Why Has Wage Inequality Increased More in the U.S. than in Europe? An Empirical Investigation of the Demand and Supply of Skill

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Abstract

During the past two decades the wage gap between high and low skill labor has increased more in the United States than in many European countries. In this paper, I use the correspondence between occupation and education to construct aggregates of skill supply, skill demand and unemployment by skill group that are comparable across countries. Using individual data for years 1983 to 1994, I find that the relative demand for skilled labor has increased to a similar extent in the U.S. and in Europe and that wage inequality remained low in Europe partly because the European relative supply of skill increased much faster than in the U.S., and partly because European relative wages were rigid, which caused an increase in unemployment among the low-skilled. (JEL, J31, J60)

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1 Introduction

Over the past two decades wage inequality has skyrocketed in the United States as well as in many other OECD countries. The literature has offered two main explanations for this. On the one hand, technological change may be skill biased.[1] On the other hand, the growth of international trade may have reduced the demand for low skill workers in advanced economies.[2] Thoenig and Verdier (2003) and Acemoglu (2003) have theorized that international trade and skill biased technical change reinforce each other in increasing wage inequality.

These explanations have one thing in common: they tend to be pervasive across similar economies. It would be difficult to argue that technical change and international trade affected very differently economies in a similar stage of development. Despite this, wages of different types of workers have evolved very differently in the U.S. and in Europe over the past two decades. Figure 1 plots the accumulated rate of growth of relative wages in the U.S., Germany, Italy and the U.K. from 1983 to 1994. The first panel, shows relative wages based on education groups. The second panel shows the evolution of real wages for non-manual workers relative to manual ones. Whereas wage inequality increased to a similar extent in the U.S. and Italy, the figure indi-

cates that wage inequality (particularly inequality between occupations) has remained fairly constant in Germany and the U.K.[3]

(FIGURE 1)

In this paper, I use a simple supply and demand model to decompose these differences in inequality trends into differences in relative demand, relative supply and relative non-employment trends in each country.

Existing attempts to quantify the role played by demand and supply have suffered from two main drawbacks. First, most studies have looked separately at either demand shocks, supply shocks or the effects of labor market institutions on wage inequality.[4] In this paper, I integrate these in a supply and demand framework in order to quantify the relative importance of each of them.

Second, previous studies have classified individuals as high and low skilled according to their level of education. Since it is by definition difficult to know the occupation of the unemployed, using education as the proxy for skill has been a sensible procedure.[5]

In this paper, I argue that the results of these analyses are very sensitive to the proxy for skill one uses, and that occupation is a better proxy for skill than education. Key to this is that relative wages changed because the returns to occupation within education changed, and not vice versa. I then use the correspondence between occupation and education for employed individuals to construct aggregate measures of skill demand, skill supply and

unemployment by skill group that are comparable across countries.

I find that the relative demand for high skilled individuals has increased in a similar way across countries and that inequality did not increase as fast in Europe as in the U.S. because of a combination of two effects: a faster increase in the European supply of skill and rigid relative wages in Europe, particularly in Germany. This last effect corresponds to an increase in the unemployment rate of the least skilled.

The outline of the paper is as follows. Section 2 describes trends in relative wages and employment. In section 3, I outline the supply and demand framework. In section 4, I argue that occupation is a better proxy for skill than education and I present the methodology to classify individuals as high and low skilled. Section 5 presents the results and section 6 concludes.

2 Relative Wages and Employments

In this paper, I use individual data on personal characteristics, wages and employment in the U.S., Germany, Italy and the U.K. between 1983 and 1994. Several studies have documented a slowdown of the rate of growth of wage inequality in the United States after 1995 (e.g., Murphy and Welch, 1999; Card, 2002), and hence years 1983 to 1994 comprise a suitable period of time for the analysis I am doing.

The data comes from four different sources: (1)United States: the Current Population Survey (CPS); (2)Italy: the Bank of Italy data set (BI) (for survey years 1984, 1986, 1987, 1989, 1991, 1993, and 1995); (3)UK: the General

Household Survey (GHS); (4)Germany: the German Socioeconomic Panel[67]. For this twelve-year period, the CPS, BI, GSOEP and GHS contain detailed information on individual characteristics and working conditions that result in 680, 125, 150 and 160 thousand observations respectively. For all three data sets, I constructed two samples, a 'wage' sample and an 'employment' sample. I use the 'wage' sample to compute hourly wages for different groups. This sample includes only individuals with strong labor market attachment and it is formed by private, not self-employed, non-agricultural males 18 to 50 years old, who have been out of school for the whole year and have been working 50 weeks or more during the past calendar year. The 'employment' sample includes all private, not self-employed, non-agricultural male individuals 18 to 65 years old, who have been out of school for the whole year. Throughout the paper, I use as the wage measure the average hourly wage of the individual computed as the ratio of yearly labor earnings divided by total yearly hours. All earning measures are deflated by the implicit price deflator for personal consumption expenditures in each country.

Figures 2, 3 and 4 show, for each of the four countries, the twelve-year evolution of wage dispersion for three different sources of earnings: years of schooling, position on the wage distribution and occupation of employment.

(FIGURE 2)

(FIGURE 3)

(FIGURE 4)

A few remarks on the education variable apply. First, individuals in Italy report only the highest degree completed. Second, the educational system in Germany is a complex one where regular training in firms is as common and important as regular education in school. Two Germans, for example, each with 18 years of education may have followed completely different paths with possibly different skill aptitudes. After sharing their 4 years at primary school or *Grundschule*, one may have enrolled in a medium skill secondary school or *Realschule* for six years, have completed three years of skilled apprenticeships, returned to vocational school for two years and gained access to any applied university or *Fachochschule* for 3 years. The other individual, instead, may have enrolled in a more academic secondary school or *Gymnasium* for 9 years to gain direct access to a superior university or *Hochschule* for approximately 5 years.

I use the correspondence between years of training and schooling into total years of education provided by Syracuse University in their GSOEP equivalent version that brings the German data into PSID equivalence. Even if one uses this correspondence, it is difficult to know how these individuals compare to each other in terms of skill and, more importantly, how do they compare with similarly educated individuals in the other countries. The impact of this problem is however mitigated by the approach that I use in this paper.

All the measures are time-invariant industry-occupation-education quantity weighted averages of log real hourly wages and hence, movements in the

price of each group come solely from movements in the prices for an industry-occupation-education cell and not from changes in the composition between these groups.

From the observation of the education and occupation classifications two different patterns emerge. The U.S. and Italy, following the first pattern, display increasing wage inequality for both of the earnings sources. In contrast, the U.K. and Germany exhibit stagnant or even decreasing wage dispersion.

Regarding wage inequality trends in the U.K., other studies (e.g., Katz, Loveman and Blanchflower, 1995; Gosling, Machin and Meghir, 2000; Machin, 1996, Schmitt, 1995 and Leslie and Pu, 1995) have found two differentiated periods, one from the late seventies to the mid eighties, with strong growth in wage dispersion, and the other from the mid eighties to the mid nineties with milder increases or constant wage inequality trends. Schmitt (1995), also uses data from the General Household Survey and he finds that between 1983 and 1988 the returns to education were flat. He does not present relative wage trends for occupational groups. Gosling, Machin and Meghir (2000), look at returns to education using data from both the Family Expenditure Survey and the General Household Survey. The numbers from the Family Expenditure Survey show small increases in the wage differential between individuals with no qualifications and the rest of the groups (about 2 log points) between 1984 and 1993 and no widening of the wage gap between the other groups over the same period of time. Their General Household Survey results show stronger growth in the wage differentials between these groups

from 1983 to 1991. It is important to note that their series are unweighted yearly averages allowing for compositional changes to play a role. My own analysis of the General Household Survey data shows that unweighted averages present stronger increases in wage dispersion for all classifications than fix-weighted ones, suggesting that compositional effects favored relatively more high skilled groups than low skilled ones over this period[8] [9].

Table 1 shows the evolution of the sample shares of different educational groups in each of the countries for this twelve year-period. The first point to stress is the enormous difference that exists among these countries in terms of their educational distributions. In Italy, for example, the proportion of individuals with less than a high school diploma represented 74.80% of the sample population, while only 21.64% of the individuals in the U.S. sample had not completed a high school degree by 1984.

(TABLE 1)

In general, the table suggests that the rate of growth of the supply of skill in each country will be sensitive to the classification of educational groups as either high or low skill groups.

Figure 5 shows the evolution of the non-employment rate in each of the countries. The non-employment rate increased more in Italy and Germany than in the U.S. and the U.K. From 1985 to 1993, the U.S. and U.K. non-employment rates increased by 9 and 14 log points, respectively. In Italy and Germany, however, the series increased by 53 and 23 log points, respectively.

(FIGURE 5)

Figure 6 presents the employment rate for different educational groups. Two patterns can be noted. First, Italy and the U.S. do not present important changes in their relative employment rates. This first pattern is consistent with the broad evidence on their relative wage trends. Second, in Germany and in the U.K. the gap between the employment rates of the high and the low educational levels has widened. This evidence is also broadly consistent with the fact that German and U.K. relative wages remained considerably flat during this period of time. The evidence on Germany is at odds with the findings of other authors, for example Nickell and Bell (1996) who find a declining unemployment rate for the "low education" group between the 1980s and early 1990s. Nickell and Bell do not specify the definition of "low education" in their paper and I suspect that using a different correspondence between training and schooling on the one hand and education on the other may account for some of the different results. Also, in this paper I present employment rate trends, which account not only for changes in unemployment rates but also for changes in labor market participation rates.

(FIGURE 6)

3 Supply and Demand Framework

Consider a demand and supply framework in which the relative skill demand changes because technical change is skill-biased.[10] The three different

candidates (employment rate differences, supply differences, and demand differences) for explaining the countries' differences in relative wage trends can be embedded together in the following production function that combines high and low skill labor with capital to produce output.

$$Y_t = F(K_t, \theta_t^u U_t, \theta_t^s S_t), \tag{1}$$

where K, U and S represent the capital, unskilled labor and skilled labor stocks, respectively. Skill-biased technical change is introduced in the formulae through θ^u and θ^s. In general, technical change will be skill-biased if the growth rate of θ^s is larger than the growth rate of θ^u. Assuming constant returns to scale, the first-order conditions with respect to the input ratios result in the following wage equations:

$$w_t^s = \theta_t^s F_2(\frac{\theta_t^u U_t}{K_t}, \frac{\theta_t^s S_t}{K_t}, 1) \tag{2}$$

$$w_t^u = \theta_t^u F_1(\frac{\theta_t^u U_t}{K_t}, \frac{\theta_t^s S_t}{K_t}, 1), \tag{3}$$

that can be log linearized in the following way:

$$ln(w_t^s) = \alpha_0 + \alpha_1 ln(\frac{\theta_t^s S_t}{K_t}) + \alpha_2 ln(\frac{\theta_t^u U_t}{K_t}) + ln\theta_t^s \tag{4}$$

$$ln(w_t^u) = \beta_0 + \beta_1 ln(\frac{\theta_t^u U_t}{K_t}) + \beta_2 ln(\frac{\theta_t^s S_t}{K_t}) + ln\theta_t^u. \tag{5}$$

Subtraction of both expressions gives the formula for the relative wage equation,

$$\begin{aligned} ln(\frac{w_t^s}{w_t^u}) &= \alpha_0 + \beta_0 + (1 + \alpha_1 - \beta_2) ln\theta_t^s - (1 + \beta_1 - \alpha_2) ln\theta_t^u \\ &\quad + (\beta_1 + \beta_2 - \alpha_1 - \alpha_2) ln(\frac{K_t}{S_t}) + (\beta_1 - \alpha_2) ln(\frac{S_t}{U_t}). \end{aligned} \tag{6}$$

According to equation 6, the wage premium, $ln(\frac{w_t^s}{w_t^u})$, varies in response to (1) changes in the skill-biased technical change components θ^u and θ^s; (2) changes in the capital stock in the presence of capital-skill complementarity, i.e., if $\beta_1 + \beta_2 - \alpha_1 - \alpha_2$ is > 0, and (3) changes in the relative employments. The first two terms are shifts in the relative demand function while the last term is the usual movement along the demand curve.[11] Defining g as the skill-biased technical change and the capital-skill complementarity components together, i.e.,

$$\begin{aligned} g_t &= (1 + \alpha_1 - \beta_2) ln(\theta_t^s - (1 + \beta_1 - \alpha_2) ln(\theta_t^u) \\ &+ (\beta_1 + \beta_2 - \alpha_1 - \alpha_2) ln(\frac{K_t}{S_t}), \end{aligned} \tag{7}$$

and σ as the parameter governing the elasticity of substitution between high and low skilled labor, one can write equation 6 in the following way:

$$ln\frac{w_t^s}{w_t^u} = \gamma_0 + gt - \frac{1}{\sigma} ln\frac{S_t}{U_t}. \tag{8}$$

Then, the difference between two countries, i and j, in their relative wage movements can be decomposed in the following way:

$$\begin{aligned} dln(\frac{w^s}{w^u})^i - dln(\frac{w^s}{w^u})^j &= (g^i - g^j) \\ &- \frac{1}{\sigma}(dln(\frac{Sup^s}{Sup^u})^i - dln(\frac{Sup^s}{Sup^u})^j) \\ &- \frac{1}{\sigma}(dln(\frac{Erate^s}{Erate^u})^i - dln(\frac{Erate^s}{Erate^u})^j), \end{aligned} \tag{9}$$

where Sup^l represents the supply of labor input l, $Erate^l$ represents the employment rate (employment over supply or 1-unemployment rate) of labor input, l and

$$ln(\frac{S}{U}) = ln(\frac{Sup^s}{Sup^u}) + ln(\frac{Erate^s}{Erate^u}). \tag{10}$$

Within this framework, one could then posit three scenarios to explain why relative wages increased faster in country i than in country j. Scenario 1: Supply differences (second term on the right hand side); Scenario 2: differences in the wage setting institutions (third term on the right hand side), or Scenario 3: relative demand change differences (first term on the right hand side).

I will take the simplifying assumption that relative skill supply is completely inelastic. This assumption implies that all supply changes are driven by shifts in supply rather than being supply responses to changes in the price

of skill. This assumption implies also that I will not be able to deal with the sources of supply differences across countries. However, I can still deal with the question as to whether supply changes overall are or not important determinants of wage inequality across countries.

Setting the value of the elasticity of substitution between high and low skill labor (σ) imposes a value for g (and vice versa). I will borrow from the existing literature the estimated values of the elasticity of demand (σ). A test for my model will be to see whether, the demand shifts (g) are not radically different across countries, given σ. A justification for this test would come from the fact that international trade and technological change are the two main suspects behind the increase in the relative demand for skilled labor across advanced economies, and one expects the magnitude of these changes to be similar across these economies.

4 High and Low Skill Labor

4.1 Skill Proxy: Occupation *vs.* Education

Theories have not yet clarified if, for example, skill-biased demand change has made education more relevant in all occupations or if it altered the occupational structure in favor of those that employ more educated individuals. Empirically, identification of the source of the changes in relative earnings is made difficult by the fact that these proxies for skill are usually strongly correlated. Some distinction, however, can be made. Consider estimating

the following wage regression:

$$lnw_{it} = \alpha_{0t} + \alpha_{1t} edyrs_{it} + \alpha_{2t} occup_{it} + \alpha_{3t} Z_{it} + \epsilon_{it}, \tag{11}$$

where Z_{it} represents individual characteristics other than education and occupation such as experience, industry and region. For the purpose of this analysis one can consider the following relationship between occupation and education:

$$occup_{it} = \beta_{0t} + \beta_{1t} edyrs_{it} + \gamma_{it} \tag{12}$$

Substituting 12 into 11 yields,

$$lnw_{it} = \delta_{0t} + (\alpha_{1t} + \alpha_{2t}\beta_{1t}) edyrs_{it} + \alpha_{3t} Z_{it} + \mu_{it} \tag{13}$$

Equation 13 shows that the returns to education in a regression that does not consider occupation is the combined effect of two forces, α_1 or a 'pure education' effect, and α_2 or a 'pure occupation' effect weighted by β_1, roughly, the correlation coefficient between occupation and education. Returns to education in an equation like 13 may change because returns to occupation within education (α_2) change, because returns to education within occupation (α_1) change or because of a combination of both forces.

Figure 7 shows the values for α_1, α_2 and the combined effect in a regression of log hourly wages on years of education, occupation of employment, years of experience and region. The results are particularly revealing for the two

countries with the strongest increase in wage inequality, Italy and the U.S. The figure shows that wage inequality increased in the U.S. and in Italy due to the fact that within education returns to occupation increased. However, the returns to education, after controlling for occupation, remained constant.[12]

(FIGURE 7)

This result does not imply that education is unimportant for the determination of skill. This result does neither imply that occupations are an input instead of an output in the skill production process. What this result suggests is that changes in the returns to occupational skills are important and dominate the changes in the returns to education. In other words, given the classification of education and occupation in the data, the occupation variable seems to capture the changes in relative wages better than the education variable. If we had better information about the education of one individual by, for example, knowing the quality of the school or university attended, the specialization or field of concentration, the grades obtained, the description of the courses completed, etc, we would probably find that the education variable explains better that individual's earnings.

(TABLE 2)

Given that the empirical fact to be explained, which is the change in the wage of some individuals relative to others, depends on these individuals' occupation more than on their education, it makes sense to label and to

group individuals according to their occupation. Besides, table 2 suggests that the choice between occupation and education is not irrelevant, since the correspondence between these two variables is far from clear-cut and, what is more important, it varies significantly across countries. The first column in the table shows the proportion of low educated individuals in non-manual occupations divided by the proportion of high educated individuals in manual occupations. This ratio decreases with the average level of education (second column in the table), i.e., the more low educated individuals are in one country, the higher the probability that some of these individuals work in non-manual occupations. Take the Italian number. That number says that the proportion of low educated individuals in non-manual occupations is 54 times higher than the proportion of high educated individuals in manual occupations, and that ratio is more than 80 times higher than in the U.S. The table then suggests that the choice between occupation and education is a relevant one, particularly in the context of international comparisons of wage inequality trends.

4.2 Classifying Occupations into High and Low Skill

Once a decision is made upon which variable will be used to classify individuals as high and low skilled, there is still the need to determine the value or category of that variable that will separate the low skilled from the high skilled.

In this paper, I label an occupation as high or low skilled in each country

by looking at the evolution of this occupation's relative wage and relative employment in that country. More precisely, I rely on the well documented finding by the previous literature, that wage inequality increased during the eighties and nineties because the demand for certain skills increased relative to the demand for other skills. All I need is that the two main suspects behind the relative demand changes, namely technological change and trade, have favored the skills employed in certain occupations at the expense of others, making then sense to identify skilled occupations by looking for a simultaneous increase of relative quantities and prices.

Definition: occupation "i" is high skilled if the relative demand for occupation "i" increased between 1983 and 1994.

Obviously, my classification of occupations into high and low skilled assumes that demand shifts have taken place. Apart from the fact that my data supports this assumption, it is not the purpose of this paper to challenge the finding of the existing literature: that relative demand for certain skills increased during the eighties and nineties; the purpose rather is to rely on this finding and on the fact that the returns to occupation have changed in an important way, to label individuals as high and low skill.

Furthermore, one would expect that the resulting classification of occupations into high and low skilled has an intuitive appeal, by grouping together occupations that are similar from the point of view of the tasks involved. Also, one would expect the implied relative demand shifts to be of similar magnitude across countries, since it would be difficult to argue that perva-

sive phenomena such as technological change and trade have affected various developed economies in a rather different way. As I will show later, the methodology that I use here to classify occupations into high and low skilled results in grouping together occupations that are similar and in relative demand shifts of similar magnitude across countries.

Tables 3-6 show the results of considering high skilled those occupations that have experience simultaneously: (i) an increase in their share of total employment, and (ii) either increasing or constant wage relative to the mean.[13]

(TABLE 3)

(TABLE 4)

(TABLE 5)

(TABLE 6)

For the three countries that present increasing relative wages–the U.S., Italy and to a lesser extent Germany–columns (3) and (6) in each table show that, with almost no exception, those occupations with wages over the mean, that employ more educated individuals and are related to non-manual tasks have experienced simultaneous increases in the employment share and wages relative to the mean, suggesting that positive relative demand shocks affected them during this period. For the two countries with lower increases in wage inequality, a positive demand shift is implied when wages remain constant relative to the mean but the share of employment increases.[14]

According to these pieces of evidence, I classified occupations into low and high skill groups as indicated in the tables. Basically, manual and service occupations are classified as low skill occupations and non-manual occupations (excluding services) as high skill occupations in all the countries except Italy for which a blue and white collar classification was the only one available. Within the broad skill groups (manual and non-manual) changes in relative wages and employments are pervasive. Aggregation does not hinder, then, important diversity in the behavior of the different occupational groups included in one aggregate.

4.3 Aggregates of Skill: Prices and Quantities

Once I have identified occupations as high and low skill, an individual's education makes her a high or low skill individual with certain probability, i.e., the probability that an individual with that education is employed in a high or low skill occupation. This way I can identify the skill of not only employed individuals but also unemployed individuals (who by definition do not have an occupation), provided that the correlation between education and occupation is similar among the employed and the non-employed. This is an important assumption.

One would be tempted to think that the unemployed, were they offered a job, would work in lower skill occupations compared to the employed, even after controlling for education. If this is the case, I am underestimating the rate of unemployment among the low skilled. On the other hand, it has

been widely documented that many unemployed in Europe are young adults waiting to find a job in accordance with their high level of education.

With respect to the aggregation procedure, I consider a simple efficiency units assumption, according to which the contribution of each individual to the high and the low skill groups depends on the probability this individual belongs to the high and the low skill group and on the time-invariant wage paid to this individual's educational-occupational group. Then, the aggregate high skill employment (E_t), supply (Sup_t) and non-employment (NE_t) in year t are calculated as follows:

$$E_t = \sum_i \sum_{j=hs} wks_{i,t} \cdot \Pr(occup_j \mid edyrs_i) \cdot w\left(edyrs_i, occup_j\right) \tag{14}$$

$$Sup_t = \sum_i \sum_{j=hs} {}_{i,t}52 \cdot \Pr(occup_j \mid edyrs_i) \cdot w\left(edyrs_i, occup_j\right) \tag{15}$$

$$NE_t = \sum_i \sum_{j=hs} (52 - wks_{i,t}) \cdot \Pr(occup_j \mid edyrs_i) \cdot w\left(edyrs_i, occup_j\right) \tag{16}$$

where, i indexes individuals, j indexes occupation, $wks_{i,t}$ is the number of weeks worked by individual i in year t, $\Pr(occup_j \mid edyrs_i)$ is the probability that one individual with those years of education works in occupation j, and $w\left(edyrs_i, occup_j\right)$ is the time-invariant average wage of individuals with that level of education and employed in that occupation.

The price of high skill labor in period t will be a weighted average of the wages of the different educational groups in each occupation at each

moment in time (W_{dj}^t) where the weights, Sh_{dj}, will be the proportion of weeks employed by each educational group in each occupation, and the weights to add occupations, Sh_j, will be the proportion of efficiency weeks employed by each occupation within the high or the low skill group over the whole period:

$$HSWAGE_t = \sum_{j=hs} Sh_j \cdot \sum_d W_{dj}^t \cdot Sh_{dj} \tag{17}$$

5 Results

Table 7 and figure 8 show the results of applying the methodology to each one of the countries. These results should be interpreted in a two-step fashion. The first step looks the extent to which relative wage and employment movements in these four countries are consistent with a similar relative demand shift in each of them.

(TABLE 7)

(FIGURE 8)

Both table 7 and the last panel of figure 8 speak in favor of a story where a similar demand shock affected the U.S., Germany and the U.K. In terms of figure 8, if these three countries faced similar demand changes, the relative employment and wage trends of the country with the lowest increase in wage inequality should be an envelope of the trends of the country with the next lower increase. The trends in the figure are consistent with this fact, that

is, the ranking with respect to changes in relative wages (U.S. 9.3 log points, Germany 1.3 log points, and U.K. -0.8 log points) is reversed when looking at the relative employment changes (U.K. 33.4 log points, Germany 28.2 log points, and the U.S. 12.1 log points).

Equation 8 can be used to gain further insight into how similar the relative demand shifts may have been between these countries. In particular, one is interested in those values of the elasticity of substitution and relative demand changes that are common to the four countries and so fit their different relative wage and employment changes. Figure 9 shows the relationship between various values of the elasticity of substitution and the implied demand changes in each of the countries. The Italian numbers show that either the relative demand shock or the elasticity of substitution needed to explain its relative price and employment changes is too large compared with the values in the other countries. Instead, an elasticity of substitution between high and low skill labor around 2.1 implies almost identical demand shifts (0.15 log points for the ten year period) for each of the three remaining countries, the US, Germany and the UK. Since there are no strong reasons a priori to believe that these countries have been affected very differently by these demand shocks during this period of time, this result is taken as speaking in favor of the methodology used here.

(FIGURE 9)

Given the results from earlier studies an elasticity of substitution of 2.1 seems within the range of reasonable values. Katz and Murphy (1992), for example, show that an elasticity of substitution of 1.4 between high and low skill labor fit the trends in relative wages and employments in the US during the seventies and the eighties under the assumption of a constant growth in relative demand. Murphy et al. (1998) show that similar values of the elasticity of substitution fit the differential trends in relative wages and employment between Canada and the US during the eighties and nineties, and Card and Lemieux (2000) show that an elasticity of substitution of 2.5 explains the differences in the age relative skill premiums between the U.S., Canada and the U.K.

With respect to step 2, one can now answer the following question: To what extent are differences in the evolution of relative supply and relative non-employment rates responsible for the different evolution of relative wages in the countries with similar demand shifts?

Before moving to table 8, the first two panels in figure 8 suggest that supply differences will be the main story behind the U.S.-U.K. contrast and that non-employment and supply differences will share the explanation of the German-U.S. contrast. While the U.K. relative supply change more than doubled the change in the U.S. (30.8 versus 12.5 log points), the relative employment rate increase in Germany outweighed the one seen in the U.S. by 8.7 log points over the same period of time.

(TABLE 8)

Consistently, the data In table 8 show that the much smaller increase in relative wages in Germany than in the U.S. (8 log points difference) can be explained equally by a faster increase in Germany than in the U.S. in the supply of skilled individuals (44%) and by a larger increase in Germany than in the U.S. in the non-employment rate of low skilled individuals (52%). In other words, the sole effect of the more rapid growth of skill supply in Germany would have depressed German relative wage growth by 3.5 log points compared to the U.S. However, relative wage growth in Germany was 8.0 log points lower than in the U.S. The extra 4.2 log points difference is explained by an increase in the relative employment rate of the high skilled in Germany versus their low skilled counterparts.

With respect to the U.S.-U.K. comparison, the data show that the contrast between their relative wage movements can be almost entirely explained by a larger increase in the supply of skilled individuals in the U.K.

I leave unexplained the different changes in relative supply across countries. These can be due to different responses to similar demand changes or to demographic factors such as the delayed baby-boom in Europe or migration flows of different skill intensity. Parikh and Van Leuvensteijn (2003), find some evidence that white-collar workers migrated from East-Germany to West-Germany after the process of reunification in response to the higher skill premium in West-Germany.

(FIGURE 10)

For comparative purposes, figure 10 shows the relative trends and the implied relative demand changes for the educational grouping of the data.[15] The figure shows that movements in relative prices and quantities in these countries are more inconsistent with similar relative demand changes than in the occupational grouping of the data. In this respect, both Italy and Germany present smaller growth in both their relative supplies and their relative wages compared to the U.S. and the U.K. As a consequence, figure 9 shows that for all values of the elasticity of substitution between high and low skill labor the implied relative demand change in Italy and Germany is much smaller than in the U.S. and U.K. It is important to note that the U.S.-U.K. comparison is less affected by the educational grouping of the data, a fact that is consistent with table 2 showing that Italy and Germany had the largest relative proportion of low educated individuals employed in high skill occupations.

6 Conclusions

Between 1983 and 1994 wage inequality increased at an unprecedented speed in the U.S. but not in many European countries. The previous literature had already named the principal suspects to explain this and similar contrasts. In this paper, I have analyzed the micro-data available in the U.S., Germany, Italy and the U.K., to asses the relative importance of each of them, namely, relative supply differences, relative demand differences and relative employment rate differences.

Two facts motivated the approach that I followed to answer this question. First, changes in the returns to occupation are more important than changes in the returns to education in explaining the wage inequality trends. Second, the proportion of individuals with a high level of education varies significantly across countries, more than the proportion of manual and non-manual workers. Together, these imply that occupation is a better proxy for skill than education, when it comes to explaining the changes in wage inequality between 1983 and 1994.

I classified occupations as high skilled if their relative demand increased between 1983 and 1994. By using the correspondence between occupation and education, I was able to construct aggregates of skill that were comparable across countries. I embedded these aggregates in a supply and demand framework and decomposed the cross-country difference in inequality trends in differences in relative supply, relative demand and relative unemployment trends.

The results can be summarized as follows. (1) The relative demand for skilled labor increased in Germany, the U.S. and the U.K. to a similar extent between 1983 and 1994. This supports the hypothesis that the two main suspects behind demand shocks, technological change and trade, have had a similar impact in developed economies. (2) These similar demand shocks have been coupled in Germany and in the U.K. by an extraordinarily rapid increase in skill supply. This explains the milder increase in wage inequality in these countries compared to the U.S. (3) In Germany, the increase in skill

supply was not enough to offset the demand shock. Despite this, relative wages remained rigid and this caused the rate of unemployment among the low skilled to increase.

The results also suggest that supply and demand conditions in Italy are different than in the other countries. In particular, the implied demand shock is significantly bigger in Italy than in the U.S., the U.K. and Germany. This result has to be taken with caution, considering the smaller size of the Italian sample and the fact that the occupation variable presents only two categories (blue-collar and white-collar). Also, the analysis might be underestimating the rate of unemployment among the low skilled. I have identified the skill of the unemployed by looking at the correspondence between occupation and education among the employed and hence, I have probably underestimated the proportion of the unemployed who are low skilled.

Finally, I left unexplained the differences in relative supply across countries. Whether these can be explained by purely demographic factors, such as the delayed baby-boom in Europe, is an important question for future research

Notes

[1]For two recent studies, see Haskel and Slaughter (2002) and Acemoglu (2002).

[2]Theories linking international trade to wage inequality have suffered from bigger criticism. Haskel and Slaughter (1999) finds that international trade, and not technical change, is the main driving force behind U.K.'s increase in inequality during the eighties. Haskel and Slaughter (2003), however, find little evidence that international trade affects relative wages in the U.S. Welsch (2004), finds that export growth in Germany during the second half of the 1980s is inversely linked to the high-skill intensity of labor. Green, Felstead and Gallie (2003), argue that the relationship between trade and skills is weak and that computer usage is very strongly associated with the process of upskillin in the U.K.

[3]Although this paper focuses on the changes in these four countries, other studies found similar differences among other OECD economies. See Freeman and Katz (1995), and Tachibanaki (1998) for various individual and cross country analyses.

[4]Acemoglu (2003a) is one of the very few exceptions.

[5]This last group of studies, sometimes using the same set of countries, has found either opposite or non-conclusive evidence when looking at the relative unemployment rate trends of the different education and experience groups. See for example Blau and Kahn (1996) and Krueger and Pischke (1997) for evidence in favor and against the role of institutions in Germany. See Edin and Topel (1997), Card, Kramarz and Lemieux (1995) for other comparative studies

[6]I thank those who made it possible for me to access these data. I thank Kevin M. Murphy for providing the CPS data, Antonio Filippin and Andrea C. Ichino for allowing me to access the BI data and Syracuse University together with the German Institute for Economic Research for providing the GSOEP data.

[8]This is consistent with the fact that the supply and the employment of more skilled individuals increased during this period of time.

[9]In a regression that controls for education, occupation and experience, I find that residual wage inequality did increase in the U.K. during this period of time. This seems to explain the observed increase in wage inequality across different deciles of the wage distribution. (figure 3).

[10]A different model would be needed to incorporate the effect of international trade, but the nature of the decomposition analysis that I present later would be the same.

[11]This flexible specification embeds more specific production functions easily. For example, Murphy et al. (1998) specify the following production function to study the different growth in relative wages between the U.S. and Canada:

$$Y_t \quad = \quad F(K_t, \theta_t^u U_t, \theta_t^s S_t) = K_t^{\alpha}[\gamma(\theta_t^s S_t)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)(\theta_t^u U_t)^{\frac{\sigma-1}{\sigma}}]^{\frac{(1-\alpha)\sigma}{\sigma-1}},$$

where σ governs the elasticity of substitution between high and low skill labor. Assuming a linear time trend for the relative demand change, i.e., assuming $\frac{d\frac{\theta_t^s}{\theta_t^u}}{dt} = g$, one can write the following relative wage equation:

$$ln\frac{w_t^s}{w_t^u} = \gamma_0 + \frac{\sigma - 1}{\sigma} gt - \frac{1}{\sigma} ln\frac{S_t}{U_t}.$$

Since $\beta_1 + \beta_2 = \alpha_1 + \alpha_2$ and $\beta_1 - \alpha_2 = -\frac{1}{\sigma}$, changes in the relative demand schedule come solely from skill-biased technical change.

[12]The returns to occupation and education are more similar for Germany and the U.K.. This is reasonable considering that wage inequality barely changed in these two countries from 1983 to 1994.

[13]In the case of constant relative wage and increasing employment share, a positive demand shift exists as long as the elasticity of the demand for that occupation is less than ∞ (in absolute value).

[14]The only exception being managerial occupation in the U.K. Given the nature of this occupation and the small decrease of its relative wage, I have included it in the high skill group.

[15]In this case, the high skill group is formed by those individuals with more than high school and the low skill group by those individuals with high school or less.

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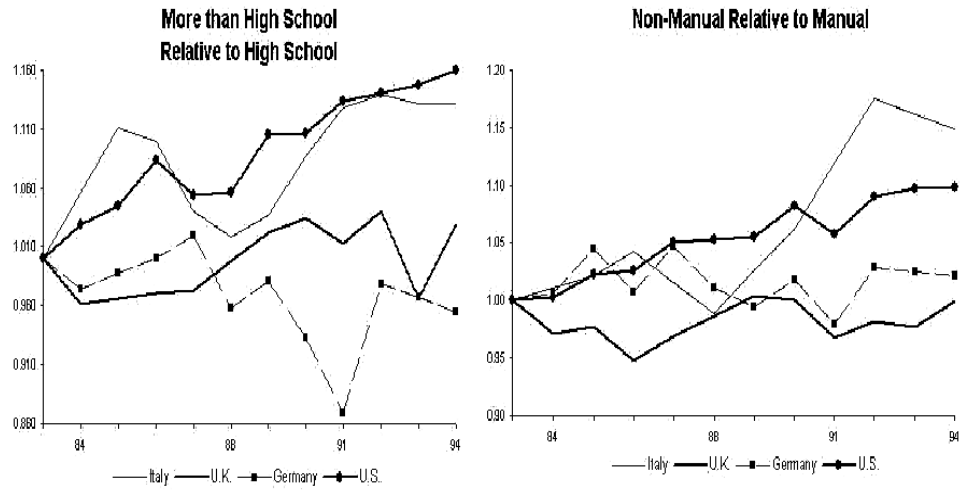
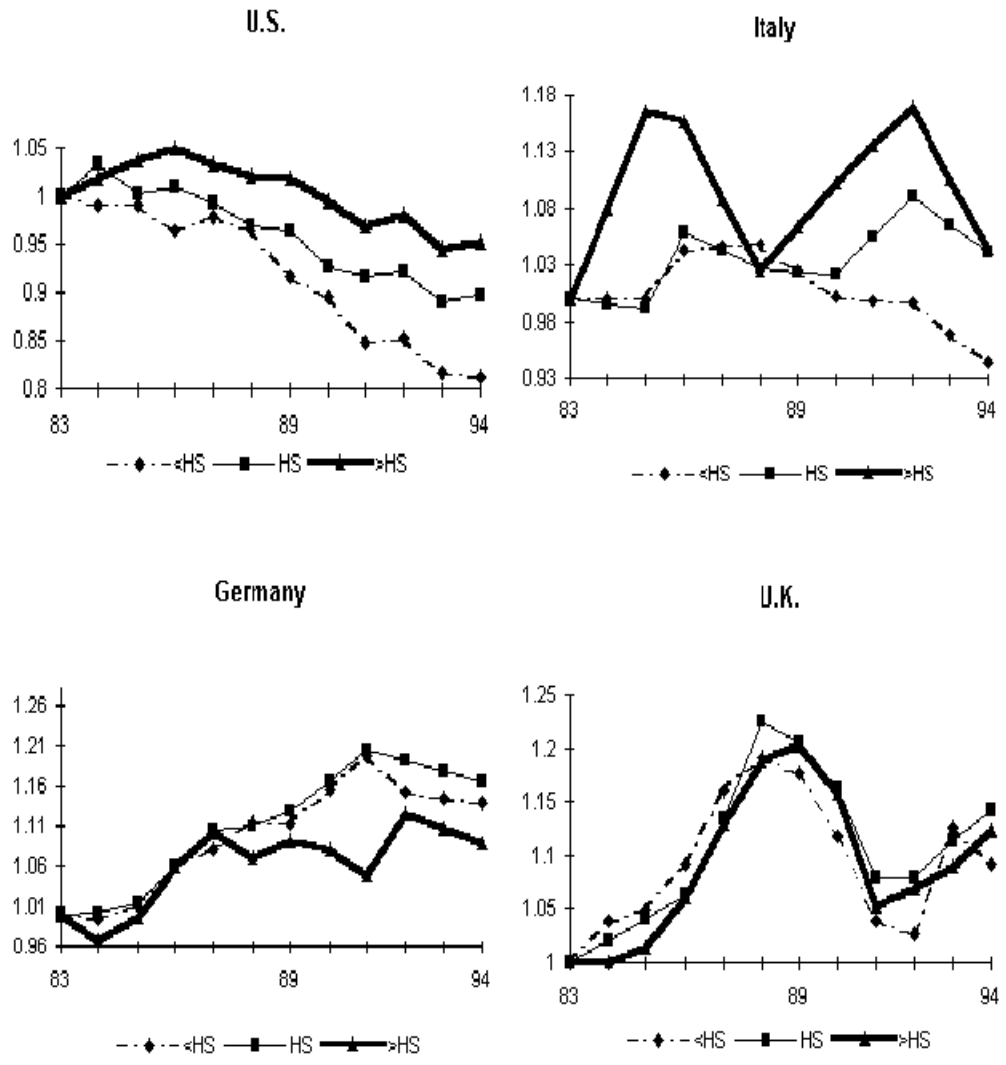
Figures and Tables

Figure 1: Change in Relative Wages. 1983-1994



Source: Author's calculations from the CPS, BI, GSOEP and GHS data sets.
Note: < HS: for Italy, less than high school diploma; for the US, less than 12 years of education completed; for Germany, less than eleven years of education completed; for the U.K., no qualification. HS: for Italy, individuals with high school diploma completed; for the US, individuals with 12 years of education completed; for Germany, individuals with 11 or 12 years of education completed; for the U.K., individuals with GCE 'O' level or similar, clerical, commercial qualifications or similar. > HS: for Italy, with college degree; for the US and Germany, with more than 12 years of education; for the UK, with college or university degree qualification, with GCE 'A' level, nursing qualification or similar. All measures are time-invariant weighted averages of the real hourly wages in the different industry and educational (occupational) groups.

Figure 2: Log Real Hourly Wages. Educational Groups.



Source: Author's calculations from the CPS, BI, GSOEP and GHS data sets.
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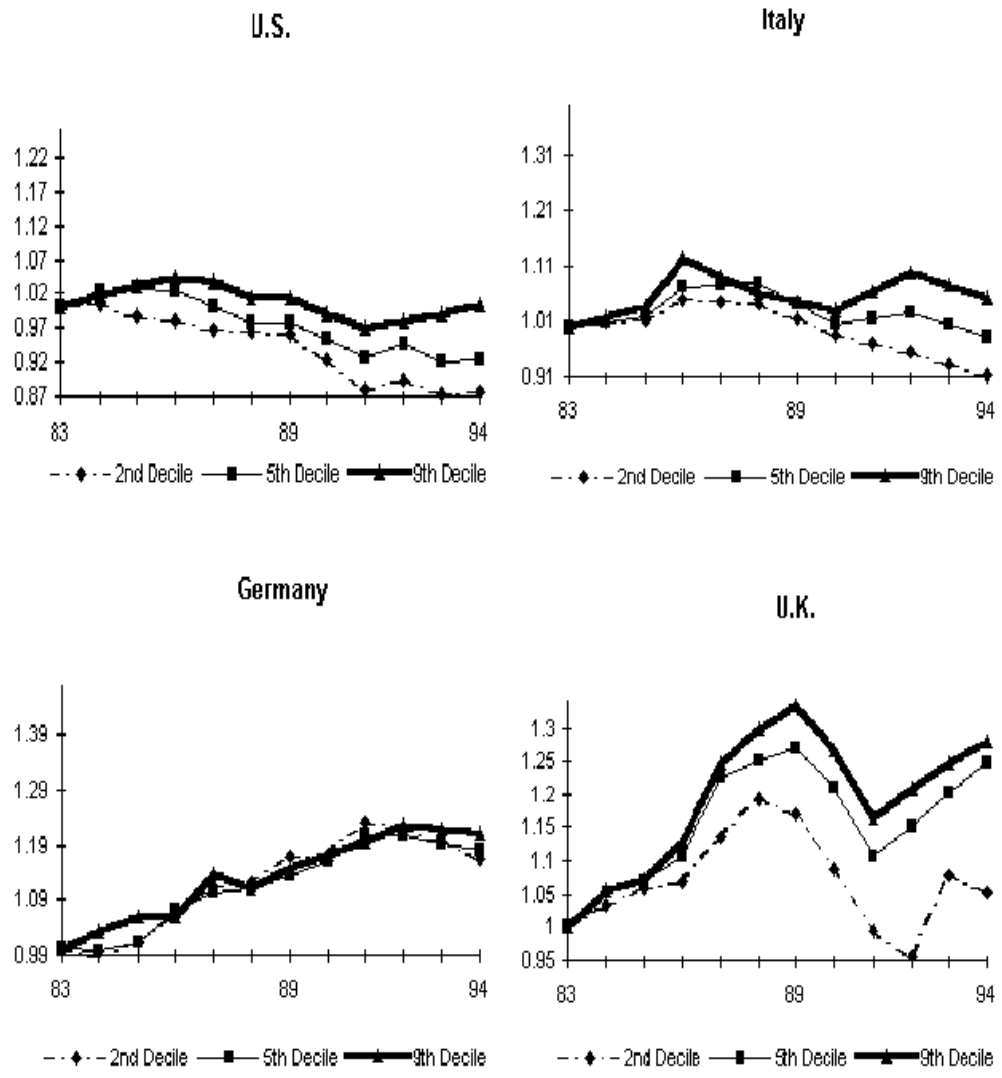
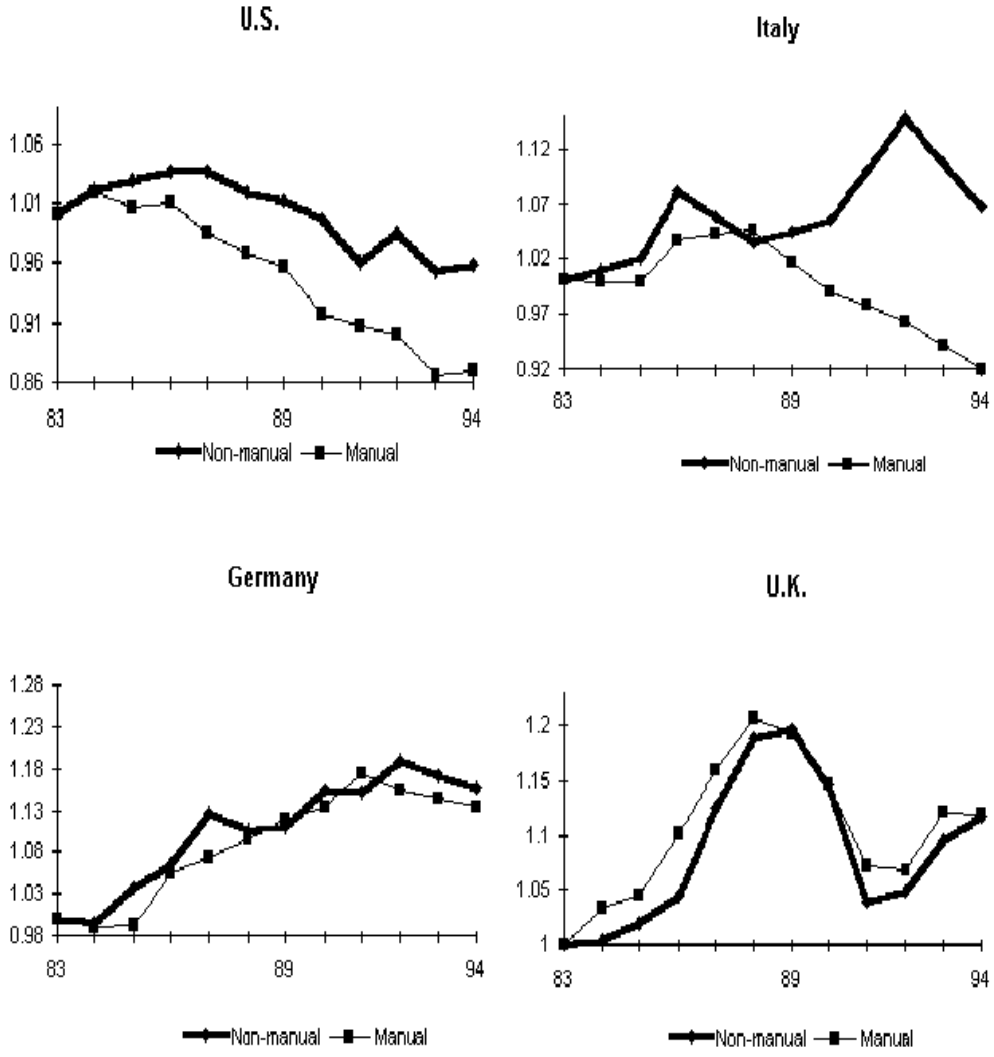
Figure 3: Log Real Hourly Wages. Decile Position on the Wage Distribution.



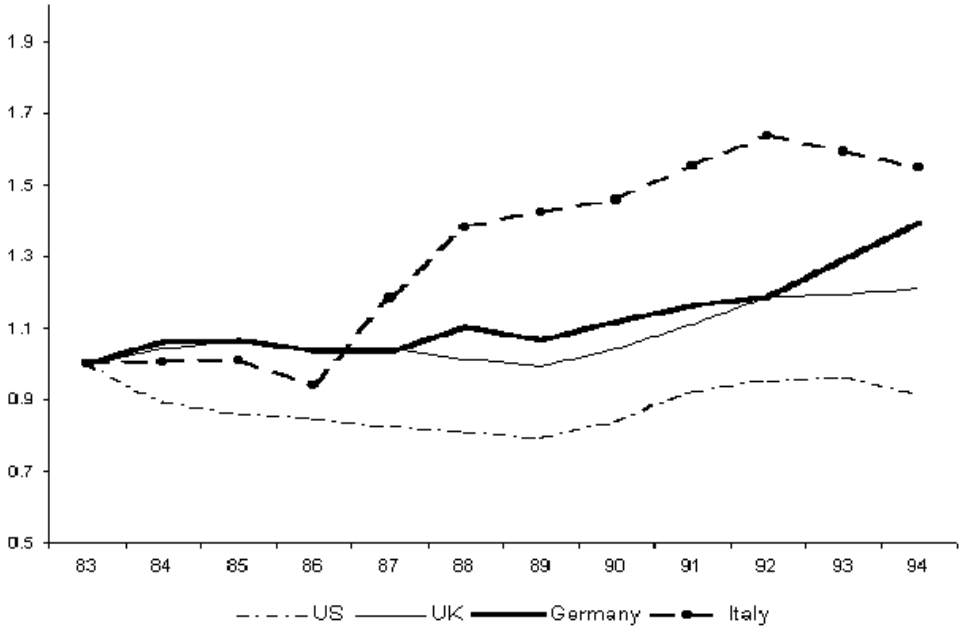
Source: Author's calculations from the CPS, BI, GSOEP and GHS data sets.
Notes: All measures are time-invariant weighted averages of the real hourly wages in the different industry, occupational and educational groups.

Figure 4: Log Real Hourly Wages. Occupation of Employment.



Source: Author's calculations from the CPS, BI, GSOEP and GHS data sets.
Notes: Non-manual occupations for the US and Germany are technical and professional, managers, sales, administrative and services. Non-manual occupations for the UK are technical and professional, managers, services and other-non-manual. Manual occupations for the US and Germany are craftsmen, operatives and laborers. Manual occupations for the UK are manual supervisors, manual skilled, manual semiskilled and manual unskilled. In the Italian data individuals report themselves as either blue collar (manual) or white collar (non-manual) employees. All measures are time-invariant weighted averages of the real hourly wages in the different industry, occupational and educational groups.

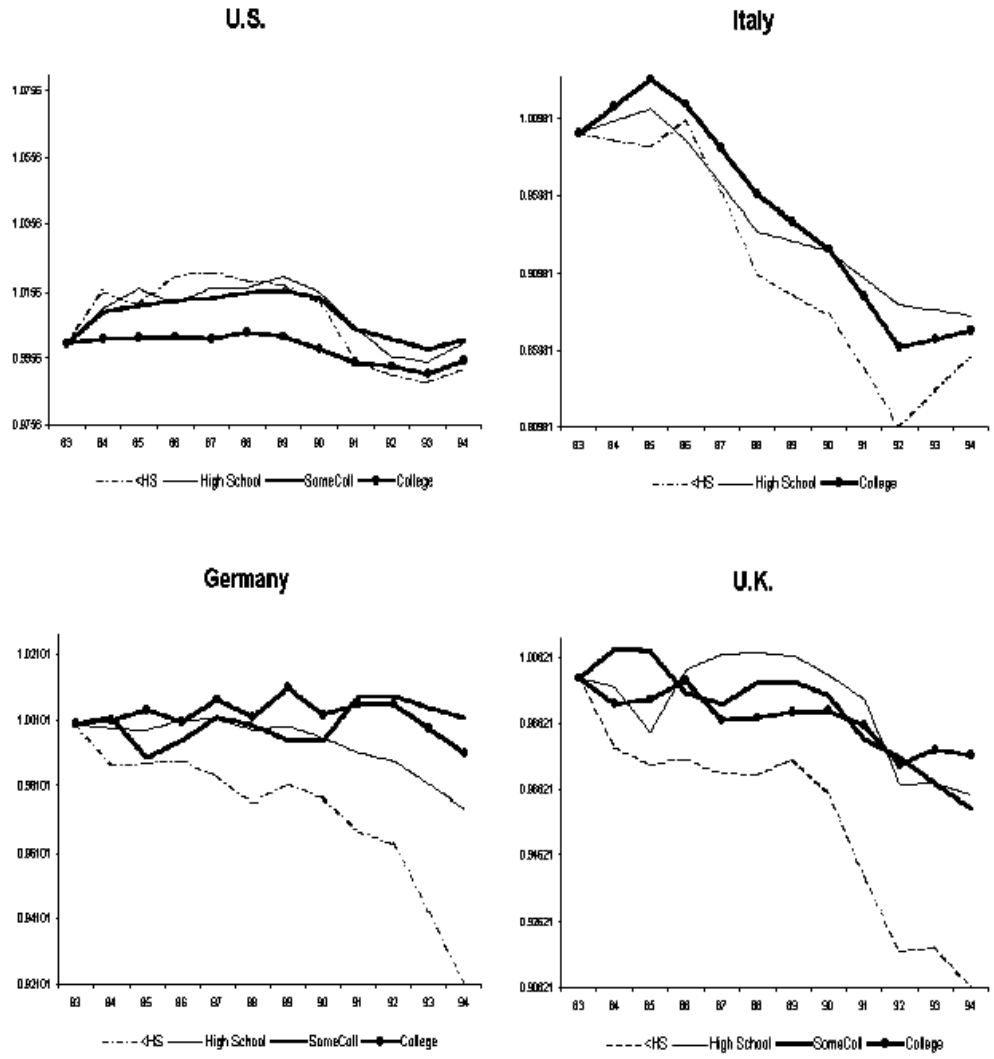
Figure 5: Evolution of Non-Employment Rates.



Source: Author's calculations from CPS, GSOEP, BI and GHS data sets.

Notes: Indexed to 1 in 1983. Percentage over the civilian labor force. The non-employment measures group the unemployed and the out-of-the-labor-force together.

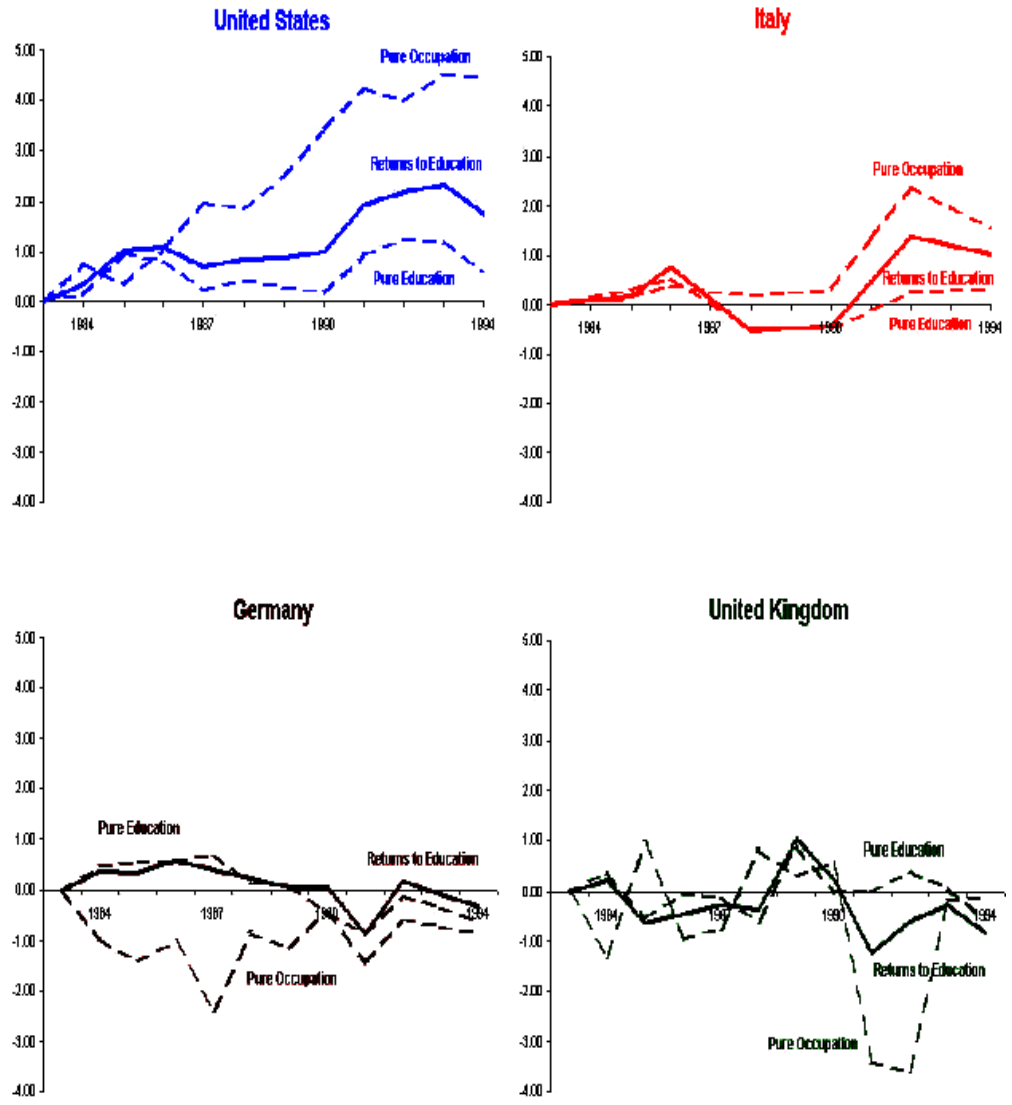
Figure 6: Evolution of Employment Rates



Source: Author's calculations from the CPS, BI, GSOEP and GHS data sets.

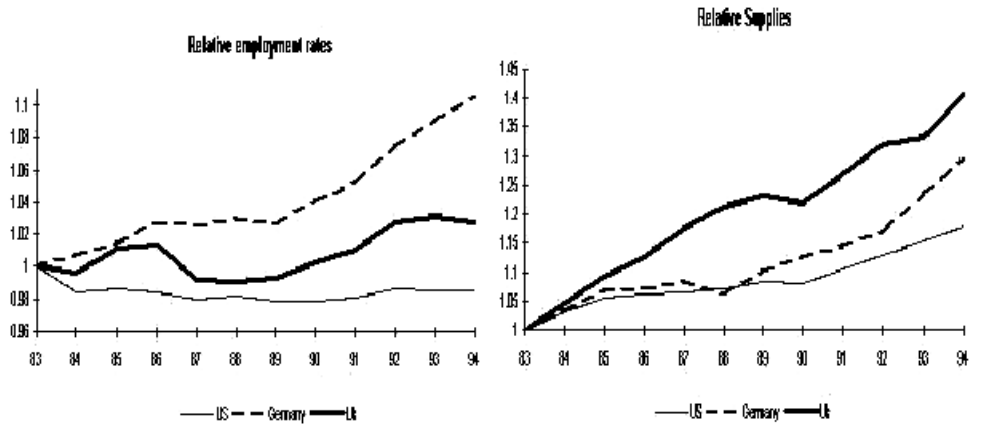
Notes: Values indexed to 1 in 1983. Employment rate is defined as total employment over total supply of the educational group and equals 1-unemployment rate. To allow maximum comparability among the U.S., Germany and the U.K., the size of the vertical axis is different from the Italian one. In the Italian data set individuals report only the highest degree completed, preventing the distinction between 'some college' and 'college' individuals.

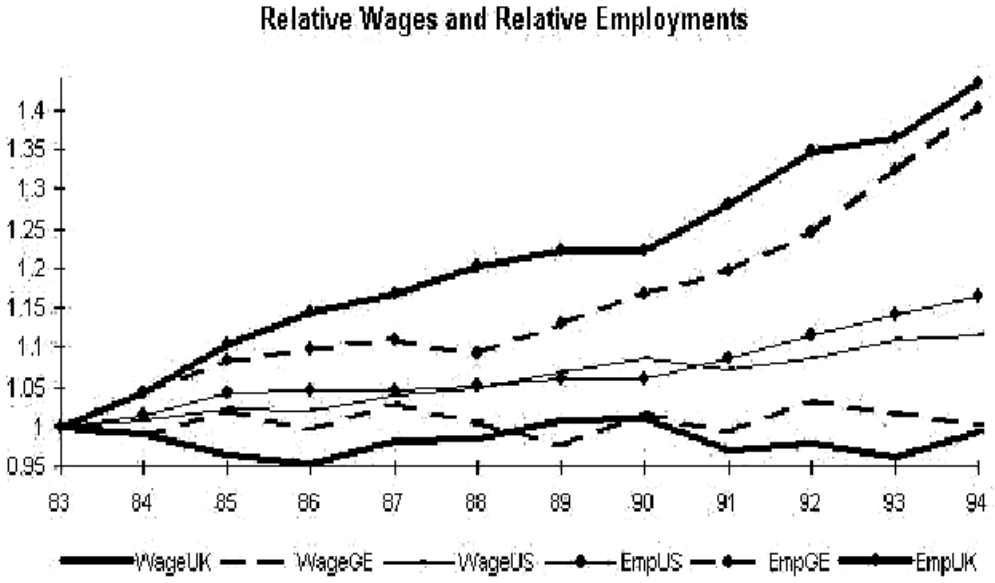
Figure 7: Within education (occupation) returns to occupation (education).



Source: Author's calculations from the CPS, BI, GSOEP and GHS data sets.
Note: Returns to occupation (education) are the coefficient of the occupation variable (education) in a regression of log hourly wages on occupation, years of education, region, and years of experience. Eight occupations, and nine regions in the U.S. regression. Two occupations and three regions in the Italian regression. Italian values are the averages of three year periods.

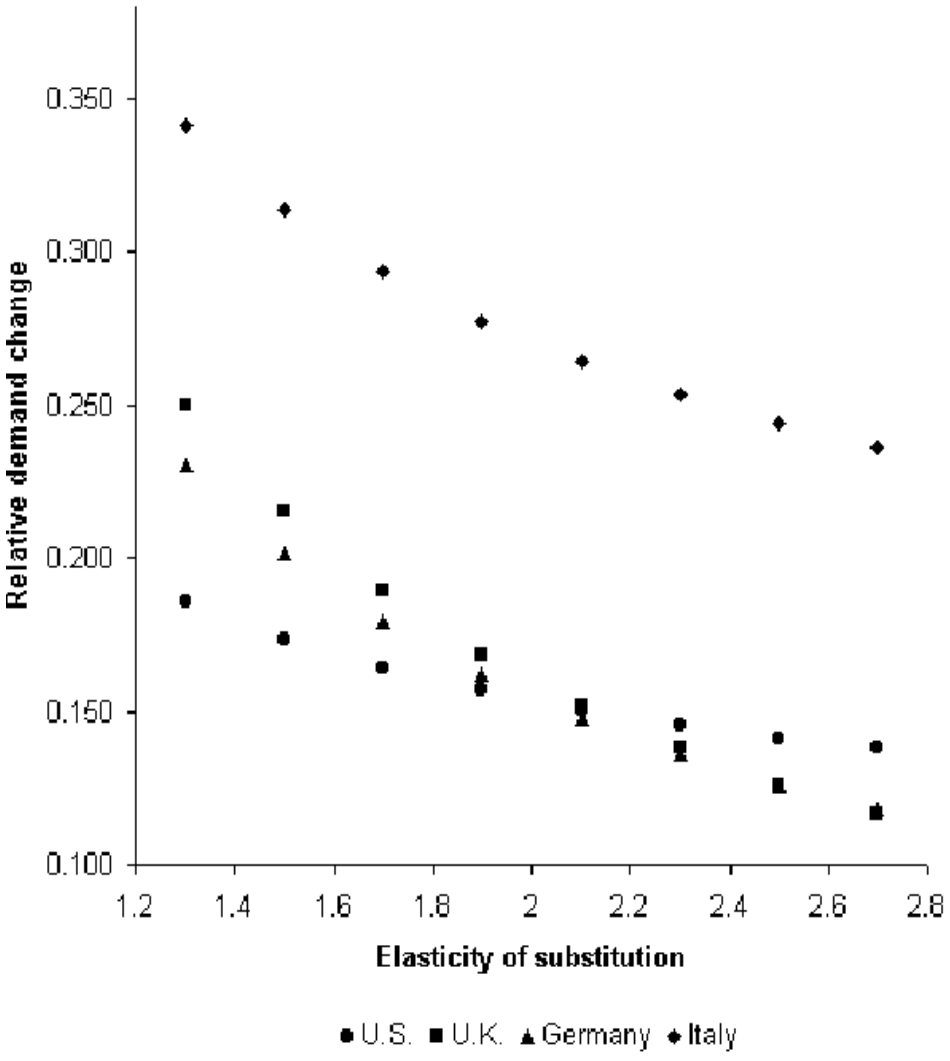
Figure 8: Relative Prices and Quantities. High over Low Skill.





Source: Author's calculations from CPS, BI, GSOEP and GHS data sets.
Note: Employment rate is defined as total employment over total supply of the skill group in particular and equals 1 minus the unemployment rate. All measures constructed accordingly to the methodology described. All measures indexed to 1 in 1983. The table shows the changes in the log.

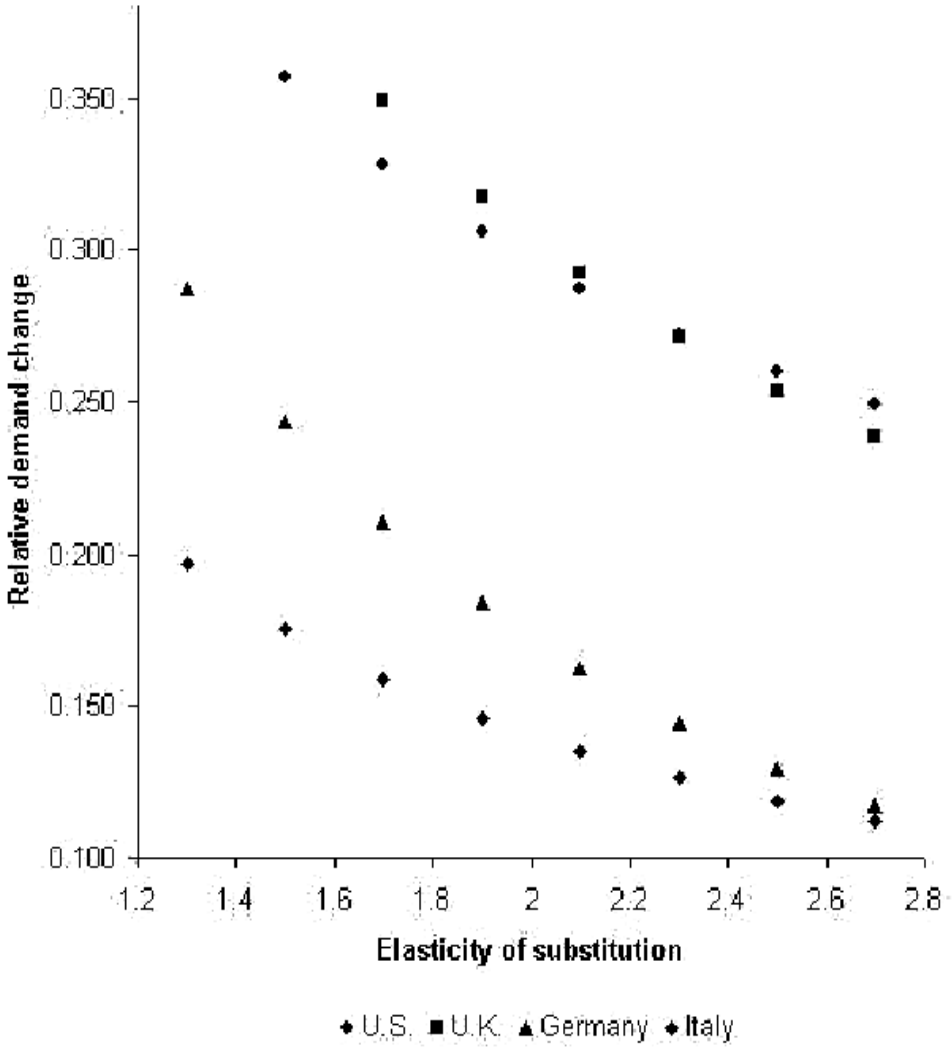
Figure 9: Relative Demand Change and Elasticity of Substitution between High and Low Skill. Occupational Grouping.



Source: Author's calculations from CPS, BI, GSOEP and GHS data sets.

Note: The implied relative demand change measure corresponds to the change for the overall period between 1984 and 1993.

Figure 10: Relative Demand Change and Elasticity of Substitution between High and Low Skill. Educational Grouping.



Source: Author's calculations from CPS, BI, GSOEP and GHS data sets.

Note: The implied relative demand change measure corresponds to the change for the overall period between 1984 and 1993.

Table 1: Sample Shares of Educational Categories

	Less than High School			With High School			With Some College		
	83-85	92-94	Δ	83-85	92-94	Δ	83-85	92-94	Δ
Italy	74.80	67.39	-0.10	19.10	25.24	0.28	.	.	.
Germany	29.02	26.17	-0.10	53.48	52.33	-0.02	8.64	9.92	0.14
US	21.64	16.51	-0.27	38.83	34.15	-0.13	17.40	24.77	0.35
UK	47.90	32.90	-0.37	20.89	24.88	0.17	21.35	28.28	0.28

	With College			Less or Equal than High School			More than High School		
	83-85	92-94	Δ	83-85	92-94	Δ	83-85	92-94	Δ
Italy	6.08	7.35	0.19	93.91	92.64	-0.01	6.08	7.35	0.19
Germany	8.84	11.55	0.27	82.51	78.51	-0.05	17.49	21.48	0.20
US	22.13	24.56	0.10	60.47	50.67	-0.18	39.52	49.33	0.22
UK	9.86	13.94	0.35	68.79	57.77	-0.17	31.20	42.22	0.30

Source: Author's calculations from the CPS, BI, GSOEP and GHS data sets.

Notes: < HS: for Italy, less than high school diploma; for the US, less than 12 years of education completed; for Germany, less than eleven years of education completed; for the U.K., no qualification. HS: for Italy, individuals with high school diploma completed; for the US, individuals with 12 years of education completed; for Germany, individuals with 11 or 12 years of education completed; for the U.K., individuals with GCE 'O' level or similar, clerical or commercial qualifications. > HS: for the US and Germany, with 13 to 15 years of education; for the UK, with GCE 'A' level, nursing qualification. CO: for Italy, with college degree; for the U.S. and Germany, with 16 or more years of education; for the U.K. with college or university degree. All measures are time-invariant weighted averages of the real hourly wages in the different industry and occupational groups.

Table 2: Correspondence between Occupation and Education.

	$\frac{Uneducated-non-manual}{Educated-manual'}$	$\frac{More-than-High-School}{Non-manual}$
Italy	54.25	0.38
Germany	1.84	0.88
U.K.	1.05	1.00
U.S.	0.65	1.15

Source: Author's calculations from the CPS, BI, GSOEP and GHS data sets.

Notes: Ten or less years of experience. Uneducated-non-manual is the proportion of efficiency weeks of individuals with high school or less employed in non manual occupations (white-collar in Italy). Educated-manual is the proportion of efficiency weeks of individuals with more than high school employed in manual occupations (blue-collar in Italy) All series are averages over the entire period.

Table 3: Evolution of Prices and Quantities, 1983-1994: U.S. Occupational Classification.

	Employment Shares			Wages from Mean				Avrg
	1984	1993	Δ	1984	1993	Δ	Skill	Educat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1 TecPrf	12.60	13.80	0.091	0.35	0.44	0.08	**HS**	16
2 Manag	22.22	23.70	0.064	0.29	0.34	0.05	**HS**	14
3 Sales	7.81	8.38	0.071	0.07	0.18	0.11	**HS**	14
4 Admin	6.60	6.80	0.030	0.04	0.00	-0.04	**LS**	13
5 Craft	24.91	23.85	-0.044	0.08	0.06	-0.01	**LS**	12
6 Servic	3.12	2.89	-0.078	-0.49	-0.54	-0.05	**LS**	12
7 Operat	17.71	16.07	-0.098	-0.10	-0.15	-0.05	**LS**	11
8 Labore	4.99	4.49	-0.104	-0.25	-0.34	-0.09	**LS**	11

Source: Author's calculations from CPS data set.

Note: (1), (2) Employment measures are time-invariant value-weighted sums of the employments of each education-industry group within each occupational category, the weights being the average hourly wages of each education-industry group over the entire period. (3) The change in the employment shares is expressed as the difference in the log shares in each period. (4), (5) Wage measures are time-invariant weighted averages of the hourly wages of each education-industry group within each occupation, the weights being the employment shares of each education-industry group over the entire period. The measures are the difference between the log wage and the log mean wage of the period. (8) Average years of education.

Table 4: Evolution of Prices and Quantities, 1983-1994: German Occupational Classification

	Employment Shares			Wages from Mean				Avrg
	1984	1993	Δ	1984	1993	Δ	Skill	Educat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1 TecPrf	11.66	15.83	0.306	0.32	0.32	0.00	**HS**	16
2 Manag	8.25	9.88	0.180	0.27	0.29	0.02	**HS**	13
3 Sales	2.41	2.77	0.137	0.09	0.13	0.04	**HS**	13
4 Admin	8.69	9.38	0.076	0.07	0.14	0.07	**HS**	12
5 Craft	41.14	37.75	-0.086	-0.12	-0.09	0.03	**LS**	11
6 Servic	2.13	1.97	-0.078	-0.20	-0.33	-0.13	**LS**	11
7 Operat	23.52	20.62	-0.132	-0.16	-0.15	0.01	**LS**	10
8 Labore	2.16	1.77	-0.202	-0.27	-0.30	-0.03	**LS**	9

Source: Author's calculations from GSOEP data set.

Note: (1), (2) Employment measures are time-invariant value-weighted sums of the employments of each education-industry group within each occupational category, the weights being the average hourly wages of each education-industry group over the entire period. (3) The change in employment share is expressed as the difference in the log shares in each period. (4), (5) Wage measures are time-invariant weighted averages of the hourly wages of each education-industry group within each occupation, the weights being the employment shares of each education-industry group over the entire period. The measures are the difference between the log wage and the log mean wage of the period. (8) Average years of education.

Table 5: Evolution of Prices and Quantities, 1983-1994: Italian Occupational Classification.

	Employment Shares			Wages from Mean				Avrg
	1984	1993	Δ	1984	1993	Δ	Skill	Educat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1 White Collar	32.00	38.00	0.166	0.13	0.20	0.07	**HS**	9
2 Blue Collar	68.00	62.00	-0.090	-0.13	-0.20	-0.07	**LS**	7

Source: Author's calculations from the BI data set.

Note: (1), (2) Employment measures are time-invariant value-weighted sums of the employments of each education-industry group within each occupational category, the weights being the average hourly wages of each education-industry group over the entire period. (3) The change in the employment shares is expressed as the difference in the log shares in each period. (4), (5) Wage measures are time-invariant weighted averages of the hourly wages of each education-industry group within each occupation, the weights being the employment shares of each education-industry group over the entire period. The measures are the difference between the log wage and the log mean wage of the period. (8) Average years of education. The Italian data reports a correspondence between degree completed and years of education, assigning 13 years to a high school degree, 17 to a college degree and 0, 5, 8 to the other three categories below high school degree.

Table 6. Evolution of Prices and Quantities, 1983-1994: U.K. Occupational Classification

	Employment Shares			Wages from Mean				Avrg
	1984	1993	Δ	1984	1993	Δ	Skill	Educat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1 Tech/Prof	9.19	12.04	0.270	0.36	0.36	0.00	**HS**	16
2 Managers	26.15	30.23	0.145	0.30	0.28	-0.02	**HS**	14
3 Other non-manual	13.77	15.11	0.093	0.01	0.02	0.01	**HS**	14
4 Services	0.49	0.48	-0.021	-0.50	-0.47	0.03	**LS**	13
5 Man-Supervisors	11.27	10.02	-0.117	0.02	-0.02	-0.04	**LS**	12
6 Man-Skilled	24.73	21.16	-0.156	-0.14	-0.13	0.01	**LS**	12
7 Man-Semi skilled	11.80	9.13	-0.256	-0.22	-0.20	0.02	**LS**	11
8 Man-Unskilled	2.60	1.82	-0.353	-0.33	-0.31	0.02	**LS**	11

Source: Author's calculations from the GHS data set.

Note: (1), (2) Employment measures are time-invariant value-weighted sums of the employments of each education-industry group within each occupational category, the weights being the average hourly wages of each education-industry group over the entire period. (3) The change in the employment shares is expressed as the difference in the log shares in each period. (4), (5) Wage measures are time-invariant weighted averages of the hourly wages of each education-industry group within each occupation, the weights being, the employment shares of each education-industry group over the entire period. The measures are the difference between the log wage and the log mean wage of the period. (8) Average years of education. In the British data individuals report their years of education in addition to the degree completed.

Table 7: High Skill Relative to Low Skill Log Measures, 1983-1994: Occupational Grouping

	Relative Employment			Relative Supplies		
	83-85	92-94	Δ	83-85	92-94	Δ
Italy	-0.750	-0.488	0.262	-0.995	-0.724	0.271
Germany	-0.698	-0.416	0.282	-0.733	-0.534	0.199
US	-0.169	-0.049	0.121	-0.264	-0.138	0.125
UK	-0.017	0.317	0.334	-0.151	0.157	0.308

	Relative Wages			Rel Employ. Rates		
	83-85	92-94	Δ	83-85	92-94	Δ
Italy	0.262	0.401	0.139	0.245	0.236	-0.009
Germany	0.357	0.370	0.013	0.035	0.118	0.083
US	0.295	0.388	0.093	0.094	0.090	-0.004
UK	0.360	0.352	-0.008	0.134	0.160	0.026

Source: Author's calculations from CPS, BI, GHS and GSOEP data sets

Note: All measures expressed as the natural log of the high skill measure divided by the low skill measure. Employment rate is defined as total employment divided by total supply of the skill group and equals 1 minus the unemployment rate. High and low skill groups defined and constructed following the previous methodology.

Table 8: Accounting for the Differences in Relative Wage Changes. 1983-1994. $\sigma = 2.1$

	Wage Differences	Supply Differences	Empl. Rate Differences	g Differences
US-GE	0.080	0.035	0.042	0.003
		44%	**52%**	**4%**
US-UK	0.101	0.087	0.015	-0.001
		86%	**15%**	**-1%**

Source: Author's calculations from CPS, BI, GSOEP and GHS data sets.

Note: all measures are the difference in the 83-94 period log change between the U.S. and Germany and the U.S. and the U.K.