t_{z}=t, t_{\alpha}=r\right)$

where α is a (vector of) demand shifters. By definition, $f_{jt,t,t}(w) \equiv f_{jt}(w)$. The notation in (A8) is redundant insofar the distribution of employment (t_z) will be univocally determined by the wage schedule (t_w) and the distribution of demand shifters (t_α), so that $f_j(w|t_w=t,.,t_\alpha=t) \equiv f_j(w|t_w=t,t_z=t,.) \equiv f_j(w|t_w=t,t_z=t,t_\alpha=t)$.

Note that movements of the labour demand curve affect the observed density of wages only through changes in the composition of employment. Suppose for example we ask what the distribution of wages would have looked like had individuals observed at time t-1 been awarded contingent wage increases and the composition of employment had varied accordingly <u>at fixed labour demand</u>. This is a shift in labour supply and can be written as:

$$\text{(A9)}\quad \begin{aligned} f(w \mid t_W = s,., t_\alpha = t-1) &= \int f(w \mid t_W = s, t_\alpha = t-1, z)\,dF(z \mid t_W = s, t_\alpha = t-1) = \\ &= \int f(w \mid t_W = s, t_\alpha = t-1, z)\,\kappa(z)\,dF(z \mid t_W = t-1, t_\alpha = t-1) \end{aligned}$$

where:

$$\text{(A10)}\quad \kappa(z) = \frac{dF(z \mid t_W = s, t_\alpha = t-1)}{dF(z \mid t_W = t-1, t_\alpha = t-1)}.$$

Equation (A10) suggests then that if one wants to assess the overall impact of the SM on the wage distribution, one can simply compute the artificial wages w_s and estimate a kernel density of this distribution, where each individual observation at time t-1 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 was set at the level implied by demand at time t. This is equivalent to computing:

$$\text{(A11)}\quad \begin{aligned} f(w \mid t_W = s,., t_\alpha = t) &= \int f(w \mid t_W = s, t_\alpha = t, z)\,dF(z \mid t_W = s, t_\alpha = t) = \\ &= \int f(w \mid t_W = s, t_\alpha = t, z)\,\varphi(z)\,dF(z \mid t_W = t, t_\alpha = t) \end{aligned}$$

where:

$$\text{(A12)}\quad \varphi(z) = \frac{dF(z \mid t_W = s, t_\alpha = t)}{dF(z \mid t_W = t, t_\alpha = t)}.$$

Note that this is a different question from asking what the structure of wages would have looked like if individuals had been awarded contingent wage increases but the distribution of employment was the one which actually occurred at time t. The two distributions are identical only to the extent that no employment change from t-1 to t can be ascribed to non-escalated wage changes. This distribution in reported in equation (A4) and one can rewrite it in the notation of this section as $f_j(w|t_w{=}s,t_z{=}t,.)$.

In this case, one can rewrite the overall change in wages at a given percentile from time t-1 to time t as:

$$
\text{(A13)} \quad \begin{aligned} \Delta w^q_{jt} \equiv & \left(w^q_{jt} - w^q_{js,t,.}\right) + \left(w^q_{js,t,.} - w^q_{js,.,t}\right) + \left(w^q_{js,.,t} - w^q_{js,.,t-1}\right) + \\ & + \left(w^q_{js,.,t-1} - w^q_{js,t-1,.}\right) + \left(w^q_{js,t-1,.} - w^q_{jt-1}\right) \end{aligned}
$$

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 escalated wage changes;
c. the change due to the employment effect of the demand shifts;
d. the change due to the employment effect of 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 in equation (6) into a component due to contingent wage changes, a component due to shifts in the (relative) demand function and a last part due to non-contingent wage changes. One can estimate the densities (A9) and (A11) via means of kernels, with the weights given by equations (A10) and (A12), respectively.

Since our interest here is only on the employment effect of the SM we do not identify separately c from d in the above decomposition. To obtain an estimate of the weights in (A10), observe that for z varying over some discrete support, these can be rewritten as:

$$\text{(A14)}\quad \kappa(z) = \exp\left(\ln \Pr\left(z \mid t_w = s, t_\alpha = t-1\right) - \ln \Pr\left(z \mid t_w = t-1, t_\alpha = t-1\right)\right)$$

i.e. they turn out to be proportional to the percentage change in the employment share of each group induced by the SM. With a model of demand, as the one derived below, it is then easy to estimate these relative weights.

e. A Model of Labour Demand

To keep things simple here we assume that the observations in our sample come either as college or a fifth-grade workers and that we have to aggregate across different age inputs. The results are substantially unchanged if, as we do in the text, we allocate those who are neither college or fifth-grade workers to one of the two groups based on their relative wages.

Assume that each educational input e in the production function in section IV results from the aggregation of different age inputs, indexed by a. For simplicity, we derive the results only for one group, say group 1:

$$\text{(A15)}\quad N_1 = \left(\sum_a \alpha_a N_{1a}\right)$$

which implies that different age inputs (within any given education group) are perfect substitutes. It follows:

$$\text{(A16)}\quad \frac{W_{1a}}{W_1} = \frac{\partial N_1}{\partial N_{1a}} = \alpha_a$$

and from the profit maximisation based on the aggregate production function in section IV:

$$\text{(A17)}\quad W_1 = \frac{\partial Y}{\partial N_1} = \alpha_1 \left(\frac{N_1}{N}\right)^{-\frac{1}{\sigma}} W^{\frac{1}{\sigma}}$$

where we have exploited the fact that Y=WN. Then:

$$\text{(A18)} \quad \left(\frac{N_1}{N}\right) = W_1^{-\sigma} W\alpha_1^{\sigma} = \left(\frac{W_1}{W}\right)^{-\sigma} W^{1-\sigma}\alpha_1^{\sigma}.$$

As the employment in each age group is determined, we assume:

$$\text{(A19)} \quad d\ln N_{1a} = d\ln N_1 .$$

Although this is only one of the possible solutions (the system in indeterminate), it is easy to see that under this hypothesis:

$$\text{(A20)} \quad \begin{aligned} d\ln N_1 &= \frac{dN_1}{N_1} = \frac{1}{N_1} d\sum_a \alpha_a N_{1a} = \frac{1}{N_1}\sum_a \alpha_a N_{1a}\, d\ln N_{1a} \\ &= d\ln N_1 \sum_a \frac{\alpha_a N_{1a}}{N_1} \equiv d\ln N_1 \end{aligned}$$

In order to derive the effect of the SM on employment we assume that this affects the wage structure only modifying relative wages. In other terms, we assume that the average wage is unaffected by the SM and it only reflects real productivity gains (which could in principle be predated by the SM). We then reweight each individual observation according to these weights according as to whether this is a college or fifth-grade equivalent.

Data Appendix

a. The Scala Mobile Data

In this section we describe the data and the procedure used to estimate contingent wage increases for the individuals in the SHIW. In Table A1 we illustrate the composition of take-home annual pay (the definition of earnings used in this study) for a typical Italian worker. Minimum contractual wages are set at the industry level for different skill levels. The sum of the contractual minimum and the cumulated escalated wage increases gives the contractual wage. 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 cumulated non-contingent wage increases plus the contractual compensation gives the monthly compensation. Thirteen times the monthly compensation gives total annual compensation.[20] If we subtract income taxes and workers' social security contributions and we add family allowances, this gives the take home annual pay, that is the measure of earnings in the SHIW.

As far as the SM is concerned, although already in existence before 1977, in that year it was extended to all employees. During the course of its life the SM underwent a number of reforms. These reforms and their timing are summarised in Table A2. In its original formulation, which we illustrate in section I, the SM 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 the 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, for whom 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. This implied a reduction of approximately 15% in the average protection of wages against inflation. In 1986 a new system was introduced establishing that the adjustment of wages to price changes was to take place every six months rather than every three. It also guaranteed a 100% coverage of a given minimum wage indexed itself, α', 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 α', changes in wages between time t-1 and time t with this renewed mechanism can be written as:

$$\Delta SM_{it} = (.75\alpha_t' + .25CW_{it})\Delta\dot{p}_t$$
$$\alpha_t' = \alpha_{t-1}'\left(\frac{P_t}{P_{t-1}}\right) = \alpha_0'\left(\frac{P_t}{P_0}\right)$$

where CW is the contractual wage. For wages below the threshold, the guaranteed increase in nominal wages was instead $\Delta w_t = \Delta p_t$, i.e. a full protection. Again, this equation can be expressed as a constant elasticity formula for relatively small changes in wages and prices:

$$\Delta sm_{it} \approx e_{it}'\Delta p_t$$
$$e_{it}' = \left(.75\frac{\alpha_t'}{W_{it-1}} + .25\frac{CW_{it}}{W_{it-1}}\right)$$

With the renewed mechanism, wage growth responded to price growth partly according to the old mechanism but with a coefficient of ¾. A residual part depended instead on the ratio between the contractual and the actual wage. The same rules as before apply but, in addition, the elasticity decreases as wages increase, given that the

[20] All employees in Italy receive a 'thirteenth-month wage' in December of each year. In some industries, like banking, a 'fourteenth' or even a 'fifteenth-month wage' is awarded but we ignore this in the computations.

contracted part of the wage tends to become proportionally smaller. Compared to the old system, for a given wage level, the elasticity decreases or increases according to whether the contracted wage is below or above the minimum wage. For very low wages, the elasticity decreases since while under the old system they were granted increases above inflation, with this new mechanism they are just given full protection. 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, we combine the individual information of earnings from the SHIW with data on escalated wage increases due to the SM. These data are published in ISTAT (various issues) and reported in Tables A3 and A4. To derive the effect on net labour income, we combine this information with data on the composition of gross labour income by decile estimated on SHIW data in 1989 (Di Biase and Di Marco, 1995). The data are reported in Table A5.

1977-1985

We first compute implied gross increases in wages from one year to another which are triggered by the SM. To do so, we simply compute the sum of contingent payments at the end of the year, allowing for a thirteenth wage, based on Table A3. If, say, the SM triggers a wage increase of l lit. starting in month m of a given year, we assume that this contributes to an increase of (14-m)l lit. in annual gross pay. We then work out the net increase according to the position of the individual in the distribution of wages (unconditional on sex) using the tax brackets reported in Table A5. Given that before 1984 tax brackets were not indexed to inflation, this implied that the effect of the SM was partly neutralised by the counteracting effect of tax system (a phenomenon known as fiscal drag). To account for this, for individuals observed in 1980, we use the tax brackets implied by their relative position in the wage distribution in 1977. We make separate (but similar) calculations for public sector workers.

1986-1993

The data for the calculations are in Table A4. The variable in column (2) is the value of the minimum wage α_t'. 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 that is 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 $CW^{(m)}$ we denote the contractual wage in month m by $\Delta SM^{(m)}$ the contingent increases awarded in the same month, it follows:

$$\Delta SM_{it}^{(5)} = \left[.75\alpha'^{(5)}_t + .25 CW_{it}^{(5)}\right]\Delta p_t^{(5)}$$

$$\Delta SM_{it}^{(11)} = \left[.75\alpha'^{(11)}_t + .25\left(CW_{it}^{(5)} + \Delta SM_{it}^{(5)}\right)\right]\Delta p_t^{(11)}$$

where $\Delta p^{(m)}$ is the six-month inflation rate in month m. Suppose we want to estimate the increase in wages triggered in May 1986. This is equal to the product of the inflation rate from October 1985 to April 1986 (2.72%) times the sum of ¾ of the minimum wage (580,000 lit.) plus ¼ of the contractual wage in April 1986. 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 a fixed proportion of the monthly wage. In the absence of any prior on the value of the ratio between contractual and actual wages, we assume that this proportion is equal to one minus the tax rate. Since there is evidence of contractual wages being inversely related to the actual wages (Erickson and Ichino 1995), inter alia) this choice has the advantage of simplifying calculations. In formulas:

$$CW_{it}^{(5)} = \frac{W_{it}}{13}\left(1-\tau_{it}\right)$$

where τ is the marginal tax rate. Observe that the estimated increases refer to gross wages. One can simply transform the data into net wages using the information in Table A5.

Appendix Table A1
The Structure of the Compensation Package of a Typical Worker in Italy

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 from Erickson and Ichino (1995).

Appendix Table A2
The Evolution of the Scala Mobile

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

Appendix Table A3
The Scala Mobile from 1977 to 1985

Quarter ending in: Year	Month	Price index (1)	Rounded price index (2)	Change in price index (3)	Nominal increase in Monthly wage (a) (4): Private	Public
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	
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. This table reports the predicted wage increase due to the SM from 1977 to 1985. 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. The system was adjourned staring 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 column (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 wage increases were imposed. (c) Only two points were awarded in July 1985, but an extra point was triggered in August as a compensation for failed coverage in the past. Source: ISTAT (various issues) and Industrial and Labor Relations Review (various issues).

Appendix Table A4
The Scala Mobile from 1986 to 1991

Semester ending		Price index	Minimum wage (a)	Proportional price change
Year	Month	(1)	(2)	(3)
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 (b)	4	198.36	858.6	2.44
92 (b)	10	201.88	873.8	1.77
93 (b)	4	205.22	888.3	1.65
93 (b) (c)	10	210.91	912.9	2.77

Notes. In 1986 a reform of the SM 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 basis on a six-month price index (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 minimum wage were fully indexed. See text for details. (a) in 1,000 lit. (b) Scala Mobile abolished. (c) Workers were awarded a flat monthly increase of lit 20,000 as a compensation for failed coverage in the past. Source: ISTAT (various issues) and Industrial and Labor Relations Review (various issues).

Appendix Table A5
The Composition of Gross Earnings by Decile

Decile	Employees' social security contributions	Personal income tax	Family allowances	Net labour 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).

Appendix Table A6
Decomposing Changes in Earnings: Ex-ante Annualised Changes (x 100)

	1977-80				1980-84				1984-89				1989-93				1977-93			
	Actual	SM	Comp.	NSM	Actual	SM	Comp.	NSM	Actual	SM	Comp.	NSM	Actual	SM	Comp.	NSM	Actual	SM	Comp.	NSM
	Δw	Δsm	Δz	Δv	Δw	Δsm	Δz	Δv	Δw	Δsm	Δz	Δv	Δw	Δsm	Δz	Δv	Δw	Δsm	Δz	Δv
Males																				
10	17.82	11.67	0.47	5.69	15.74	8.60	0.75	6.39	7.11	2.48	-0.08	4.71	4.18	1.60	0.25	2.33	10.54	5.51	0.31	4.72
25	17.82	9.40	0.47	7.95	14.79	6.95	0.50	7.34	6.99	2.08	0.00	4.91	4.88	1.35	0.20	3.33	10.44	4.49	0.26	5.69
50	17.42	7.73	0.80	8.89	14.79	5.85	0.45	8.49	7.19	1.72	0.08	5.39	5.58	1.15	0.15	4.28	10.61	3.74	0.33	6.54
75	15.95	6.13	1.07	8.75	14.74	4.90	0.45	9.39	7.71	1.44	0.16	6.11	5.93	0.95	0.15	4.83	10.57	3.06	0.40	7.11
90	15.42	4.80	1.27	9.35	15.39	4.10	0.50	10.79	7.87	1.20	0.20	6.47	6.73	0.80	-0.05	5.98	10.88	2.50	0.41	7.97
Females																				
10	28.55	20.07	3.33	5.15	15.14	10.90	-0.20	4.44	9.47	3.32	1.96	4.19	0.23	2.00	0.85	-2.62	12.16	8.03	1.40	2.73
25	22.15	13.40	1.33	7.42	14.94	8.60	-0.30	6.64	8.07	2.60	0.68	4.79	3.48	1.55	0.30	1.63	11.28	5.86	0.46	4.96
50	20.09	9.93	1.33	8.82	14.64	6.85	-0.05	7.84	7.87	2.08	0.28	5.51	4.98	1.25	0.15	3.58	11.13	4.54	0.36	6.23
75	18.95	7.40	1.27	10.29	14.29	5.50	-0.05	8.84	7.75	1.68	0.16	5.91	6.08	1.05	0.15	4.88	11.07	3.55	0.31	7.21
90	17.75	5.67	1.47	10.62	13.79	4.50	-0.30	9.59	7.75	1.32	0.08	6.35	6.68	0.95	0.15	5.58	10.87	2.84	0.26	7.77

Notes. The table provides the contribution of the ex-ante contingent payments (Δsm), the compositional effect (Δz) and the residual ex-ante non-contingent component (Δv) to changes in earnings (Δw) at selected quantiles of the distribution.

Appendix Table A7
The Evolution of the Structure of Earnings in the US

	Levels					Annualised changes *100				
	1977	1980	1984	1989	1993	1977-80	1980-84	1994-89	1989-93	1977-93
	Log nominal earnings									
Males										
10	14.34	14.70	15.16	15.44	15.59	12.09	11.54	5.55	3.73	7.82
25	14.71	15.06	15.57	15.85	15.99	11.69	12.84	5.59	3.58	8.04
50	15.06	15.43	15.98	16.26	16.43	12.55	13.74	5.59	4.18	8.58
75	15.36	15.74	16.32	16.63	16.82	12.82	14.44	6.27	4.63	9.13
90	15.63	16.01	16.61	16.94	17.16	12.82	14.99	6.67	5.38	9.58
Females										
10	13.89	14.30	14.83	15.12	15.32	13.69	13.24	5.75	4.98	8.92
25	14.19	14.60	15.16	15.48	15.69	13.69	14.09	6.47	5.28	9.43
50	14.51	14.90	15.51	15.87	16.09	13.29	15.09	7.19	5.58	9.90
75	14.81	15.21	15.84	16.23	16.47	13.42	15.79	7.75	5.93	10.37
90	15.07	15.49	16.13	16.54	16.78	13.89	15.94	8.23	6.18	10.70
	Earnings inequality									
Males										
SD	0.53	0.53	0.58	0.60	0.61	0.02	1.33	0.37	0.33	0.53
90-10	1.29	1.31	1.45	1.51	1.57	0.73	3.45	1.12	1.65	1.76
75-25	0.65	0.68	0.75	0.78	0.82	1.13	1.60	0.68	1.05	1.09
10-50	-0.72	-0.73	-0.82	-0.82	-0.84	-0.47	-2.20	-0.04	-0.45	-0.76
90-50	0.57	0.58	0.63	0.68	0.73	0.27	1.25	1.08	1.20	1.00
Females										
SD	0.48	0.48	0.52	0.56	0.58	-0.01	0.92	0.90	0.46	0.63
90-10	1.18	1.18	1.29	1.42	1.46	0.20	2.70	2.48	1.20	1.79
75-25	0.62	0.61	0.68	0.75	0.77	-0.27	1.70	1.28	0.65	0.94
10-50	-0.61	-0.60	-0.67	-0.75	-0.77	0.40	-1.85	-1.44	-0.60	-0.99
90-50	0.57	0.58	0.62	0.67	0.69	0.60	0.85	1.04	0.60	0.80

Notes. The table reports different measures of wage dispersion in the US based on the kernelized densities, and the associated annualised changes . 'SD': is the standard deviation of the logarithm of earnings . '90-10' is the 9 to 1 log decile gap. The other measures are defined similarly. Source: March CPS.

Appendix Table A8

Decomposing Changes in Earnings: Ex-post Annualised Changes (x 100) - At fixed Sample Composition

	1977-80			1980-84			1984-89			1989-93			1977-93		
	Total	SM	NSM	Total	SM	NSM	Total	SM	NSM	Total	SM	NSM	Total	SM	NSM
	Δw	$\eta\Delta sm$	Δw^*	Δw	$\eta\Delta sm$	Δw^*	Δw	$\eta\Delta sm$	Δw^*	Δw	$\eta\Delta sm$	Δw^*	Δw	$\eta\Delta sm$	Δw^*
Males															
10	17.12	5.60	11.52	14.71	4.13	10.58	7.07	1.19	5.88	4.00	0.77	3.23	10.10	2.65	7.45
25	16.68	4.51	12.16	14.04	3.34	10.70	6.97	1.00	5.97	4.46	0.65	3.81	9.93	2.16	7.77
50	16.26	3.71	12.55	13.98	2.81	11.17	7.08	0.83	6.26	5.28	0.55	4.73	10.08	1.80	8.28
75	15.01	2.95	12.07	14.32	2.35	11.96	7.41	0.69	6.72	6.04	0.46	5.58	10.22	1.47	8.75
90	13.67	2.31	11.37	14.56	1.97	12.59	7.66	0.58	7.08	6.44	0.38	6.06	10.21	1.20	9.01
Females															
10	24.12	9.64	14.48	14.03	5.23	8.79	8.84	1.59	7.24	0.49	0.96	-0.47	10.92	3.85	7.06
25	20.53	6.44	14.10	13.85	4.13	9.72	8.15	1.25	6.90	2.40	0.74	1.66	10.46	2.82	7.65
50	18.38	4.77	13.61	14.06	3.29	10.77	7.66	1.00	6.66	4.78	0.60	4.18	10.55	2.18	8.37
75	16.88	3.55	13.33	13.84	2.64	11.20	7.64	0.81	6.84	5.93	0.50	5.43	10.50	1.70	8.79
90	15.97	2.72	13.25	13.32	2.16	11.16	7.77	0.63	7.14	6.03	0.46	5.57	10.26	1.36	8.90

Notes. The table provides the contribution of the estimated ex-post contingent ($\eta\Delta sm$) and non-contingent (Δw^*) (i.e. latent) wage changes to changes in earnings (Δw) at selected quantiles of the distribution. The values are estimated based on specification (7) in Table 5. Total is obtained as the sum of SM and NSM and differs from Actual wage growth in Table A6 because this is obtained at fixed sample composition.

Table 1
The Scala Mobile at Work: An Illustration

	Levels						
	Initial earnings	Initial price index	Final price index	Change in price index	SM point	Contingent increase	Final earnings
	W_{it-1}	P_{t-1}/P_0	P_t/P_0	$\Delta P_t/P_0$	α_t	$\Delta SM_t=\alpha_t \Delta P_t/P_0$	$W_{is}=W_{it-1}+\Delta SM_t$
	(1)	(2)	(3)	(4)=(3)-(2)	(5)	(6)=(4)*(5)	(7) =(1)+(6)
High	461	162	167	5	2.40	12	473
Low	192	162	167	5	2.40	12	204
High / low	2.40						2.32

Notes. The table shows the salient features of the Scala Mobile. The data refer to the first quarter, 1978. In the first column of the top panel we report the level of earnings at the end of 1977 for two individuals respectively at the top and bottom decile of the distribution (males and females together). Their relative wage is 2.40. Columns (2) and (3) report respectively the value of the price index (January 1977=100) in January 1978 and 3 months later, and the associated increase (4). Column (7) reports the nominal increase in wages accruing to each individual obtained as the product of the price increase (4) and the value of the SM point (5). This is the same for both individuals. In column (7) we report the value of wages in April 1978 under the assumption that there is no other source of wage increase. This is simply the sum of the initial wage (1) and the escalated wage increase (7). Because of the SM, the relative earning decreases from 2.40, to 2.32, i.e. a reduction of 3%.

Table 2
Summary Statistics: Means/Proportions

	1977	1980	1984	1989	1993	Total/Average
			Males			
No. Obs.	1,640	1,560	1,964	4,065	3,307	12,536
Log (Real Earnings/1000)	3.748	3.804	3.835	3.933	3.923	3.873
Education (No. of years)						
College (18)	5.02	7.31	7.19	7.26	7.41	7.00
High School (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
Age						
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
			Females			
No. Obs.	707	806	1,079	2,226	1,975	6,813
Log (Real Earnings/1000)	3.398	3.588	3.616	3.772	3.710	3.669
Education (No. of years)						
College (18)	7.19	10.51	14.09	13.05	13.44	12.40
High School (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
Age						
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

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 13th-month wage. Proportions might not add up to 100 because of missing values.

Table 3
The Evolution of the Structure of Earnings

	Levels					Annualised changes *100				
	1977	1980	1984	1989	1993	1977-80	1980-84	1994-89	1989-93	1977-93
	Log nominal earnings									
Males										
10	7.95	8.49	9.12	9.47	9.64	17.82	15.74	7.11	4.18	10.54
25	8.16	8.69	9.29	9.64	9.83	17.82	14.79	6.99	4.88	10.44
50	8.35	8.87	9.47	9.83	10.05	17.42	14.79	7.19	5.58	10.61
75	8.57	9.05	9.64	10.02	10.26	15.95	14.74	7.71	5.93	10.57
90	8.76	9.23	9.84	10.24	10.50	15.42	15.39	7.87	6.73	10.88
Females										
10	7.36	8.22	8.82	9.30	9.31	28.55	15.14	9.47	0.23	12.16
25	7.84	8.50	9.10	9.50	9.64	22.15	14.94	8.07	3.48	11.28
50	8.11	8.71	9.29	9.69	9.89	20.09	14.64	7.87	4.98	11.13
75	8.32	8.89	9.46	9.85	10.09	18.95	14.29	7.75	6.08	11.07
90	8.52	9.06	9.61	9.99	10.26	17.75	13.79	7.75	6.68	10.87
	Price index									
	4.61	5.05	5.61	5.91	6.12	14.82	13.89	6.03	5.43	9.49
	Earnings inequality									
Males										
SD	0.36	0.34	0.32	0.32	0.37	-0.67	-0.63	0.00	1.35	0.00
90-10	0.81	0.74	0.73	0.76	0.87	-2.40	-0.35	0.76	2.55	0.34
75-25	0.41	0.35	0.35	0.39	0.43	-1.87	-0.05	0.72	1.05	0.12
10-50	-0.40	-0.39	-0.35	-0.35	-0.41	0.40	0.95	-0.08	-1.40	-0.06
90-50	0.41	0.35	0.38	0.41	0.46	-2.00	0.60	0.68	1.15	0.28
Females										
SD	0.47	0.39	0.34	0.31	0.40	-2.63	-1.19	-0.56	2.29	-0.39
90-10	1.16	0.84	0.78	0.70	0.96	-10.80	-1.35	-1.72	6.45	-1.29
75-25	0.49	0.39	0.37	0.35	0.45	-3.20	-0.65	-0.32	2.60	-0.21
10-50	-0.74	-0.49	-0.47	-0.39	-0.58	8.47	0.50	1.60	-4.75	1.03
90-50	0.42	0.35	0.31	0.31	0.38	-2.33	-0.85	-0.12	1.70	-0.26

Notes. The table reports log nominal earnings at selected percentiles and different measures of dispersion based on the kernelized densities, and the associated annualised changes. 'SD': is the standard deviation of the logarithm of earnings. '90-10' is the 9 to 1 log decile gap. The other measures are defined similarly.

Table 4
Decomposing Changes in Earnings Inequality: Ex-ante Annualised Changes (x 100)

	1977-80				1980-84				1984-89				1989-93				1977-93			
	Actual	SM	Comp.	NSM	Actual	SM	Comp.	NSM	Actual	SM	Comp.	NSM	Actual	SM	Comp.	NSM	Actual	SM	Comp.	NSM
	Δw	Δsm	Δz	Δv	Δw	Δsm	Δz	Δv	Δw	Δsm	Δz	Δv	Δw	Δsm	Δz	Δv	Δw	Δsm	Δz	Δv
Males																				
90-10	-2.40	-6.87	0.80	3.67	-0.35	-4.50	-0.25	4.40	0.76	-1.28	0.28	1.76	2.55	-0.80	-0.30	3.65	0.34	-3.01	0.10	3.25
75-25	-1.87	-3.27	0.60	0.80	-0.05	-2.05	-0.05	2.05	0.72	-0.64	0.16	1.20	1.05	-0.40	-0.05	1.50	0.12	-1.43	0.14	1.41
10-50	0.40	3.93	-0.33	-3.20	0.95	2.75	0.30	-2.10	-0.08	0.76	-0.16	-0.68	-1.40	0.45	0.10	-1.95	-0.06	1.77	-0.01	-1.83
90-50	-2.00	-2.93	0.47	0.47	0.60	-1.75	0.05	2.30	0.68	-0.52	0.12	1.08	1.15	-0.35	-0.20	1.70	0.28	-1.24	0.09	1.43
Females																				
90-10	-10.80	-14.40	-1.20	4.80	-1.35	-6.40	-0.85	5.90	-1.72	-2.00	-0.28	0.56	6.45	-1.05	-0.30	7.80	-1.29	-5.19	-0.60	4.50
75-25	-3.20	-6.00	0.27	2.53	-0.65	-3.10	-0.15	2.60	-0.32	-0.92	-0.04	0.64	2.60	-0.50	-0.05	3.15	-0.21	-2.31	-0.01	2.11
10-50	8.47	10.13	1.73	-3.40	0.50	4.05	0.60	-4.15	1.60	1.24	0.28	0.08	-4.75	0.75	0.30	-5.80	1.03	3.49	0.64	-3.10
90-50	-2.33	-4.27	0.53	1.40	-0.85	-2.35	-0.25	1.75	-0.12	-0.76	0.00	0.64	1.70	-0.30	0.00	2.00	-0.26	-1.70	0.04	1.40

Notes. The table provides the contribution of the ex-ante contingent payments (Δsm), the compositional effect (Δz) and the residual ex-ante non-contingent component (Δv) to changes in earnings inequality (Δw).

Table 5

The Effect of the Scala Mobile on the Structure of Earnings. Dependent Variable: Annualised Changes in Earnings

	OLS	2SLS	OLS	2SLS	OLS	OLS	2SLS
		(q_{jt}, q_{jt}^2) *time*gender		(q_{jt}, q_{jt}^2) *time*gender			q_{jt}^3 *time*gender
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Scala Mobile	0.647	0.712	0.631	0.634	0.623	0.520	0.525
	(0.107)	(0.129)	(0.060)	(0.058)	(0.085)	(0.113)	(0.120)
Controls	(q_{jt}, q_{jt}^2)*time time*gender		Δw_{jt}^{USq} time*gender		(q_{mjt}, q_{mjt}^2) *time time*gender	(q_{mjt}, q_{mjt}^2) *time*gender	
(Latent changes in wage structure)	Same within gender groups		US		Same across gender groups	Group-specific	
Hausman test		-0.192		-0.062			-0.026
		(0.134)		(0.114)			(0.074)
R^2	0.994	0.994	0.988	0.988	0.993	0.998	0.994

Notes. The table reports the results of a regression of annualised total changes in earnings on annualised contingent changes ('Scala Mobile') at each percentile q_{jt} of the (gender) earnings distribution between 1977 and 1993 (1977-1980, 1980-1984, 1984-1989, 1989-93) for men and women together and at fixed sample composition. Top and bottom five percentiles are excluded. Number of observations 720. All specifications include the interaction between year dummies with a gender dummy. Specifications (1) and (2) include the interaction between a quadratic term in q_{jt} and year dummies. Specifications (3) and (4) include the wage growth in the US. Specification (5) conditions on a quadratic in q_{mjt}. Specifications (6) and (7) include the full interaction of a quadratic in q_{jt}, a gender dummy and time dummies. Hausman test is a test for the null hypothesis that the 2SLS estimates are statistically indistinguishable from the corresponding OLS estimates. The statistic is asymptotically distributed as a Normal (0,1).

Table 6
Decomposing Changes in Earnings Inequality: Ex-Post Annualised Changes (x 100)
- At Fixed Sample Composition

	1977-80			1980-84			1984-89			1989-93			1977-93		
	Total	SM	NSM	Total	SM	NSM	Total	SM	NSM	Total	SM	NSM	Total	SM	NSM
	Δw	$\eta\Delta sm$	Δw^*	Δw	$\eta\Delta sm$	Δw^*	Δw	$\eta\Delta sm$	Δw^*	Δw	$\eta\Delta sm$	Δw^*	Δw	$\eta\Delta sm$	Δw^*
Males															
90-10	-3.45	-3.30	-0.15	-0.14	-2.16	2.02	0.59	-0.61	1.20	2.45	-0.38	2.83	0.12	-1.44	1.56
75-25	-1.67	-1.57	-0.10	0.28	-0.98	1.26	0.44	-0.31	0.75	1.58	-0.19	1.77	0.29	-0.68	0.97
10-50	0.86	1.89	-1.03	0.73	1.32	-0.59	-0.01	0.36	-0.37	-1.27	0.22	-1.49	0.02	0.85	-0.83
90-50	-2.59	-1.41	-1.18	0.58	-0.84	1.42	0.58	-0.25	0.83	1.16	-0.17	1.33	0.13	-0.60	0.73
Females															
90-10	-8.15	-6.92	-1.23	-0.71	-3.07	2.36	-1.06	-0.96	-0.10	5.54	-0.50	6.04	-0.65	-2.49	1.84
75-25	-3.65	-2.88	-0.77	-0.01	-1.49	1.48	-0.51	-0.44	-0.07	3.54	-0.24	3.78	0.04	-1.11	1.15
10-50	5.74	4.87	0.87	-0.03	1.94	-1.97	1.18	0.60	0.58	-4.29	0.36	-4.65	0.37	1.68	-1.31
90-50	-2.42	-2.05	-0.37	-0.74	-1.13	0.39	0.11	-0.36	0.47	1.25	-0.14	1.39	-0.29	-0.81	0.52

Notes. The table provides the contribution of the estimated ex-post contingent ($\eta\Delta sm$) and non-contingent (Δw^*) (i.e. latent) wage changes to changes in earnings inequality (Δw). The values are estimated based on specification (7) in Table 5. Total is obtained as the sum of SM and NSM and differs from Actual wage growth in Table 4 because this is obtained at fixed sample composition.

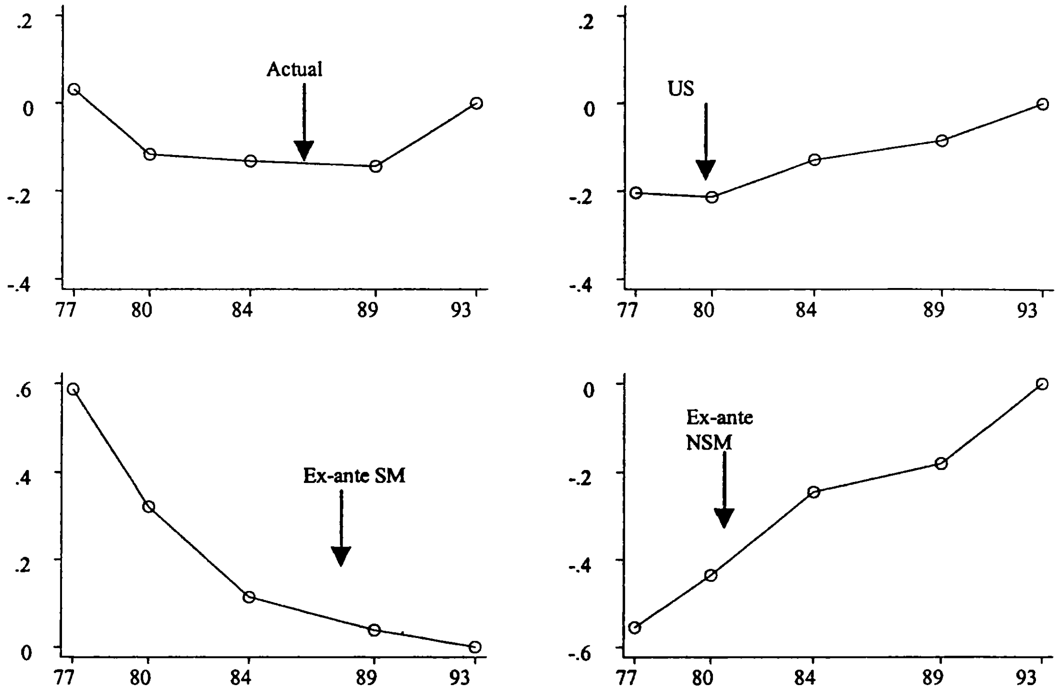
Table 7

The Effect of the SM on Earnings Inequality via Employment Changes, 1977-93 – Annualised changes (x 100)

	Estimated			Actual Δz
	Elasticity of substitution			
	.5	1.41	4	
Males				
90-10	0.00	0.04	0.10	0.10
75-25	0.01	0.01	0.08	0.14
10-50	0.01	0.00	-0.03	-0.01
90-50	0.01	0.04	0.08	0.09
Females				
90-10	-0.01	-0.03	-0.14	-0.60
75-25	0.01	0.01	0.00	-0.01
10-50	0.00	0.02	0.19	0.64
90-50	-0.01	0.00	0.05	0.04

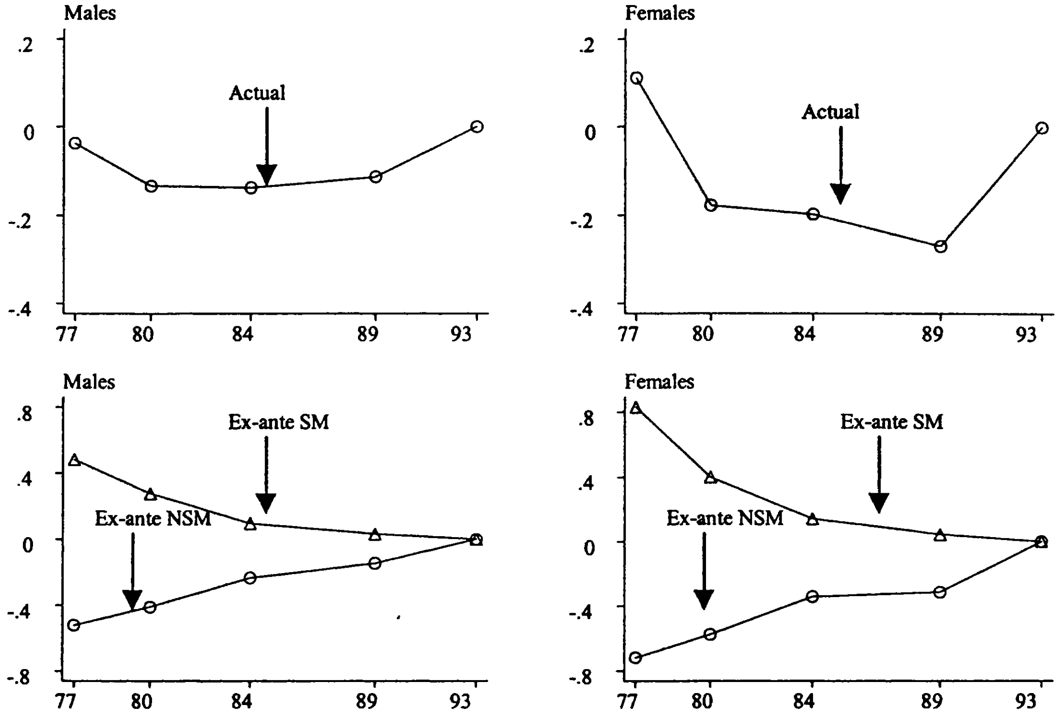
Notes. The table provides the estimated impact of the employment effect of the ex-post contingent payments on changes in wage inequality for different measures of the elasticity of substitution. See main text for details of calculations.

Figure 1
The Evolution of the 9-1 Log Decile Earnings Gap in Italy and the US and the Ex-Ante Effect of the SM. Males plus Females (1993=0) - At Fixed Sample Composition.



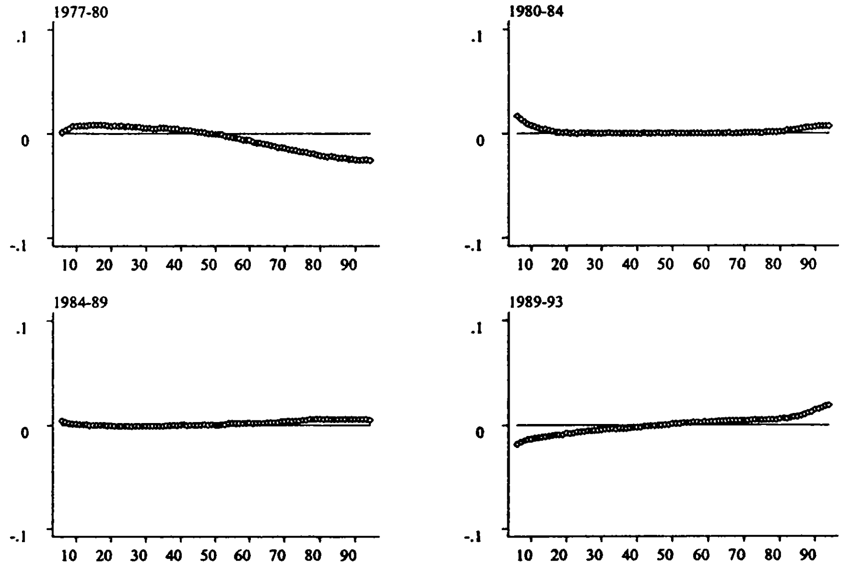
Notes. In the left-hand top panel, the picture reports the actual evolution of the 9-1 log decile earnings gap in Italy (w) for men and women together while in the right-hand panel, it reports the evolution of the 9-1 decile earnings in the US. In the left-hand bottom panel, it reports the estimated trend in the gap for the case in which the SM was the only source of wage change (ex-ante SM: sm) and in the right-hand bottom panel the trend in ex-ante non-contingent wage changes (ex-ante NSM: v) obtained as a difference between Actual and SM. Both series are obtained controlling for changes in observable characteristics and are standardised to 1993=0. The level of inequality in 1993 is equal to 0.88 in Italy and 1.57 in the US. Source: SHIW, March CPS and ISTAT (various issues).

Figure 2
The Evolution of the 9-1 Log Decile Earnings Gap in Italy and the Evolution of the Scala Mobile by Gender. (1993=0) . At Fixed Sample Composition.

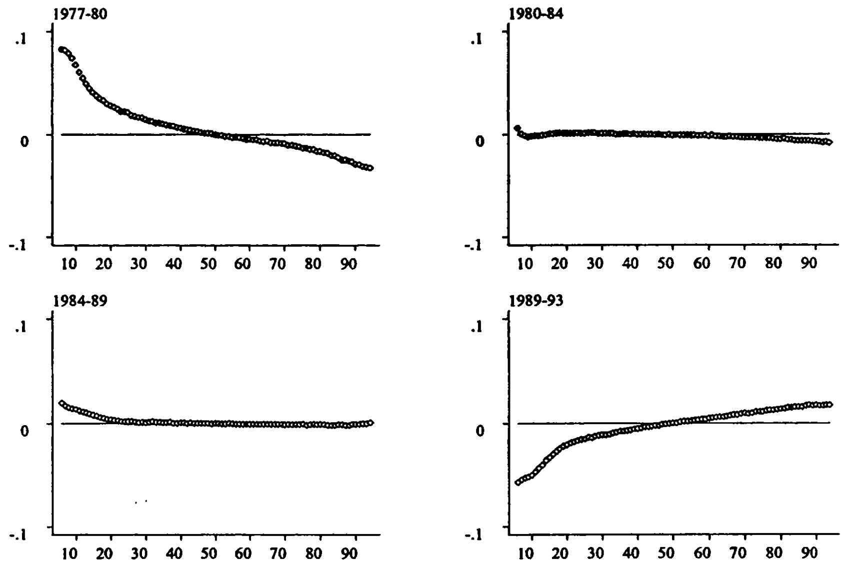


Notes. See notes to Figure 1. The level of inequality in 1993 is equal to 0.87 and 0.96 for men and women respectively.

Figure 3
Actual Changes in the Distribution of Earnings by Percentile. Males plus Females.
At Fixed Sample Composition.



Males

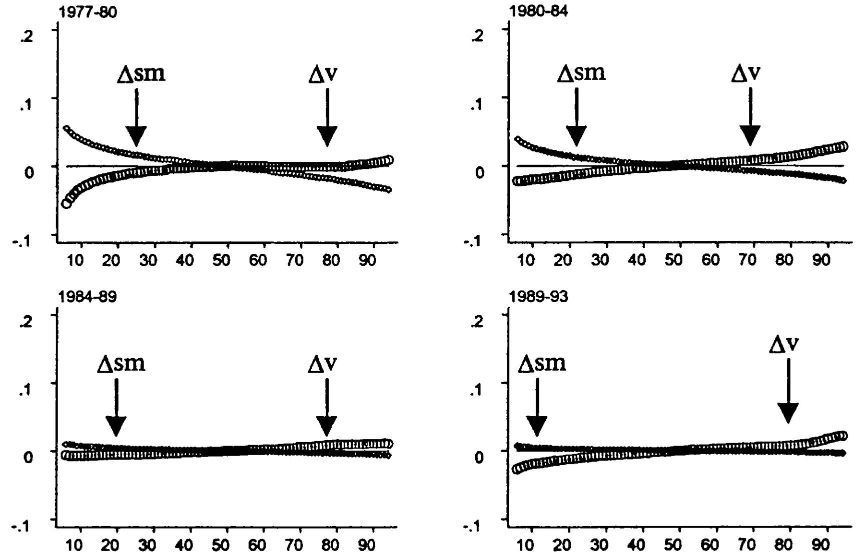


Females

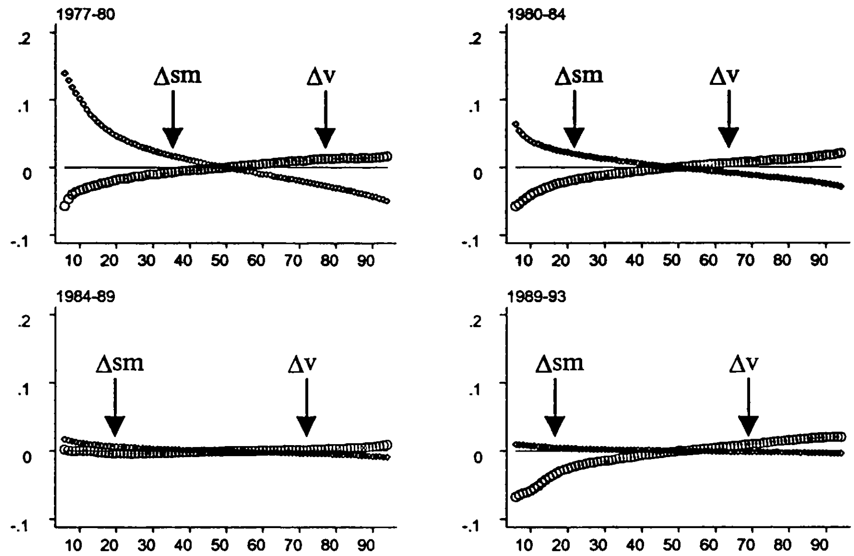
Notes. The Figure reports the changes in log wages at each percentile of the distribution (Δw). Changes are annualised and standardised to changes at the median. The series are obtained at fixed sample composition. Source: SHIW.

x

Figure 4
Decomposing Changes in the Distribution of Earnings by Percentile: Ex-ante Effects.
At Fixed Sample Composition.



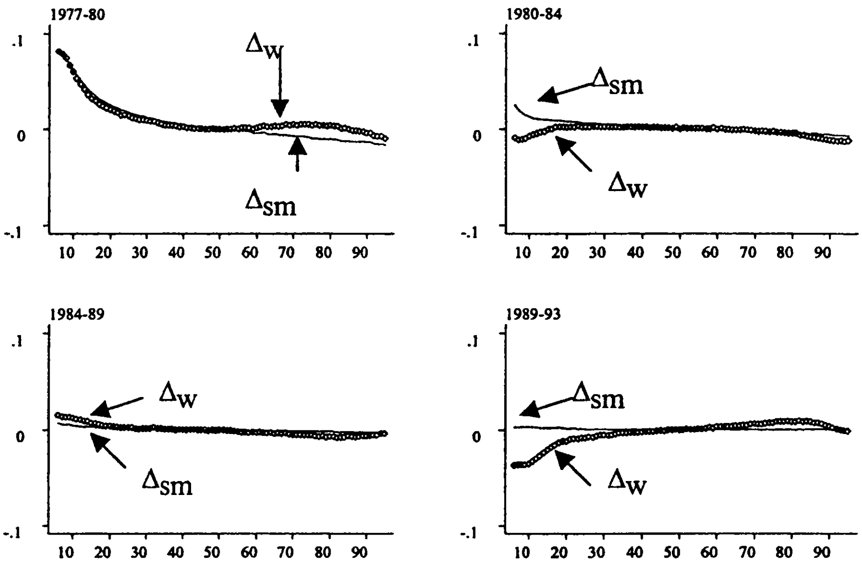
Males



Females

Notes. The Figure reports the ex-ante escalated wage changes (Δsm), and ex-ante non-escalated wage changes (Δv). Changes are annualised and standardised to changes at the median. The series are obtained at fixed sample composition. Source: SHIW and ISTAT (various issues).

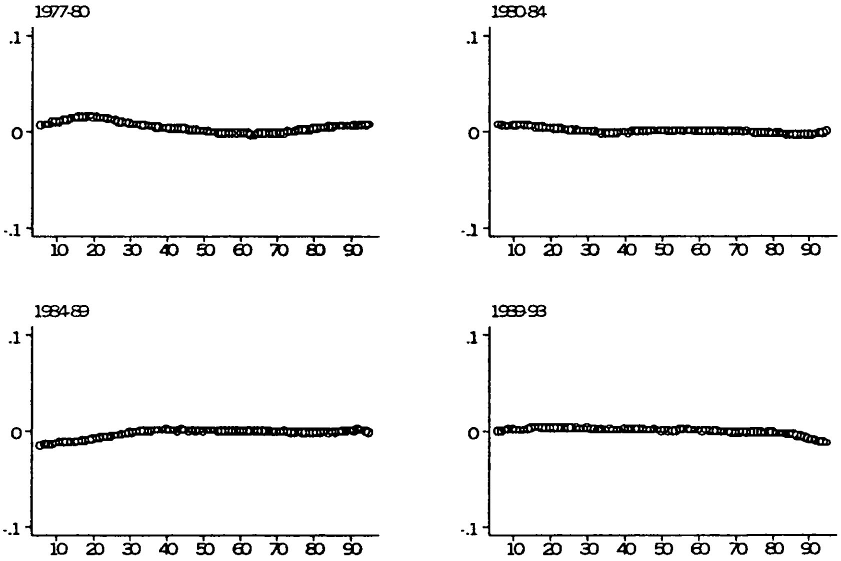
Figure 5
The Ex-ante Effect of the SM on the Female-Male Earnings Differential by Percentile and the Actual Earnings Change - At Fixed Sample Composition.



Notes. The picture reports the difference between the annualised ex-ante effect of the SM for men and women at each percentile of the (gender) distributions of log wages (Δsm) and the actual wage change (Δw). All series are standardised to changes at the median. Source: SHIW and ISTAT (various issues).

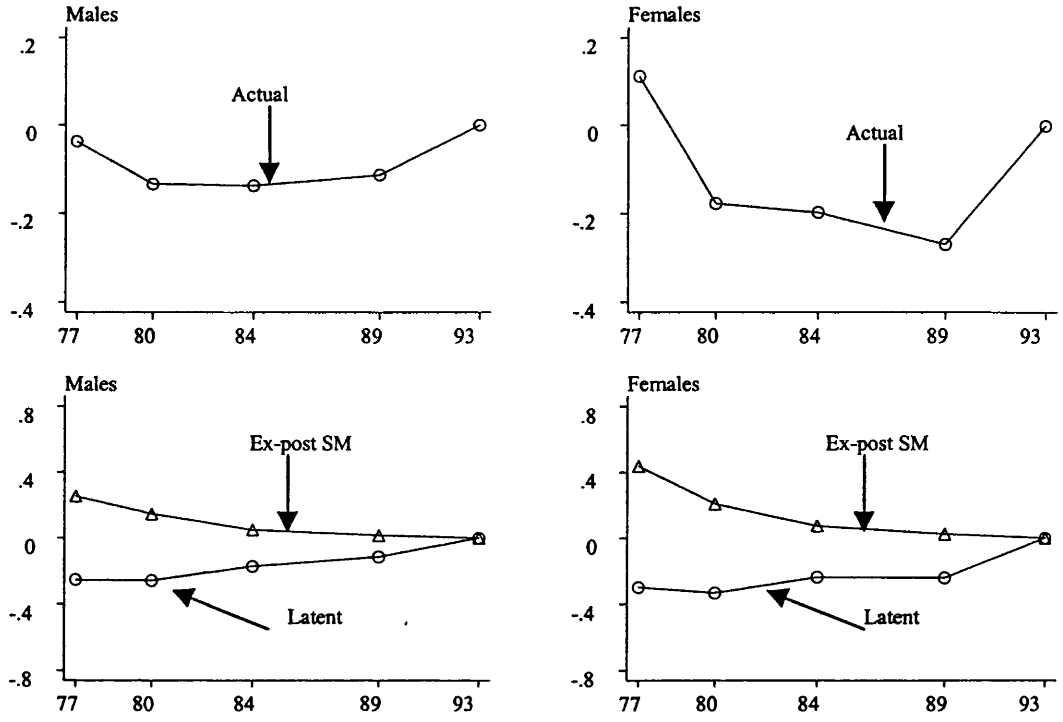
Figure 6

The Change in the Female-Male Earnings Differential by Percentile in the US. At Fixed Sample Composition.



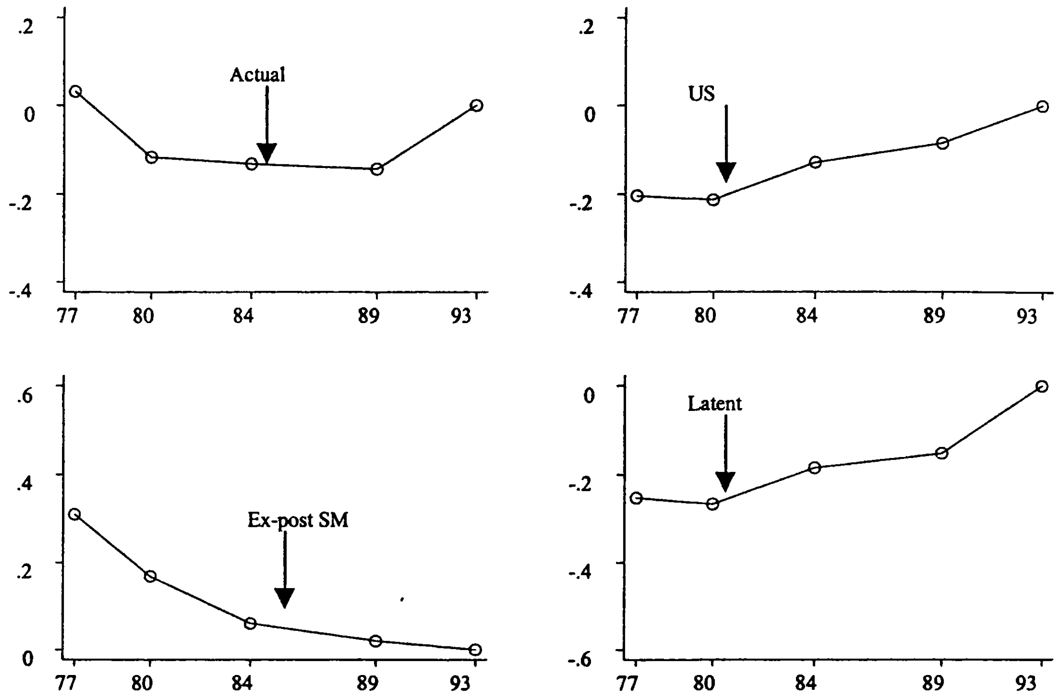
Notes. The picture reports the difference between the actual wage change for men and women in the US at each percentile of the (gender) distributions (Δw^{US}). All series are standardised to changes at the median. Source: March CPS.

Figure 7
The Evolution of Actual and Latent Earnings Inequality in Italy by Gender (1993=0).
At Fixed Sample Composition.



Notes. In top panel, the picture reports the actual evolution of the 9-1 log decile earnings gap (w) by gender while in the bottom panel it reports the estimated ex-post effect of the SM (η sm) and the trend in latent wage inequality (w*). The estimate of η is based on Specification (7) in Table 5. All series are obtained at fixed sample composition and are standardised to 1993=0. Source: SHIW, March CPS and ISTAT (various issues).

Figure 8
The Evolution of Actual and Latent Earnings Inequality in Italy. Males plus Females (1993=0). At Fixed Sample Composition.



Notes. In the left-hand top panel, the picture reports the actual evolution of the log 9-1 decile earnings gap in Italy (w) for men and women together while in the right-hand panel, it reports the evolution of the 9-1 decile earnings in the US. In the left-hand bottom panel, it reports the estimated ex-post effect of the SM (ηsm) and in the right-hand bottom panel the trend in latent wage inequality (w*). The estimate of η is based on Specification (7) in Table 5. All series are obtained controlling for changes in observable characteristics and are standardised to 1993=0. Source: SHIW, March CPS and ISTAT (various issues).

Chapter 4

Changes in the Structure of Earnings in Italy in the 1980s: Changing Institutions or Changing Market Forces?

In this chapter we study the effect of the Scala Mobile on changes in returns to education in Italy between the late 1970s and the early 1990s.

The idea of this chapter as well as the data used are very much as the ones in chapter 3, where we look at the effect of the Scala Mobile on changes at each percentile of the unconditional distribution of earnings, separately for men and women. This framework, however, has at least three advantages with respect to the analysis in the previous chapter and is a natural complement to it.

First, it examines changes in the wage structure 'between' groups (by education and age). It is known that changes in the wage structure between and within groups in the US are somewhat distinct economic phenomena (Juhn *et al.*, 1993). Broadly speaking, the former show a downward trend in the 1970s and an upward trend in the 1980s, while the latter appear to have risen monotonically over both decades. One would like to know whether the same happened in Italy and – if this is not the case – how one can explain the different trends.

Secondly, this framework provides an explicit way to test for the hypothesis that the trends in the wage structure are shaped by changes in the structure of labour supply and labour demand. One can do so by using data on the evolution of labour force and employment by education. This hypothesis has had some success in explaining changes in the returns to education in the US in the last three decades (see among others Katz and Murphy, 1992 and Card and Lemieux, 2000) and one would like to be reassured that the results of chapter 3 are robust to the inclusion of explicit controls for changes in market forces.

The third feature that makes of the present analysis of interest is that it uncovers the effect the Scala Mobile on the earnings structure by postulating that in the absence of this institution the gender earnings gap would have changed at a constant rate over the whole period of observation. Based on this alternative identification strategy, one can use the results of this chapter as a robustness check for those obtained in chapter 3.

The plan of the chapter is as follows. In section I we provide evidence on the evolution of returns to education and other dimensions of changes in the structure of earnings over the period of observation. In section II we show how the Scala Mobile potentially affected the earnings structure, by compressing it from the bottom, and how this potential declined over time. In section III we correlate changes in the earnings structure to changes in the indexation mechanism and finally in section IV we test for the robustness of our results to the inclusion of explicit controls for changes labour supply of different skill groups. Section V summarises and concludes.

I. Changes in the Earnings Structure: 1978-1992

a. The Data

The data we use are again the individual records of the Bank of Italy SHIW (Survey of Households'Income and Wealth), for the period 1977-1993. The interested reader will find more information on the survey and the data used in this analysis in the previous chapter. In this chapter we look at earnings changes by cells defined over 4 categories of education (5^{th} grade or below, 8^{th} grade, 13^{th} grade and College or above), 4 age groups (21-30, 31-40, 41-50, 51-65) and gender. Since some of the cells tend to be relatively small, and the associated estimates rather imprecise, we take average log earnings for each cell over three-year intervals centred around the following years: 1978, 1981, 1985, 1988 and 1992.[1] In the following we will refer for brevity to 1978 to mean the average value between 1977 and 1979 and similarly for the other years. Our basic observations are then the 160 cells defined by the interaction of education (4), sex (2) age (4) and time (5).

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

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

[1] We only take data for the first and last year of each time interval to calculate averages (so, respectively: 1977 and 1979; 1980 and 1983; 1984 and 1986; 1987 and 1989; 1991 and 1993). To calculate average values by cell we regress individual wages over a full set of cell dummies and a set of year dummies within each sub-period. The coefficient on each cell dummy is the estimated average log wage by cell.
[2] In the previous chapter we have looked at those aged 18-65. In this chapter we drop those aged below 21 because the associated cells are far too small to be amenable to analysis.

b. Descriptive Evidence

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

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

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

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

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

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

Overall, whatever dimension one looks at, it appears that the distribution compresses from the bottom favouring in particular women and less educated workers. Incidentally, note that the compression seems to be stronger for those groups who start with a more dispersed initial distribution of wages: these are again women (compared to men) and older workers (compared to younger workers). At the top some decompression is going on. Interestingly, while the compression from the bottom seems to come to a halt in the late 1980s, the trend at the top seems to be unaltered. If anything one would suspect that something changed for low skilled workers. As argued in chapter 3 all these three features (higher increases for those in the bottom tail of the wage distribution, faster compression within groups with more dispersed wages and timing of the change) are consistent with the effect of the Scala Mobile on the cross sectional distribution of wage changes and with changes in its 'toughness' over time. As changes at the top are concerned, we know that the Scala Mobile had a relatively weak effect there. A way to interpret the data then is that, if the compression at the bottom came from the indexation, in the absence of indexation earnings would have decompressed at the bottom too.

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

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

where w is log wages and the subscript 'c' refers to cell means.[3]

In column (1) of Table 2 we report the estimation results for the marginal distribution of wage changes (equation (1)). Education is a linear term that represents the minimum numbers of years necessary to achieve any formal level of education while age is given by the midpoint in each interval.[4] For brevity we only report the coefficients on education and sex.

The dependent variable is given by the annualised wage change over each time interval (1978-1981, 1981-1985, 1985-1988, 1988-1992), expressed in percentage points.

Estimation is performed on the 128 cell differences using GLS with weights given by the inverse sampling variance of the dependent variable. Although the estimates show some convexity in changes to returns to education, they are pretty imprecise. To achieve more precision, we impose some parametric restrictions on the evolution of changes in returns to education, by restricting to a quadratic trend in column (2) (which takes the value 0 in the first period, 1 in the second, etc.). In column

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

(3) we restrict to a linear trend and in column (4) we impose no variation in changes in returns to education over the different periods. For any of these specifications, we report a goodness-of-fit test that gives an indication as to whether the model fits the data as well as the unrestricted specification of column (1). As it can be seen from the table, specifications (2) and (3) do as well as the model in column (1). But as we restrict changes in returns to education to be constant, we have a significant loss of fit. If one takes the most parsimonious model of column (3), one can conclude that changes in returns to education show some positive trend, which is to say that returns to education (in log levels) accelerate over time. While in the first period of observation, differentials reduce by approximately 0.25 percentage points (-0.087 x 3), their decline tends gradually to slow down. Between 1981 and 1985 they reduce by around 0.1 percentage points ((-0.087+0.062) x 4) and they start then to increase, with a rise of 0.1 percentage points in the second half of the 1980s ((-0.087+0.062 x 2) x 3) and an increase of almost 0.5 percentage points in the last sub-period ((-0.087+0.062 x 3) x 4). To get an idea of the magnitude of the changes, our estimates suggest that the differential between 13th grade and 8th grade reduces by approximately 2 percentage points between 1978 and 1985 and subsequently rises by 3 percentage points. To visualise the trend, in figure 2 we have depicted the evolution of the return one extra year of education obtained by cumulating the changes in returns to education as predicted from specification (3) in Table 2. The series is standardised to the level in 1977, as estimated in a separate cross-sectional regression.

Interestingly, the male-female earnings gap also reduces during the period of analysis. Most of the decline takes place between 1978 and 1981, with a fall of more than 5 percentage points in three years (1.419 x 3). The gender gap reduces, although at a slower pace, in the subsequent periods, and in the last period of observations it reverts

[4] The education variable takes the values: 5, 8, 13, 18. The age variable takes the values: 25, 35, 45, 57.5.

to its trend as it increases by almost 2 percentage points in four years ((1.419-1.838) x 4). In the rest of the chapter we attribute the differential evolution of the gender gap over different time intervals to the effect of the Scala Mobile. We have argued in section 3 how the Scala mobile was potentially able to produce this pattern and in the next section we provide evidence that indeed it was the Scala Mobile – and not other forces – to shape variations around this trend.

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

A Institutional Features

In this section we will briefly recall the institutional features of the indexation mechanism. The interested reader is advised to refer to the discussion in chapter 3. In its original formulation the escalator implied the same quarterly flat increase in nominal wages (SM point) for all employees for any point increase in the consumer price index. If by W we denote nominal wages, by α the Scala Mobile point, by P the level of prices, by 0 some base period for computing price changes, the contingent increase in wages from time t-1 to time t for individual i, denoted by ΔSM_{it}, is:

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

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

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

The relative wage of two individuals i and j ($W_i > W_j$) then changes with the SM as follows:

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

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

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

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

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

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

b. The evolution of the SM: Econometric Evidence

In this section we integrate data on earnings with information on contingent payments based on the institutional parameters of the model (the SM point and the series of changes in prices) as published in ISTAT, *Annuario Statistico Italiano* (various issues). We estimate contingent wage increases for each individual in the sample and then we average across individuals in each cell by pooling observation across contiguous years, as in section I. More details on the exact procedure used in this chapter to impute SM payments to individuals in the SHIW sample and the evolution of the SM are contained in chapter 3.

In Figure 2 we report the annualised inflation rate: this declines from approximately 14% in the late 1970s-early 1980s, to around 6% in the late 1980s-early 1990s. That itself contributed to the decline in the potential equalising effect of the SM (see equation (4)).

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

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

As discussed in the previous chapter, two main reasons contributed to the decline. First, under the pressure of rank and file workers and the association of entrepreneurs, in 1983 the Government reduced the value of the SM point by approximately 15% relative to its 1977 level. Later, in 1986, the system was made semi-proportional (approximately by granting a 100% coverage of a given minimum wage, plus a 25% coverage of the difference between the actual wage and the minimum wage). This further dampened the equalising effect of the SM. One might notice that the graph shows some slight convexity: for any proportional difference in relative wages, the potential equalising effect of the SM declines as we move to the top of the wage distribution (see equation (4)). That is to say that, for any given difference in wages, one would expect the SM to have a relatively strong effect at the bottom of the distribution, namely among women and low educated workers, which is substantially what we found in the data in section I. Also, and most important, the SM is likely to have a stronger

[5] We have regressed contingent wage changes by cell in the first period (1978-81) on a third order polynomial in the level of initial wages. We have then used the estimated coefficients and the value of current inflation to make predictions in any other period.

effect on inequality within those groups where initial inequality is higher, i.e., again, for women relative to men and for older workers relative to younger ones.

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

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

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

c. The Effect of the SM on Earnings: Econometric Specification and Identification

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

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

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

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

Figure 5 reports the gender earnings gap for the four education groups in which we have classified the individuals in the sample. One can easily see that most of the compression in the gap comes from the bottom on the distribution, i.e. those with 5^{th} grade. As we move up the distribution, the gap stays basically constant over time, with possibly some increase at the end. Also, one might notice that low educated workers start from a relatively higher gap (around 40%) and over time this is brought in line with the gap of the other groups (around 20%). Both these hypothesis speak in favour of our identifying assumption and suggest, if anything, that in the absence of the SM women would not have fared much better in the early 1990s than in the late 1970s.

d. Estimation Results

In Table 4 we report the results of our estimation. We regress annualised changes in wages by cell on annualised contingent wage increases, a linear term in education, a quadratic term in age, all interacted with year dummies. The model includes also a gender dummy, but no interaction between sex and year dummies. It is interesting to see that once we condition on latent changes in the wage structure as picked up by the restrictive specification in (8), the Scala Mobile shows a strong effect of the distribution of wages changes. It turns out that about 80% of wage changes translate into total ones. The point estimate is not very precise and suggests that one cannot reject a value of $\eta=1$.

In the remaining columns of Table 4 we report more restrictive specifications for the evolution of changes in returns to education. As in the previous table, a specification with a quadratic term in the linear trend is not rejected while more restrictive specifications do not to fit the model as well as in column (1). Column (2) tells a simple story: conditional on contingent wage increases, wage differentials by education grow all over the period of observation, although at a declining rate. By the end of the period, returns accelerate again. The return to one extra year of education increases by around 0.7 percentage points between 1977 and 1981 (0.224*3), 0.3 percentage points between 1981 and 1985 ((0.224-0.209+0.061)*4), 0.15 percentage points between 1985 and 1988 ((0.224-0.209*2+0.061*2^2)*3) and finally by 0.6 percentage points in the last period ((0.224-0.209*3+0.061*3^2)*4). By cumulating these changes, this gives a rise in latent returns to education of 1.7 percentage points over 14 years. This implies, to get an idea, that returns to 8^{th} grade relative to 5^{th} grade would have increased over the period of observation by about 5 percentage points. Analogously, returns to 13^{th} grade relative to 8^{th} grade would have increased by about 8.5 percentage points in 14 years.

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

Under our maintained assumption that deviations around a linear trend in the gender earnings gap only depend on the SM, one can use the interaction of the gender dummy and the year dummies in equation (8) as an instrument for the SM. In Table 5, column (1) we report the 2SLS estimates for model (8). For brevity we only report the estimates for the same specification as in column (2) of Table 4, i.e. the one with a quadratic trend interacted with a linear term in education. It turns out that the point estimate declines from 0.808 in Table 4 to 0.599. Yet, estimates are pretty imprecise and one cannot distinguish statistically between the two. This is confirmed by the value of the exogeneity test at the bottom of the table. This suggests that one cannot reject equality of OLS and 2SLS estimates. Interestingly the 2SLS estimates push the coefficient on the gender dummy to zero, suggesting that indeed the gender earnings gap would have stayed constant if not for the SM.

Based on these results, we are in a position to estimate a counterfactual series of changes in returns to education. To do so, we simulate a series of wage changes that is obtained by attributing to each cell a contingent wage growth as the one implied by the SM. Since part of the observed decline in the equalising effect of the SM is due to changes in the inflation rate across periods, in constructing this counterfactual distribution we fix the SM point at its value in the first period (equation (6)). Also, because we know that not all of the contingent wage changes translated into total ones, we use the estimated value for η from column (1), Table 5 (η=0.599) to compute this counterfactual wage distribution.

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

Note that by the end of the period returns to education would have started to increase, even at fixed SM toughness. That happens because latent returns to education (the term in education and its interaction with time in equation (8)) increase over time.

We estimate that if latent inequality had not increased and the SM had not been curbed, between 1978 and 1992 returns to education would have decreased by approximately 2 percentage points, almost five times as much as our estimates in Figure 6.

IV. Changes in Supply and Demand

One of the hypotheses which has encountered some success in explaining changes in the wage structure in the US in the last 30 years is one which postulates that these changes can be explained simply by a trend in demand for skilled workers (maybe due to skill-biased technological change) coupled with some (assumed exogenous) variation in labour supply around this trend. For example, Card and Lemieux (2000) show that the variations in the college premium in US the 1970s (when it decreased) and 1980s (when it increased) can be completely explained by changes in the relative labour supply of college workers, (i.e. their acceleration in the 1970s and their deceleration in the 1980s) relative to a steadily growing demand. Implicitly they have in mind a very simple model of the labour market, where the interplay of demand and supply affects equilibrium prices. In this chapter we follow a similar approach, and we assume that in the face of some trend in demand for highly educated labour relative to poorly educated one, relative supply changes will imply some variation in relative wages. The interest of this exercise is to check whether the trend in the SM obscured wage reactions to changing supply and demand conditions. Sine we do not have direct have information on the level of educational attainment for both employed and unemployed workers in the SHIW, [6] we use for this purpose published data for each of the cells as provided in ISTAT, *Forze di Lavoro* (various issues). Our measure of labour supply is simply the number of individuals in the labour force in each cell. In Table 6 we present the basic data.

[6] Data on the educational attainment in the SHIW are only available for income recipients until 1987, which excludes most first-job seekers.

One can see that, over the whole period, the proportion of highly educated workers increases but there is no clear break in the trend to explain the reversion in returns during the 1980s. If the u-shaped trend in returns to education in Figure 2 were to be due to changes in labour supply, one would expect to see some deceleration in the supply of highly educated individuals in the second half of the 1980s (assuming again a steady growth in the demand for skills). The evidence in Table 6 lends little support to this.

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

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

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

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

In Table 5 we report the result of this estimation exercise, again using specification (2) in Table 4. For comparison, in column (2) we set $\eta'=0$, i.e. we restrict the SM to have no effect on the wage distribution. If one ignored the effect of the SM, one would conclude that increases in labour supply depressed wages at fixed demand. The point estimate is approximately -0.08 and statistically different from zero at standard significance levels, suggesting that wages are weakly but significantly responsive to changes in labour supply. In column (3) we explicitly control for changes in the SM. The estimate ($\eta'=0.724$) leaves the result of the previous section unchanged, namely that contingent payments translated into total wage changes without being completely undone by market forces. The coefficient of the labour supply term, on the other hand, is in the order of -0.04 and statistically not different from zero. In column (4) we report the 2SLS estimates using the same instrument as in column (1).[7] The coefficient on the SM is 0.599, which is remarkably similar to the value in column (1), while the coefficient on the labour supply term remains essentially unchanged and

[7] In order for the interaction of sex and year dummies to be a valid instruments, it is necessary to assume that gender differentials in labor supply growth do not affect the structure of wages. A look at Table 8, (cont'd on next page)

statistically insignificant. The implied estimate for the growth in latent returns to education is also similar to the one implied by specification (2) in Table 5 (1.7 percentage points in 14 years). Overall, these results show that the conclusions of section II are essentially robust to the inclusion of explicit controls for changes in the structure of labour supply. As argued in the Technical Appendix, implicitly these results suggest - as often argued- that the equilibrium in the Italian labour market is determined along a flat (portion of the) labour supply curve corresponding to some exogenous level of wages. Changes in labour demand, therefore, mainly affect unemployment.

V. Conclusions

In this chapter we have examined changes in returns to education in Italy from the late 1970s to the early 1990s. We have shown that, consistently with the results of chapter 3, the Scala Mobile tended to compress the structure wages and, as it was curbed in the 1980s, wage differentials started to become more unequal. This happened because, at the same time, there was an underlying tendency for returns to education to increase.

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

At the end of the chapter we also look explicitly at the role of supply and demand. Freeman and Katz (1995) suggest a supply-demand-institution explanation for the different trends in wage differentials on the two sides of the Atlantic during the 1980s, and one would like to know what is the relative contribution of these different

however, shows that the relative labor supply growth of women if anything decreases in the late 1980s (cont'd on next page) explanations to the trend in returns to education in Italy. We find that, even after controlling explicitly for the effect of changes in labour supply, our results are substantially unchanged. Our estimates suggest that despite the fact that the supply of highly educated labour increased relative to poorly educated labour, its effect on changes in returns to education was essentially negligible. It appears that changes in demand for educated labour potentially explain why latent returns to education tended to grow, while the SM counteracted this trend by acting in the opposite direction.

implying a rise in the female-male earnings gap, which is the opposite of what we observe.

References

Card, D. "Cost-of-Living Escalators in Major Union Contracts", *Industrial and Labor Relations Review*, 37, 1983, 34-48.

Card, D. and T. Lemieux, "Can Falling Supply Explain the Rising Return to College for Younger Men? A cohort-Based Analysis", *mimeo,* Center for Labor Economics, University of California at Berkeley, March 2000.

DiNardo, J., N. Fortin, and T. Lemieux, "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach", *Econometrica*, 64, 1996, 1001-44.

Erickson, C. and A. Ichino, "Wage Differentials in Italy: Market Forces, Institutions, and Inflation", in *Differences and Changes in The wage Structure*, Freeman, R. and L. Katz (eds.) NBER Comparative Labor Markets Series. Chicago and London: University of Chicago Press, 1995, 265-305.

Freeman, R. and L. Katz, "Differences and Changes in Wage Structures: Introduction and Summary", in *Differences and Changes in The wage Structure*, Freeman, R. and L. Katz (eds.) NBER Comparative Labor Markets Series. Chicago and London: University of Chicago Press, 1995, 1-22.

ISTAT, *Annuario Statistico Italiano*, Rome.

ISTAT, *Forze di Lavoro,* Rome.

Juhn, C., K. Murphy and B. Pierce, "Wage Inequality and the Rise in Returns to Skills", *Journal of Political Economy*, 101, 1993, 410-442.

Katz, L. and K. Murphy, "Changes in Relative Wages, 1963-1987: Supply and Demand Factors", *Quarterly Journal of Economics*, 107, 1992, 35-78.

Lee D., Wage inequality in the US during the 1908s: Rising dispersion or falling minimum wage?, *Quarterly Journal of Economics,* August 1999, 114, 997-1023.

Technical Appendix

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

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

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

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

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

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

On the supply side assume that:[8]

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

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

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

[8] Note the similarity of this labour supply with the wage curve in chapter 1. For values of the employment rate close to 1, this labour supply can be written as $\ln W_{ae}=\ln\theta_{ae}-\gamma_{ae}\ln u_{ae}$, where $\ln\theta_{ae}=\ln\lambda_{ae}-\lambda\ln(N/L)$ and $\gamma_{ae}=\lambda u_{ae}$..

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

(A3)

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

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

The coefficient on the log labour force share is a combination of real wage flexibility and the elasticity of substitution. It can be shown that a sufficient condition for the coefficient to be in line with the empirical results (≈0.04), is either that the elasticity of wages w.r.t. to the labour force share (along the labour supply, λ) is remarkably low (≈0.025) or that the elasticity of substitution across education groups is remarkably high (>10), or both. Since the existing evidence on the degree of substitutability between labour inputs with different levels of education points to a value of σ relatively low (≈2, see for example Katz and Murphy, 1992), the estimates in Table 5 suggest that wages must be relatively unresponsive to changes in unemployment.

Table 1
Changes in the Structure of Earnings: Relative Log Earnings by Cell

	Log wages					Annualised log changes (x 100)			
	1978	1981	1985	1988	1992	1978-81	1981-85	1985-88	1988-92
I. Education									
College	.13	.14	.14	.17	.20	.38	-.11	.96	.68
13th grade	.08	.07	.07	.06	.07	-.29	-.19	-.32	.32
8th grade	-.03	-.02	-.04	-.03	-.06	.25	-.35	.12	-.66
5th grade	-.12	-.12	-.09	-.10	-.09	-.06	.73	-.08	.16
II. Gender									
Males	.08	.07	.07	.06	.07	-.41	.03	-.36	.21
Females	-.15	-.12	-.13	-.11	-.12	.76	-.07	.67	-.39
III. Age									
21-30	-.11	-.11	-.12	-.09	-.13	.07	-.18	.85	-1.08
31-40	.03	.03	.03	.01	.02	-.02	-.08	-.59	.16
41-50	.06	.05	.06	.05	.08	-.19	.05	-.19	.69
51-56	.03	.04	.05	.05	.06	.21	.34	-.01	.33
IV. Education and gender									
Males									
College	.21	.24	.23	.26	.27	1.07	-.31	.99	.31
13th grade	.19	.17	.16	.15	.16	-.80	-.28	-.10	.11
8th grade	.05	.04	.04	.03	.02	-.17	-.07	-.38	-.15
5th grade	-.03	-.05	-.03	-.05	-.03	-.65	.56	-.92	.70
Females									
College	.05	.04	.04	.07	.11	-.35	.11	.93	1.06
13th grade	-.06	-.05	-.05	-.07	-.04	.37	-.07	-.60	.61
8th grade	-.21	-.17	-.21	-.17	-.24	1.25	-1.01	1.32	-1.87
5th grade	-.40	-.35	-.30	-.23	-.29	1.72	1.24	2.45	-1.46
V. Education and age									
Age: 21-30									
College	-.01	.04	.09	.13	.07	1.87	1.10	1.43	-1.49
13th grade	-.05	-.07	-.06	-.06	-.08	-.61	.06	-.01	-.33
8th grade	-.17	-.15	-.17	-.13	-.21	.72	-.57	1.15	-1.98
5th grade	-.23	-.25	-.27	-.17	-.18	-.66	-.50	3.39	-.39
Age: 31-40									
College	.11	.11	.12	.15	.17	.06	.18	1.12	.42
13th grade	.11	.11	.09	.06	.08	.05	-.48	-.94	.35
8th grade	.00	.00	-.01	-.03	-.04	.16	-.37	-.42	-.46
5th grade	-.12	-.14	-.10	-.14	-.11	-.53	1.06	-1.42	.73
Age: 41-50									
College	.11	.11	.12	.15	.17	-.40	-1.14	1.07	1.70
13th grade	.11	.11	.09	.06	.08	-.47	-.10	-.35	.73
8th grade	.00	.00	-.01	-.03	-.04	-.10	-.26	-1.17	.82
5th grade	-.12	-.14	-.10	-.14	-.11	.00	.75	.41	.28
Age: 51-65									
College	.22	.21	.16	.19	.26	1.09	-.44	-.40	2.26
13th grade	.20	.19	.18	.17	.20	.02	-.32	.50	1.52
8th grade	.08	.08	.07	.03	.07	-.17	.15	1.15	-.35
5th grade	-.11	-.11	-.08	-.07	-.06	.36	.86	-.76	-.19

Notes. The table reports the average log earnings by cell at five points in time: 1978, 1981, 1985, 1988 and 1992, and the annualised proportional change (x 100) over each time interval. Earnings are standardised relative to the average earning at each point in time. Aggregation across elementary cells is performed using a fixed weighting scheme, with weights given by the average proportion of each cell over time. Source: SHIW individual records.

Table 2
Changes in the Structure of Earnings
Dependent Variable: Annualised Proportional Changes in Earnings by Cell (x 100).

		Specification (1)		(2)		(3)		(4)	
years of education		-.008	(.079)	-.018	(.074)	-.087	(.052)	.037	(.024)
	*81-85	-.047	(.092)						
	*85-88	.020	(.093)						
	*88-92	.123	(.087)						
	*trend			-.063	(.097)	.062	(.023)		
	*trend^2			.036	(.027)				
Female		1.335	(.674)	1.345	(.670)	1.419	(.670)	1.286	(.687)
	*81-85	-1.342	(.783)	-1.364	(.777)	-1.460	(.776)	-1.396	(.797)
	*85-88	-.409	(.791)	-.404	(.787)	-.529	(.784)	-.395	(.804)
	*88-92	-1.776	(.734)	-1.789	(.730)	-1.838	(.732)	-1.614	(.747)
Adj. R2		.944		.944		.944		.941	
Chi2				.29	(.59)	4.51	(.10)	22.00	(.00)
D.f.				1		2		3	

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

Table 3
Changes in the Scala Mobile
Dependent Variable: Annualised Proportional Contingent Changes in Earnings by Cell (x 100).

	Specification							
	(1)		(2)		(3)		(4)	
years of education	-.332	(.027)	-.317	(.024)	-.213	(.017)	-.057	(.006)
*81-85	.196	(.031)						
*85-88	.271	(.028)						
*88-92	.296	(.027)						
*trend			.205	(.026)	.061	(.006)		
*trend^2			-.037	(.007)				
Female	2.915	(.226)	2.900	(.227)	2.793	(.255)	2.630	(.343)
*81-85	-1.827	(.261)	-1.797	(.260)	-1.687	(.293)	-1.627	(.394)
*85-88	-2.369	(.239)	-2.360	(.239)	-2.210	(.269)	-2.089	(.361)
*88-92	-2.636	(.230)	-2.620	(.231)	-2.523	(.260)	-2.322	(.348)
Adj. R2	.984		.984		.980		.962	
Chi2			1.33	(.25)	29.47	(.00)	132.76	(.00)
D.f.			1		2		3	

Notes. See notes to Table 2.

Table 4
The Effect of Scala Mobile on the Structure of Earnings
Dependent Variable: Annualised Proportional Earnings Changes by Cell (x 100).

	Specification							
	(1)		(2)		(3)		(4)	
Scala mobile	.818	(.203)	.808	(.203)	.686	(.199)	.727	(.173)
years of education	.252	(.097)	.224	(.092)	.079	(.067)	.105	(.028)
*81-85	-.203	(.095)						
*85-88	-.172	(.101)						
*88-92	-.112	(.098)						
*trend			-.209	(.101)				
*trend^2			.061	(.027)	.011	(.026)		
Female	-.490	(.243)	-.482	(.243)	-.390	(.244)	-.419	(.233)
Adj. R2	.947		.947		.945		.946	
Chi2			2.09	(.15)	13.63	(.00)	14.06	(.00)
D.f.			1		2		3	

Notes. The table reports the results of a regression of annualised proportional earnings changes by cell over annualised proportional contingent earnings changes. See also notes to Table 2.

Table 5
The Effect of Scala Mobile on the Structure of Earnings : Further Analysis

	Specification							
	(1)		(2)		(3)		(4)	
	2SLS		OLS		OLS		2SLS	
			Labor supply		Labour supply		Labour supply	
Scala mobile	.599	(.261)			.724	(.209)	.599	(.259)
Labour supply			-.077	(.030)	-.047	(.031)	-.045	(.031)
years of education	.164	(.103)	.038	(.075)	.233	(.092)	.197	(.102)
*trend	-.175	(.105)	-.059	(.095)	-.191	(.101)	-.171	(.105)
*trend^2	.055	(.027)	.033	(.027)	.056	(.027)	.053	(.028)
Female	-.320	(.274)	1.323	(.654)	-.448	(.243)	-.350	(.271)
Adj. R2	.948		.947		.948		.948	
Chi2	2.42	(.12)	.46	(.50)	2.27	(.13)	2.47	(.12)
D.f.	1				1		1	
Exogeneity test	.493	(.389)					.334	(.411)

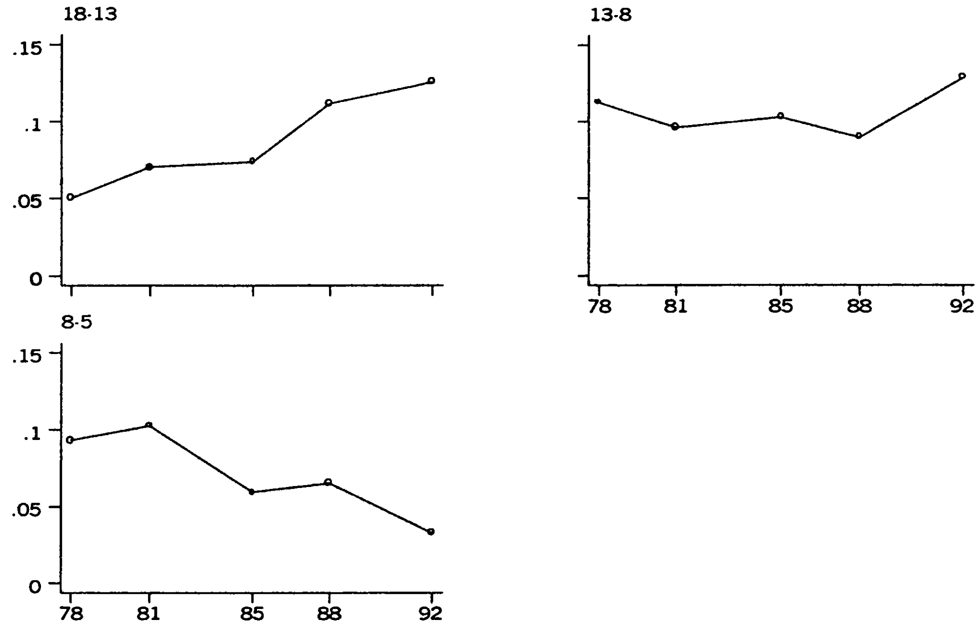
Notes. The table reports the results of a regression as the one in column (2), Table 4. 2SLS are obtained using the interaction of a sex dummy with time dummies as an instrument for the 'Scala mobile'. 'Labour supply' is the log of the relative labour force share of each educational groups within cells defined by sex and time. 'Exogeneity test' is a test for the exogeneity of contingent earnings changes. Under the null hypothesis that contingent changes are exogenous, the statistic is distributed as a t-student. P values in brackets. See also notes to Table 4.

Table 6
Changes in the Structure of Labour Supply

	Levels					Annualised log changes (x 100)			
	1978	1981	1985	1988	1992	1978-81	1981-85	1985-88	1988-92
I. Education									
College	4.79	5.37	6.31	6.81	7.81	3.81	4.02	2.54	3.43
13th grade	15.67	18.54	22.28	25.98	28.56	5.60	4.60	5.13	2.36
8th grade	24.47	28.38	33.33	35.91	40.44	4.93	4.02	2.48	2.97
5th grade	55.06	47.71	38.08	31.30	23.19	-4.78	-5.64	-6.53	-7.50
II. Gender									
Males	68.75	67.07	65.42	63.83	62.77	-.83	-.62	-.82	-.42
Females	31.25	32.93	34.58	36.17	37.23	1.75	1.22	1.50	.72
III. Age									
21-30	25.65	25.88	26.64	27.75	29.23	.30	.72	1.36	1.30
31-40	27.53	27.13	28.20	27.71	27.13	-.49	.97	-.58	-.53
41-50	25.23	25.13	24.01	24.02	24.01	-.13	-1.14	.02	-.02
51-56	21.59	21.86	21.15	20.51	19.63	.41	-.82	-1.02	-1.10
IV. Education and gender									
Males									
College	3.12	3.42	3.93	4.08	4.57	3.06	3.53	1.20	2.85
13th grade	9.68	11.08	12.95	14.62	15.92	4.51	3.90	4.05	2.14
8th grade	17.26	19.51	22.44	23.80	26.57	4.08	3.50	1.96	2.75
5th grade	38.70	33.06	26.10	21.33	15.70	-5.24	-5.92	-6.73	-7.65
Females									
College	1.68	1.96	2.38	2.73	3.24	5.15	4.87	4.64	4.26
13th grade	6.00	7.46	9.33	11.37	12.64	7.28	5.59	6.57	2.65
8th grade	7.21	8.87	10.89	12.10	13.87	6.89	5.13	3.53	3.40
5th grade	16.37	14.65	11.98	9.97	7.49	-3.70	-5.02	-6.12	-7.17
V. Education and age									
Age: 21-30									
College	1.07	1.05	.95	.87	1.06	-.74	-2.59	-2.79	4.94
13th grade	6.79	8.01	9.21	10.42	11.13	5.50	3.50	4.13	1.64
8th grade	10.27	11.78	13.37	14.12	15.47	4.57	3.16	1.84	2.27
5th grade	7.52	5.05	3.12	2.33	1.57	-13.29	-12.05	-9.69	-9.80
Age: 31-40									
College	1.69	2.06	2.69	2.88	2.90	6.73	6.67	2.28	.14
13th grade	4.54	5.43	7.09	8.38	8.99	6.02	6.66	5.57	1.75
8th grade	7.27	8.45	10.29	10.79	12.14	4.99	4.94	1.57	2.95
5th grade	14.03	11.18	8.12	5.66	3.10	-7.57	-7.99	-12.06	-15.03
Age: 41-50									
College	1.01	1.15	1.44	1.76	2.38	4.18	5.61	6.84	7.49
13th grade	2.47	2.97	3.70	4.54	5.51	6.11	5.50	6.89	4.83
8th grade	4.31	5.11	6.24	7.04	8.29	5.71	5.00	3.99	4.10
5th grade	17.44	15.90	12.63	10.67	7.82	-3.06	-5.76	-5.61	-7.78
Age: 51-65									
College	1.02	1.11	1.23	1.29	1.47	2.85	2.62	1.50	3.20
13th grade	1.88	2.13	2.28	2.63	2.93	4.19	1.71	4.75	2.65
8th grade	2.62	3.04	3.43	3.96	4.54	4.93	3.02	4.76	3.46
5th grade	16.07	15.58	14.21	12.64	10.69	-1.04	-2.30	-3.90	-4.17

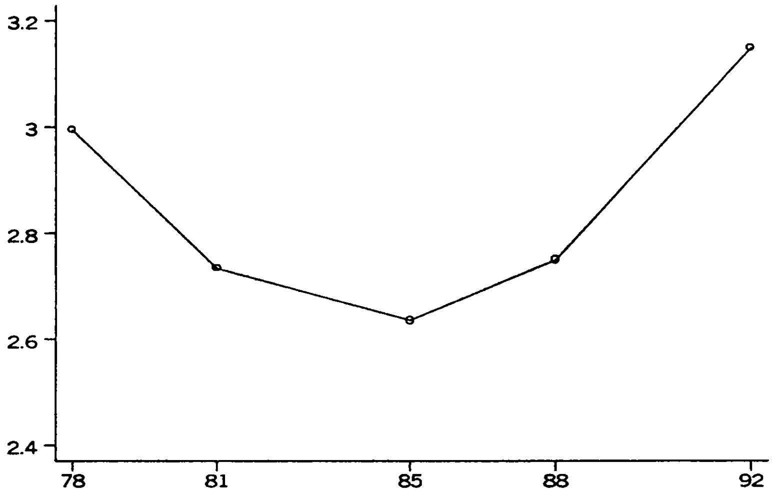
Notes. The table reports the share of each cell in the labour force. Source: ISTAT, *Forze di Lavoro* (various issues).

Figure 1
Changes in the Structure of Earnings: Differentials by Education



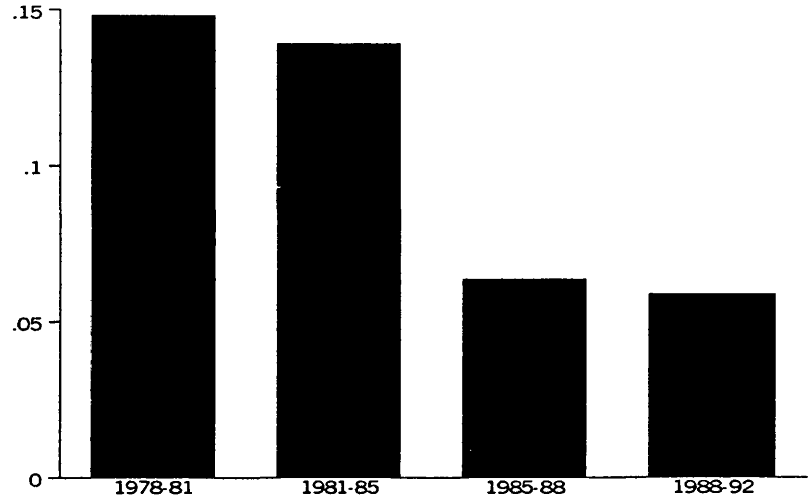
Notes. The picture reports unconditional log earnings differentials by years of formal education for men and women together. The top left-hand panel reports the differential between college graduates (18) and those with 13th grade (13). Analogously, the other two panels report the differential between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

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



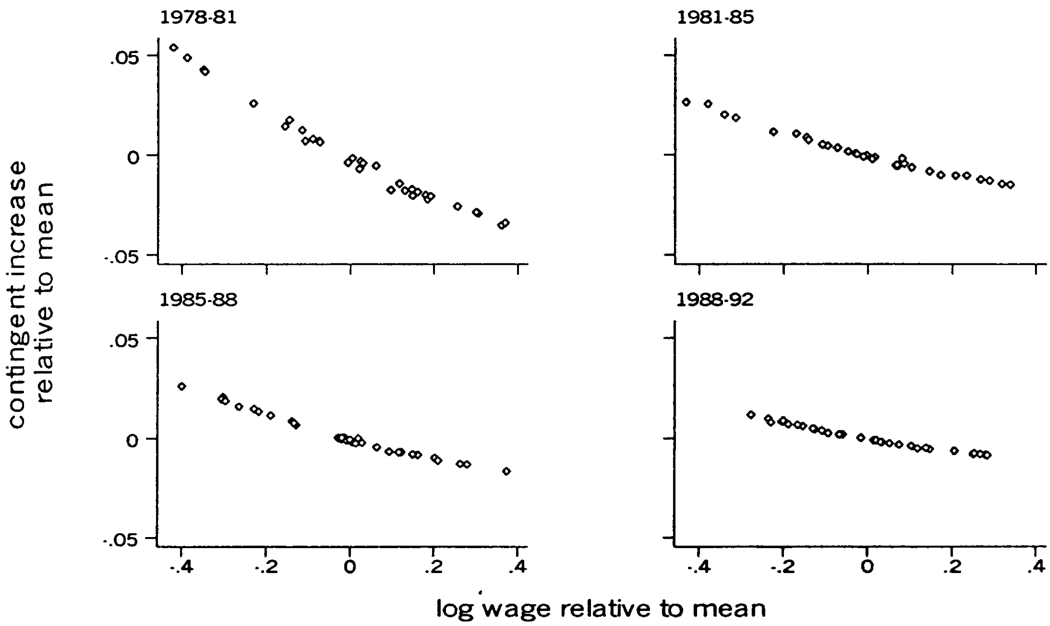
Notes. The figure reports the estimated return to one extra-year of education, conditional on gender, age and a common macroeconomic effect. The values are expressed in percentage points. The series is obtained based on the results of specification (3) in Table 2. See text for details. Source: SHIW individual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

Figure 3
The Inflation Rate



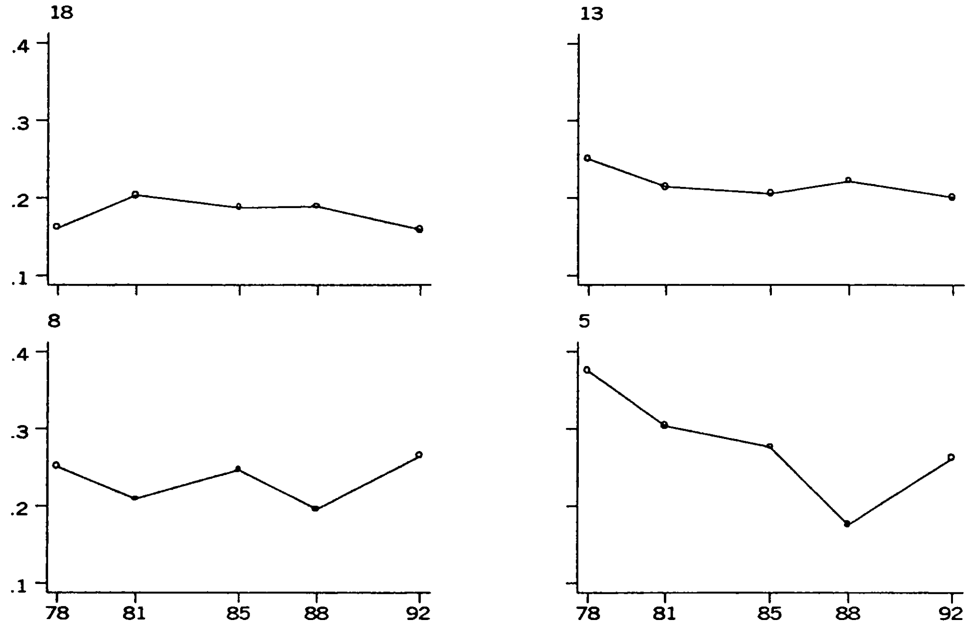
Notes. The picture reports the annualised inflation rate in consumer prices over four sub periods: 1978-1981, 1981-1985, 1985-1988, and 1988-1992. Source: ISTAT *Annuario Statistico Italiano* (various issues).

Figure 4
The Decline in the Scala Mobile Toughness



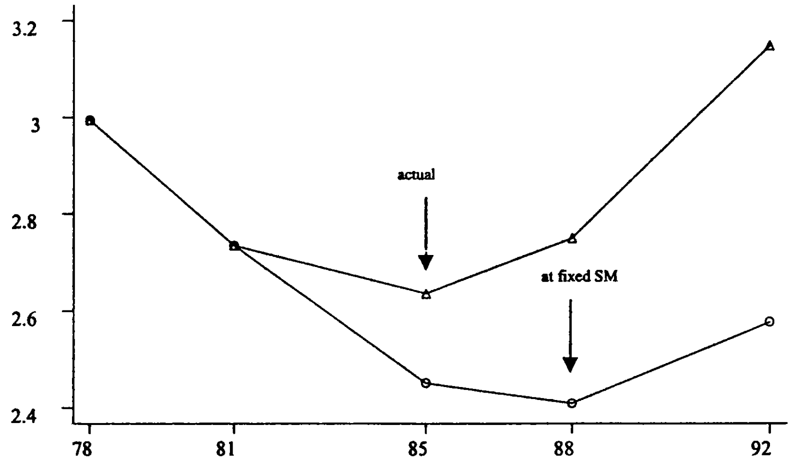
Notes. The figure reports on the horizontal axis the average initial level of earnings and on the vertical axis the average annualised contingent earnings changes as implied by the Scala Mobile in each sub-period for the 32 cells defined by age, sex and education. Data are obtained at fixed inflation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

Figure 5
Changes in the Gender Earnings Gap by Education



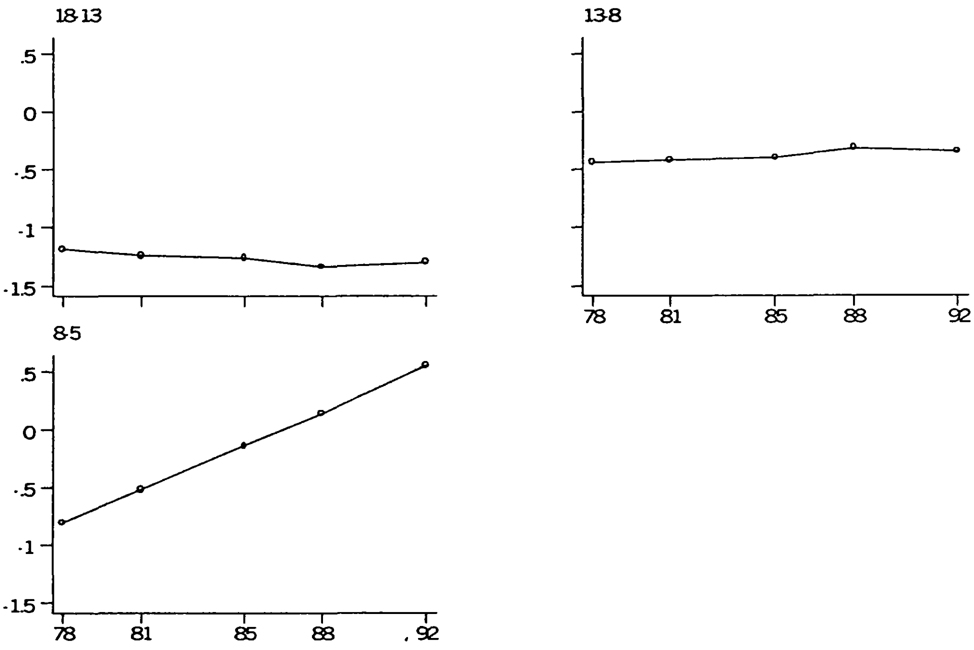
Notes. The picture reports the male-female log earnings differential by education. The top left-hand panel reports the differential between male and female college graduates (18). Analogously, the other panels report the differential between those with 13th grade, 8th grade, and 5th grade. All series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

Figure 6
The Effect of the Scala Mobile on the Average Return to One Extra-Year of Education



Notes. The figure reports the estimated returns to one extra-year of education, conditional on gender, age and a common macroeconomic effect (same as in Figure 2) and the estimated counterfactual distribution obtained by setting the Scala Mobile point to its value between 1978 and 1981. The series is estimated based on the estimates in column (1), Table 5. Source: SHIW individual records and ISTAT *Annuario Statistico Italiano* (various issues).

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



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

Chapter 5

A Simple Model of the Labour Market: US vs. Continental Europe

In this chapter we show how an extremely stylised model of the labour market can broadly account for the different results found throughout this dissertation. Our aim is to illustrate schematically the 'structural' differences between the labour markets on the two sides of the Atlantic as well as the evaluate the effect of changes in market forces on the performances of these two economies.

In carrying out this exercise we will concentrate on a comparison between the US and continental Europe, for which Italy is taken as a case-study. The results for the UK can be rationalised by considering this country as an intermediate case between the US and continental Europe.

It is worth underlying that there is no presumption that this is the 'true' model of the labour market. Both its simplicity and its ability to predict the stylised facts presented in chapters 1 to 4, however, are powerful reasons to give it some consideration.

Let us briefly summarise the results of chapters 1 to 4. During the 1980s:

1. The demand for skills increased at a similar rate across the OECD.
2. The supply of skills decelerated in the US (in the 1980s) but not in continental Europe.
3. It follows that the growth in demand for skills outpaced the supply of skills in the US but not in continental Europe.
4. Institutions tended to compress the wage structure in favour of unskilled workers in continental Europe (Italy) but not in the US.

5. Returns to skills increased in the US but not in continental Europe. There is evidence that in the absence of institutional rigidities (and controlling for employment changes), the wage structure would have evolved similarly in the US and continental Europe (Italy).
6. The employment structure shifted towards skilled workers across the all of OECD, although more so in Europe, where this shift translated into some rise in the unemployment rate of the unskilled. There is evidence that institutional rigidities are able to explain part of the shifts in the employment structure in continental Europe (Italy).
7. Wages seem unresponsive to changes in the structure of labour supply in continental Europe but are generally regarded as flexible in the US.

To try and account for this set of facts, let us consider a model of the labour market where equilibrium is determined by the intersection of a relative labour demand for skills (derived for simplicity from a Cobb-Douglas production function with CRTS) and a relative wage curve:

(1a) $\ln(W_1/W_2)=\ln(\alpha_1/\alpha_2)-\ln(N_1/N_2)$

(1b) $\ln(W_1/W_2)=\ln(\theta_1/\theta_2)+\lambda \ln(N_1/N_2)-\lambda \ln(\beta_1/\beta_2)$

where, by convention, 1 is skilled labour and 2 unskilled labour. W denotes wages, N employment, β (relative) labour force, α is some technology parameter ($\alpha_1+\alpha_2=1$) and θ is a measure of skill specific wage pressure, possibly due to institutional rigidities. λ is a measure of real wage flexibility. This model has been used, although with some variations, throughout chapters 1 to 4.[1] To keep things simple we assume, as we have done throughout the analysis, that labour supply does not respond to wage changes.

In equilibrium the wage and employment structures are a linear combination of institutions and market forces:

(2a) $\ln(W_1/W_2)=(1-k)[\ln(\alpha_1/\alpha_2)-\ln(\beta_1/\beta_2)]+k\ln(\theta_1/\theta_2)$

(2b) $\ln(N_1/N_2)=k[\ln(\alpha_1/\alpha_2)-\ln(\theta_1/\theta_2)]+(1-k)\ln(\beta_1/\beta_2)$

where $k=1/(1+\lambda)$.

An extremely stylised (and arguably over-simplistic) representation of the US vs. continental Europe if that in the former wages are perfectly flexible (i.e. $\lambda=\infty$), while in the latter wages are rigid ($\lambda=0$).[2] In the first case k=0, while in the second k=1. So that the two equations describing equilibrium are, respectively, for the US:

(3a) $\ln(W_1/W_2)=\ln(\alpha_1/\alpha_2)-\ln(\beta_1/\beta_2)$

(3b) $\ln(N_1/N_2)=\ln(\beta_1/\beta_2)$

and for Europe:

(4a) $\ln(W_1/W_2)=\ln(\theta_1/\theta_2)$

(4b) $\ln(N_1/N_2)=\ln(\alpha_1/\alpha_2)-\ln(\theta_1/\theta_2)$

So that in the US any imbalance between demand and supply of skills translates directly into changes in relative wages (3a). Also, employment rates vary at the same rate across skills groups (3b), so that the difference in unemployment rates between unskilled and skilled workers remains approximately constant ($u_1-u_2=\ln(N_1/N_2)-$

[1] In chapter 4 we show how the model of chapter 1 is essentially nested into this more general model. It is worth underlying that in this model wages are not a convex function of unemployment (they are a function of unemployment rather than log unemployment), an assumption that has been used in chapter 1 to derive the theoretical effect of mismatch on aggregate unemployment. Since our estimates show that mismatch is negligible in continental Europe, in order to keep things simple we ignore this feature of the wage curve in this chapter.

[2] In chapter 3 we have shown that $\lambda\approx0$ in Italy (see result 7). As the US is concerned, both Katz and Murhpy (1992) and Card and Lemieux (2000) implicitly assume that $\lambda\approx\infty$, as assumption that we have also used in chapter 2.

$\ln(\beta_1/\beta_2)$=0). Both employment and wages only depend on market forces and any labour market imbalance is only reflected into changes in the wage structure.

By the opposite token, in continental Europe relative wages only reflect the effect of institutions (4b),[3] while the difference in unemployment rates between unskilled and skilled workers (u_2-u_1) reflects the difference between relative demand and relative supply, net of any relative wage pressure in favour of skilled workers (4b).

In Table 1 we have reported the results 1 to 7 where the symbol + (-) implies positive (negative) changes. In Figure 1 we provide a graphical illustration of these two economies. The basic difference between the US and continental Europe is that in the former the labour supply curve is vertical in the relative wage-employment space while in the latter this is flat. Relative labour demand has shifted similarly in both economies (from D to D') but relative labour supply has shifted to the right in the US (from S to S') because of the (assumed exogenous) changes in the composition of the labour force, while this has shifted downward in Europe (from S to S') because of (increased) institutional rigidities.

Let see how our model fits the data. One way to look at the US experience is that in this country relative wages have decompresses ($\ln(W_1/W_2)$=+) because of a rise in demand for skills not matched by an equal rise in supply ($\ln(\alpha_1/\alpha_2)$-$\ln(\beta_1/\beta_2)$=+). In Europe, however, it appears that institutions have maintained the wage structure relatively unchanged ($\ln(W_1/W_2)$)=$\ln(\theta_1/\theta_2)$)=-/0). As employment goes, all the increase in the relative labour supply of skilled workers in the US ($\ln(\beta_1/\beta_2)$=+) has translated into an equal rise in relative employment ($\ln(N_1/N_2)$=+). In Europe, instead, relative employment rates have increased sensibly in favour of the skilled ($\ln(N_1/N_2)$=+++/++) as a combined effect of a rise in demand ($\ln(\alpha_1/\alpha_2)$=++) and a decline in relative wage

[3] This is what we called relative wage pressure in chapter 1.

pressure ($\ln(\theta_1/\theta_2)$=-/0). Changes in unemployment rate differentials, however, have been mitigated by the pronounced growth in the supply of skills ($u_1-u_2=\ln(N_1/N_2)-\ln(\beta_1/\beta_2)$=+/0).

As argued in chapter 3, at fixed employment ($\ln(N_1/N_2)=0$) and in the absence of institutional rigidities, wage pressure in continental Europe would have seconded the rise in relative demand ($\ln(\theta_1/\theta_2)=\ln(\alpha_1/\alpha_2)$=++) (see 4b), so that (from 4a) wages would have risen in favour of skilled workers ($\ln(W_1/W_2)=\ln(\alpha_1/\alpha_2)$=++). This is exactly what one would have observed in the US at fixed employment structure ($\ln(\beta_1/\beta_2)=\ln(N_1/N_2)=0$).[4] This is result 5. In essence, since the trends in the demand for skills are of comparable magnitudes on the two side of the Atlantic (see result 1), everything else being equal, the wage structure would have evolved at a similar rate.

One might wonder what would have happened if the supply of skills had not seconded the rise in relative demand in Europe (i.e. if $\ln(\beta_1/\beta_2)$<++), something which seems to have happened in the US. Equations (4a) and (4b) illustrate that in this case we would have observed a more pronounced rise in the difference between the unemployment rates of the two skills groups ($u_1-u_2=\ln(N_1/N_2)-\ln(\beta_1/\beta_2)$>+/0) but this would have had no appreciable effect on the wage structure.

[4] Of course, even if we allow the employment structure to vary, the model predicts that given the changes in the exogenous variables, we would observe some changes in the wage structure ($\ln(w_1/w_2)=\ln(\alpha_1/\alpha_2)-\ln(N_1/N_2)$=+) which is what happened in the US.

References

Card, D. and T. Lemieux, "Can Falling Supply Explain the Rising Return to College for Younger Men? A cohort-Based Analysis", *mimeo,* Center for Labor Economics, University of California at Berkeley, March 2000.

Katz, L. and K. Murphy, "Changes in Relative Wages, 1963-1987: Supply and Demand Factors", *Quarterly Journal of Economics*, 107, 1992, 35-78.

Table 1
Changes in the US and European Labour Markets in the 1980s

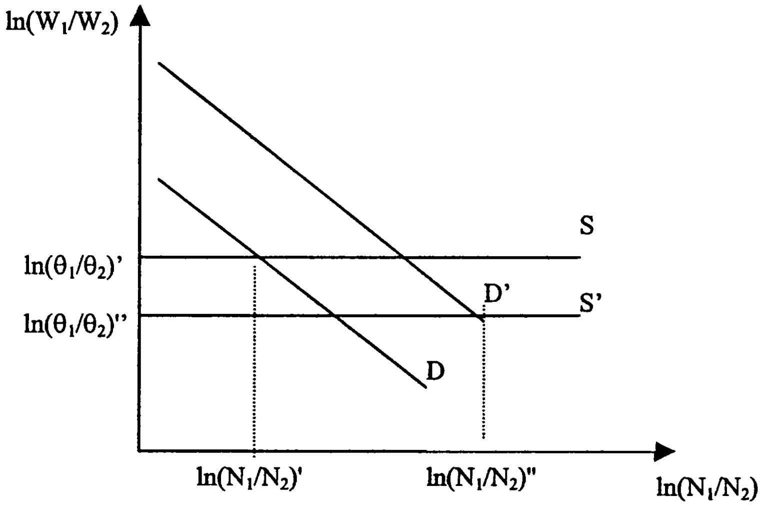
	1	2	3	4	5	6	7
	$\ln(\alpha_1/\alpha_2)$	$\ln(\beta_1/\beta_2)$	$\ln(\alpha_1/\alpha_2)$- $\ln(\beta_1/\beta_2)$	$\ln(\theta_1/\theta_2)$	$\ln(W_1/W_2)$	$\ln(N_1/N_2)$	λ
US	++	+	+	0/+	+	+	∞
EU	++	++	0	-/0	-/0	+++/++	0

Notes. The table reports the basic results of chapters 1 to 4 for the US and continental Europe.

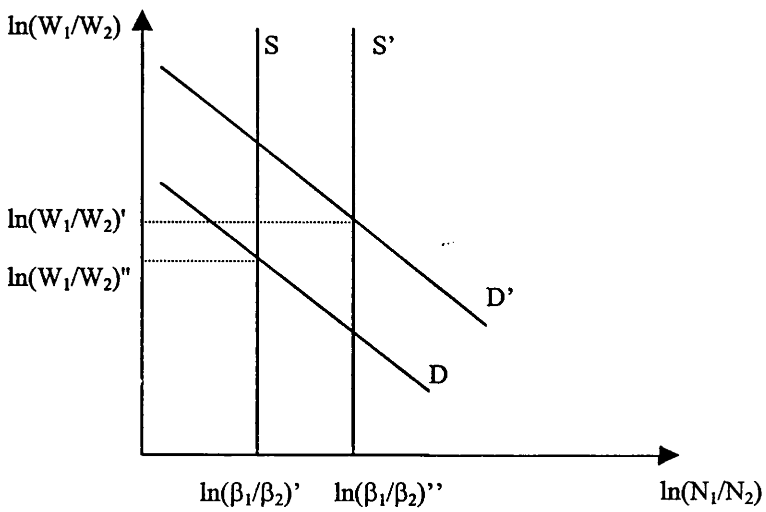
Figure 1

Changes in the US and European Labour Markets in the 1980s

Continental Europe



US



Notes. The figure reports a stylised representation of the labour markets in continental Europe and the US. D is the relative demand for skilled labour while S is the relative wage curve.

Conclusions

In this work we have analysed the trends in the wage and employment structures in a number of OECD countries during the 1970s and 1980s and we have tried to separately assess the contribution of changes in market forces and institutions in shaping these trends.

Chapters 1 and 2 analyse the occurrence of skill biased change in a number of OECD countries. In chapter 1 we propose a simple model to think about the occurrence and consequences of skill biased change. Based on data on the evolution of employment, unemployment and wages by education (high and low) for as many as 11 OECD countries, we find that, with the exception of the UK and the US, there is a little evidence of an increased imbalance between the demand and the supply of skills across the OECD in the 1970s and 1980s. While the relative demand for skills increased steadily in almost all the countries analysed, in continental Europe this trend in relative demand was matched by an approximately equal increase in the relative supply of skills.

In chapter 2 we extend the analysis of chapter 1 by allowing for a continuous distribution of skills (human capital) in the population. We concentrate on the fortunes of those at any given point of the skills distribution and we show how one can use data on a variable which is only imperfectly correlated with human capital (i.e. education) to infer the occurrence of skill biased change. The main advantage of this approach is that it allows to control for different educational structures across countries and for the fact that the secular increase in the skill attainment of the population implies that the same level of education corresponds to different points in the skills distribution as time goes on. Based on data for five countries, for which information on wages, employment and unemployment for four educational groups is available, we find very similar results to the ones in chapter 1.

In chapter 3 we concentrate on the labor market experience of a 'typical' continental European country. We use SHIW micro data to document the trends in wage inequality in Italy between 1977 and 1993 and we show that, after a marked compression in the late 1970s, beginning in the mid 1980s wage inequality started to increase. We analyse the role played by a unique institution, the Scala Mobile, in shaping these trends. The Scala Mobile – literally escalator – was a wage indexation mechanism granting the same absolute wage increase to all employees as prices rose, thereby potentially compressing the wage distribution. Over time, the potential equalising effect of this institution was curbed and in 1991 the Scala Mobile was abolished. We show that the Scala Mobile had a considerable equalising effect which in turn was responsible for most of the early compression in wage inequality. As the Scala Mobile was curbed, observed wage inequality tended to increase. In order to separately identify the effect of the Scala Mobile from changes in market forces, we have assumed that in the absence of this institution inequality would have changed similarly for men and women. Although this hypothesis is ultimately untestable with our data, we show that US data lend some support to it. Interestingly, the data show that, in the absence of indexation, wage inequality in Italy would have risen throughout the 1980s and early 1990s at a rate comparable to the one observed in the US, suggesting that the pressure towards higher inequality of earnings in the 1980s was not a phenomenon unique to the US.

In chapter 4 we test whether the effect of the Scala Mobile on changes in the wage structure in Italy might mask price responses to changes in the supply and demand for skills. As a consistency check for the results in chapter 3, we use a different identification strategy for the effect of the Scala Mobile, namely that, in its absence, the gender earnings gap would have varied at a constant rate (i.e. along a linear trend) over the period of analysis. Based on data on wages, employment and unemployment by education, we find that wages of Italian workers are essentially insensitive to labour supply changes and that a combination of rising demand for skills and changes in (the counteracting effect of) institutions account for the observed trends in returns to skills in Italy. Interestingly, the point estimates for the effect of the Scala Mobile over changes in wages are essentially indistinguishable from the ones in chapter 3.

Finally chapter 5 shows how one can rationalise the results of chapters 1 to 4 in terms of an extremely simple (and arguably over-simplistic) model of the labour market with two types of labour: skilled and unskilled. Our empirical results are consistent with the occurrence of a generalised increase in the relative demand for skills across the OECD and with different degrees of wage 'flexibility' on the two sides of the Atlantic. The failure of relative supply to keep the pace with this rising demand and the high sensitivity of wages to the pressure of market forces are consistent with the decompression in the wage structure which took place in the US (and in the UK) during the 1980s. Institutional rigidities, on the other hand, are able to explain why the wage structure remained essentially unchanged in continental Europe over this period and while in turn employment shifted towards the skilled, seconding the shift in the structure of labour demand.

One related issue which is largely overshadowed both in the present work and in most of the empirical literature in labor economics - and which we think should deserve more attention - concerns the effect of changes in market forces over changes in labor market institutions. Indeed, little 'hard' evidence is so far available on how institutions are born, how they are transformed and how they finally disappear, and why different institutional arrangements emerge in different economies.

In terms of the present analysis, one might wonder, for example, why the Scala Mobile emerged in Italy in the 1970s and not, say, in the US. Is it reasonable to take these differences in institutional arrangements as exogenous? Or does it make more sense to believe that these differences can partly be ascribed to the endogenous effect of different fundamentals of the economy? Analogously, is it reasonable to take the gradual decline of the Scala Mobile in the 1980s as exogenous? Or is it more reasonable to argue that this decline was due to the circumstance that this institutions was unsustainable in the face of a latent trend towards higher inequality of market wages? Clearly, our conclusions are sensitive to what one believes being the relationship between market forces and institutions, since, if one took the extreme view that institutions only 'reflect' market forces, one might end up concluding that the evolution of wage inequality in Italy was exclusively the effect of changes in the relative demand for skills.

One fundamental element which in our opinion is missing from this debate regards the 'political economy' of institutions. Indeed it is mostly through the political process that changes in the fundamentals of the economy translate into institutional arrangements. Despite there being a rich theoretical literature on the political economy of institutions, it appears as if empirical labor economists have so far done too little to embody this dimension in their analysis. Most of the flourishing literature on natural experiments - which is so dear to applied labor economists -, for example, is based implicitly or explicitly on the assumption that institutional changes in the labour market are purely exogenous. Little is known on how institutions depend on changes in market forces via the effect that these forces exert on citizens' political preferences, voting patterns or lobbing efforts on the part of pressure groups and companies. It appears that the collection of data on the political process leading to the adoption, modification or dismissal of certain institutional arrangements might prove enlightening to try to get to a better understanding of the functioning of the labor markets and the emergence of different institutional standards across the world.