Shifts in the Demand and Supply of Skills in the OECD

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Abstract

There is a lot of evidence of increases in the relative demands for skilled labor in recent years. But, increases in wage inequality (in the US) or increases in relative employment among the skilled (in the EU) will only result from these shifts if the supply of skilled labor does not keep pace with the demand. The purpose of this paper is to propose a framework for thinking about the impact of changes in the demand and the supply of skills and propose a measure of the gap between the demand and the supply of skills that is independent of the definitions of skill. Using data from six countries we demonstrate how this measure can be used to assess the importance in skill-biased change in understanding labor market changes in recent years. Our findings suggest that while the relative demand for skills has increased more then the relative supply in the US and UK starting from the 1980s, this has not occurred in the other European countries in our sample. We find, however, evidence of a rise in the gap between relative demand and supply in Italy and the Netherlands starting from the early 1990s.

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Introduction

The evolution of the demand for and supply of skills is critical for the evolution of labor markets (for an excellent recent summary, see Katz and Autor, 1999). If the demand for skilled labor runs ahead of the supply then, in a competitive labor market, the result will be an increase in wage inequality.[1] If relative wages do not adjust then the relative employment rates of the less-skilled will fall and it is likely that aggregate unemployment rate will rise[2]. These ideas have led many commentators (e.g. the 1996 OECD Jobs Study) to argue that the rise in wage inequality in the US and the UK in the 1980s and 1990s and the rise in unemployment in the Continental European countries is the result of the demand for skilled labor running ahead of the supply.

There is a lot of evidence that the demand for skilled labor is increasing (see, for example, Berman, Bound and Griliches, 1994; Berman, Bound and Machin, 1998). But there is a strong suspicion that the demand for skilled labor has been increasing since the onset of industrialization (see Goldin and Katz, 1998) so one should not think of this as a new trend and the evidence for an acceleration in the rate of growth is much weaker.

There are fewer studies which attempt to assess whether the demand for skills has been increasing faster than the supply. Perhaps the most persuasive work has been done for the US by Katz and Murphy (1992), Murphy, Riddell and Romer (1998) (who also consider Canada) and Card and Lemieux (2000) (who consider Canada and the UK). For example, Card and Lemieux conclude that the variation in the college-high school graduate wage premium (an important component of wage inequality) can best be explained by variations in the rate of growth of the supply of skilled labor together with steady growth in the demand for skilled labor. There are other studies which have attempted to test one of the implications of the hypothesis that the demand for skills has increased faster than the supply by looking for

[1] This was the view of Tinbergen (1975) who described the evolution of the wage distribution as the outcome of a race between technological progress (which increased the demand for skilled labor) and increasing access to education.

evidence that unemployment rates have increased faster for the less-skilled in Europe (e.g. OECD, 1994; Nickell and Bell, 1995; Manacorda and Petrongolo, 1999 and Card, Kramarz and Lemieux, 1999). Results are mixed though most studies conclude it is hard to find such evidence.

This paper proposes a new, very simple index of the gap between the demand and the supply of skills that is easily computed given readily available data on wages, employment rates and labour force shares by education. We show that this index is, under certain assumptions, independent of the classification of education used so that it can be used to compare the gap between the demand and the supply of skills across countries without worrying about the comparability of measures of educational attainment3. One has to make certain assumptions to derive these results, but we show how these assumptions can be tested and check the robustness of our results to alternative assumptions.

The plan of the paper is as follows. In the next section, we present the basic data on the evolution of wages, employment and unemployment by education for six OECD countries for which we have data. We then present a simple theoretical model to describe the basic set-up and ideas. The third section then shows how this approach can be implemented in practice and presents our basic results. These are that both the US and the UK show an increase in the demand relative to the supply of skills but that none of the Continental European countries do. The fourth section performs a number of robustness checks for our model.

1. Basic evidence

In this section we present the basic data on changes in the employment, unemployment and wage structures by education for six OECD countries. While this evidence is broadly

[2] This result depends on the particular shape of the labour supply curve but, the consensus is that wages are a convex function of unemployment in which case the result holds.

3 While the OECD has put considerable effort into standardizing 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, 1995) suggests large differences in literacy levels across countries even among individuals with the same ISCED level of education.

consistent with several other studies in the area, the point of this section is to show that, in the absence of a clear framework for thought, it is difficult to infer whether the change in the demand for skills exceeds the change in the supply of skills.

We use data on six countries: France, Germany, Italy, the Netherlands, the UK and the US. This selection was determined by availability of the relevant data more than anything else but they obviously capture an important sub-set of the OECD countries encompassing a wide range of experiences. For each country we have in each year data on labour force shares, unemployment rates and wages for four roughly comparable educational groups. We pool males and females and we count the number of employed heads by pooling employees and self-employed workers. Wages refer only to employees. For four of the countries in our data set (Italy, Germany, UK and US) micro data are available (respectively: SHIW, GSOEP, GHS and CPS), while for the other two countries (France and the Netherlands) data on wages, employment and unemployment come from published statistics. More details on the data sources and definition of the different educational categories as well as the definition of wages are provided in the Data Appendix.

In Figure 1 we plot the evolution of the labor force shares for each of these educational groups where level 1 is the lowest level of educational attainment and 4 the highest. This can be though of as a measure of (relative) labor 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. For most of the countries, however, one can see clear evidence of increasing educational attainment.

Figure 2 presents the information on the evolution of a commonly used measure of relative demand (see, for example, Berman, Bound and Griliches, 1994): the wage bill shares.[4] The figure shows once again the increase in the shares of the more educated groups. Wage bill shares obviously combine information on labor force shares, relative employment rates and

[4] This is he appropriate measure of relative demand under the assumption that the underlying production function is a Cobb-Douglas (see below).

relative wages so Tables 1 and 2 present the data for the evolution of employment rates relative to the average employment rate and wages relative to average wages5. The data shows some wage decompression in the US and UK in the 1980s and part of the 1990s (a trend that has been documented elsewhere e.g. Schmitt, 1995, Katz and Autor, 1999) but the deterioration of the relative employment of the least-skilled seems to have occurred in most countries and is not obviously more maked in the Continental European countries as is sometimes claimed.

As it is clear that both the relative demand and supply of educated labor is increasing, one needs some way of comparing the two trends. Of course, having more than two educational groups complicates greatly our ability to infer at a glance the occurrence and magnitude of a shift in relative demand. This is the reason why others have used a binary partition of the data by education. In the rest of the paper, however, we argue that one can make efficient use of data for more than two education groups and we propose a model which is able - at least in principle - to account for the different trends by education based on the evolution of a one-dimensional measure of the imbalance between the demand and the supply of skills.

2. A Model of the labor market with a continuous distribution of skills

We assume that there is a single index of skill (or human capital) denoted by h (a similar approach is taken by Juhn, Murphy and Pierce, 1993, and Card and Lemieux, 1996). This is assumed to be 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 1 so that:

(1) $\beta(h,t)=\phi(h-\mu_{st})$

5 Note that while a weighted average of wages (or employment rates) relative to the average must equal one in every year, changes in the weights over time because of increases in educational attainment can mean that relative wages (or employment rates) can decline for all education groups. This is evidence of a composition effect.

where ϕ is the density function of a standard normal. The hypothesis that the variance of this distribution is one is simply a normalization that rescales the units of h. 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, in the following 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.

On the demand side, suppose that the aggregate production function can be written as the following Cobb-Douglas production function[6]:

(2) $Y(t)=A(t)\exp\{\int\alpha(h,t)\log N(h,t)dh\}$

where N(h, t) is the employment at date t of those with skill level h, Y(t) is total output and A(t) is the state of aggregate technology. (2) should be thought of as a long-run 'reduced form' production function after one has concentrated out the profit-maximizing choice of other inputs so it makes sense to assume that there are constant returns in labor. The restriction on $\alpha(h,t)$ is that the integral with respect to h should sum to one so that density functions are a useful source of possible functions for $\alpha(h,t)$. To keep matters simple let us suppose that this has the following form:

(3) $\alpha(h,t)=\phi(h-\mu_{at})$

where, again, ϕ is the density function of a standard normal. The assumption that the 'variance' of this distribution is one is not innocuous. It implies that the variances of demand and supply are the same. While there is no a priori reason for this to be the case, this simplifies greatly the algebra. Below we will remove the hypothesis that the 'variances' of demand and supply are the same and show one can easily test for this hypothesis within the framework of our econometric model.

[6] We discuss the consequences of having a more general specification of the production function later.

At each moment in time there is a 'most desired' level of skill 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 labor market is perfectly competitive, (3) then leads to the following familiar labor demand curve:

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

where variables without h arguments denote aggregate variables and W(.) are wages. One can convert this to a relationship between relative wages and unemployment rates using the fact that $N(h,t)/N(t)=n(h,t)/n(t)\beta(h,t)$, where n(h,t) is the employment rate of someone with skill level h at date t:

(5) $\log W(h,t) - \log W(t) = \log [\alpha(h,t)/\beta(h,t)] + \log n(t) - \log n(h,t)$

(5) is a trade-off between their relative wage and the relative employment for workers with human capital h rate along the labor demand curve. The slope of this trade-off is -1 (from the Cobb-Douglas assumption) and the position of this trade-off is determined by $\alpha(h,t)/\beta(h,t)$.

To understand the workings of the model, it is helpful to write the labour demand curve of (5) not in terms of human capital, h, but in terms of the position in the skills distribution F. The reason for this is that the distribution of the position in the skills distribution is stable through time (it is uniform on the unit interval) while the distribution of human capital is not. Given the supply of human capital as given by (1), we have that:

(6) $h(F,t)= \mu_{st} + \Phi^{-1}(F)$

where Φ is the c.d.f. of the standard normal distribution. (6) can be used, together with (5) and (3) to derive:

(7) $\log W(F,t) - \log W(t) = \log D(F,t) + \log n(t) - \log n(F,t)$

where log D(F,t) is defined as:

(8) $$\log D(F,t) = \log [\alpha(h(F,t),t)/\beta(h(F,t),t)]= \log [\phi(\Phi^{-1}(F)-(\mu_{at}- \mu_{st}))/ \phi(\Phi^{-1}(F))]=$$

$$= \mu_t \Phi^{-1}(F)- \mu_t^2/2$$

and $\mu_t=\mu_{at}- \mu_{st}$, is the gap between the demand and the supply of skills. Since D(F,t) integrates to one, this can be thought of an index of <u>relative</u> imbalance between demand and supply for the person at position F,[7] which in the following we will refer generically to as mismatch. Net relative demand will be increasing (decreasing) in F as μ_t>(<)0 which can be interpreted as the demand for skills running ahead (behind) the supply of skills8.

Notice also that the position of the relative demand curve for a person at any given position in the skills distribution depends only on μ_t i.e. on the gap average between the demand and the supply for skills. If μ_{st} increases over time (as a result of increasing educational attainment) and μ_{at} increases over time (as a result of skill-biased change) but the gap between them remains the same so that μ_t remains constant then (8) tells us that everyone's relative labor demand curve will remain in the same position and there would be no reason to think that there would be increases in wage inequality and/or unemployment.

In order to get a visual impression of the model, in Figure 3 we have simulated the distribution of demand and supply ($\alpha(h)$ and $\beta(h)$) assuming that $\mu_{st}=0$ and $\mu_{at}=0.2$, so that $\mu_t=0.2$ In the top two panels of we have reported these simulated densities alongside the index of relative demand ($\log D(h,t)=\log \alpha(h,t)/\beta(h,t)$. All series are expressed as a function of h which is reported on the horizontal axis. In the two bottom panels we have reported the same variables expressed as a function of $F=\Phi(h-\mu_{st})$. Notice that log D(F,t) is a monotonic transformation of F.

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[7] $\int_0^1 D(h(F),t)\, dF = \int_0^1 \alpha(h(F),t)/\beta(h(F),t)\, dF = \int_{-\infty}^{\infty} \alpha(h,t)/\beta(h,t)\, \beta(h,t)\, dh = \int_{-\infty}^{\infty} \alpha(h,t)\, dh = 1$.

8 The economically relevant case is where $\mu_t>0$ and our estimates below will suggest very strongly that this is the case. 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 $\mu_t>0$.

Now consider what is likely to happen if the demand for skills increases faster than the supply so that μ_t increases. By differentiating (8) with respect to μ_t 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 so that the relative labor demand curves will shift.[9] In Figure 4 we have simulated an increase in demand. In order to perform our exercise, we have assumed that μ_a rises from 0.2 to 0.4. One can see that the relative demand function (α(F)) shift rightward while the relative demand index log D(F) tilts upward.

Notice also that based on our assumption D(F,t) in (8) is log-normally distributed with mean 0 and variance $(e^{\mu_t^2} - 1)$. In the bottom panel of Figure 6, we have reported the density of D(F,t) before and after the rise in relative demand. One can easily see that the index becomes more dispersed at μ_t grows. Notice finally that along the labor demand and at fixed relative employment rates, equation (7) implies that log wages are normally distributed, which is known to be a not too bad approximation to the true density of wages. If wages are determined along the labor demand, the density in the bottom panel of Figure 3 is effectively the distribution of log wages and one can easily see how a rise in μ_t increases wage inequality.

Of course, nothing we have done so far allows us to predict the final impact of a rise in μ on the inequality of wages and employment rates. In order to do so, we need to close the model and we do so by allowing for a generic labor supply. Assume that:

(9) $\log W(F,t) - \log W(t) = \log \theta(F,t) + \gamma \log n(F,t)$

where γ is the elasticity of labor supply and log θ(F,t) is a skill-specific intercept. In equilibrium:

(10a) $\log W(F,t) - \log W(t) = \gamma/(\gamma+1)[\log D(F,t) - \log N(t)] + 1/(\gamma+1) \log \theta(F,t)$

(10b) $\log n(F,t) - \log n(t) = 1/(\gamma+1)[\log D(F,t) - \log \theta(F,t) - \log N(t)]$.

Equations (10a) and (10b) make the obvious point that the effect of changes in the relative demand and supply of skills will depend on the elasticity of labor supply. The more sensitive

[9] This derivative is $(\Phi^{-1}(F) - \mu_t)$

are relative wages to changes in employment, the more shifts in relative demand will translate into an increase in the dispersion of wages and the less it will translate into an increase in the dispersion of employment rates. So, the model can readily explain why the US with a high degree of flexibility has had a rise in wage inequality while the continental European countries with relative wage rigidity has primarily had shifts in employment rates.

We have said nothing about the impact of a shift in relative demand on the aggregate employment rate. If $\gamma=\infty$, then it is easy to see from (10a) that employment rates will be unchanged. But, if $\gamma<\infty$ then it is easy to prove that a rise in μ will increase the aggregate unemployment rate if [logD-logθ] is increasing in F.[10]

The discussion so far, suggests using $\mu_t=(\mu_{at}-\mu_{st})$ 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.

3. Measuring Skill Mismatch

a. Methodology

In this section we show how one can use the information presented in section 1 to estimate the measure of skill mismatch defined in section 2. The theory of the previous sections has all been in terms of human capital (h) or the individual's relative position in the human capital distribution (F). This is a potential source of problems as we neither observe human capital directly nor do we observe employment rates by position in the skills distribution.[11] 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 paper we have used education as the

[10] From (10b), it follows $\partial((1+\gamma)\log n(F)-\log n)/\partial\mu=\partial\log D(F)/\partial\mu$. which, based on Talyor's approximation, can be rewritten as $-\partial((1+\gamma)u(F)-u)/\partial\mu=\Phi^{-1}(F)-\mu$. Integratinng out with respect to F and using the fact that $\int u(F)dF=u$, it follows $\partial u/\partial\mu=\mu/\gamma$ which is positive is $\mu>0$.

[11] We do observe however wages by position in the skill's distribution, although the distribution refers only to the employed workers rather than the whole population.

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:

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

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

(12) $$\begin{pmatrix} s_{it} \\ \varepsilon_{it} \end{pmatrix} \sim N\left(\begin{bmatrix} \mu_{st} \\ 0 \end{bmatrix}, \begin{pmatrix} \sigma_{st}^2 & \rho_{s\varepsilon}\sigma_{st}\sigma_{\varepsilon t} \\ \rho_{s\varepsilon}\sigma_{st}\sigma_{\varepsilon t} & \sigma_{\varepsilon t}^2 \end{pmatrix}\right)$$

The assumption that ability has mean zero is simply a normalization that can be made without loss of generality. This specification allows for schooling to be correlated with ability (as is sometimes claimed). Equations (11) and (12) obviously lead to (1) with $1=\sigma^2_{st}+\sigma^2_{\varepsilon\tau}+2\rho_{s\varepsilon}\sigma_{st}\sigma_{\varepsilon\tau}$.

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.

Now consider how we can use this information to measure the gap between relative demand and relative supply. In the Technical Appendix we show 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 do 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:

(13) $A_{st}=\Phi((s-\mu_{st})/\sigma_{st}-\rho(\mu_{at}-\mu_{st}))$

where ρ is the correlation coefficient between h and s (and of course $\rho = (\sigma_{st} + \rho_{s\varepsilon}\sigma_{\varepsilon t})$). One can check that for h=s (in which case $\rho=1$ and $\sigma_{st}=1$) this expression is nothing but the expression the c.d.f. of a standard normal variable.

Observe now that since 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}:

(14) $B_{st}=\Phi((s-\mu_{st})/\sigma_{st})$

By inverting equation (13) and using (14) to eliminate $[(s-\mu_{st})/\sigma_{st}]$ we can derive our basic estimating equation:

(15) $\Phi^{-1}(B_{st})= \Phi^{-1}(A_{st}) + \rho\, \mu_t$

In spite of the complexity of the theoretical framework, the estimation of this equation is very simple. Take data on cumulative labor force and wage bill shares by education, transform them using the inverse normal c.d.f. and take their difference. But for sampling and labor market errors, this difference is our measure of imbalance between the relative demand and supply of skills and in principle this should be independent of education. This independence implies that our approach does not rely on educational categories being the same for all countries or over time in the same country.[12]

(15) suggests that one should use data on wage bill and labor force shares to investigate whether skill mismatch has increased or decreased. Others however have arrived at the same conclusion without going through the explicit theoretical framework we have provided so that one might legitimately wonder why the model is needed at all. But, while there are some circumstances in which one does not need a theoretical model to conclude there has been a rise in skill mismatch, there are others when it is needed. For example suppose we had only two skill groups and the wage bill share of the low-skill group went from

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

70% to 60% at the same time as the labor force share was constant at 80%. One could easily conclude that there had been a rise in skill mismatch.[13] But if the fall in the wage bill share coincided with a fall in the labor force share from to 80% to 70% then one has to make some judgement about whether the fall in the wage bill share is larger or smaller than the fall in the labor force share. This is where a theoretical model can provide guidance as, if (15), is the correct model then skill mismatch will actually have fallen in this circumstance.[14] However, one must also be careful to check that the theoretical model is an adequate representation of the data. and in section 4 of the paper we will propose a test of goodness of fit.

As far as identification goes, notice that since the shares in equation (15) 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, there is no way to test for the goodness of fit of model (15). For the model to fit the data, the difference on the left hand side of equation (15) should be the same for each educational group. So one needs at least three educational groups in order to test for the fit of the model. Even with more than two educational groups, however, identification of equation (15) is somewhat problematic since one cannot separately identify μ_t from ρ. Any time-series (cross-sectional) inference on changes in relative demand based on the estimation of equation (15) requires the assumption that the correlation between education and human capital does not change over time (across countries). We will return to this issue in section 4.

b. Empirical Evidence

In Table 3 we estimate model (15) for our sample of countries. We regress the difference in the inverse normal c.d.f. of the labor force on the inverse normal c.d.f. of the wage bill shares

[13] In this case equation (15) suggests a rise in $\rho\mu_t$ from 0.317 to 0.588.

with a coefficient equal to one plus a set of year dummies. As, the dependent variable will, by construction, be heteroscedastic and correlated within years we exploit this to estimate the model efficiently via feasible GLS.[15]

All the estimated intercepts in the Table are positive implying that demand is running ahead of supply, assuming, as seems reasonable, that the correlation coefficient between education and human capital is positive. This simply says that the share of the wage bill going to high education groups exceeds their share in the labor force because their wages or employment rates are or both higher than the average. In terms of levels, it appears that the imbalance between relative demand and relative supply is higher in the US and the UK than in the rest of the countries. Italy, in particular, shows a particularly low value for the estimated level of mismatch.

In terms of trends, the US shows a strong rise in skill mismatch from the 1980s until the early 1990s since when it has been constant. The UK shows a similar increase in the 1980s which continues into the mid 1990s. The Continental European countries have a more complicated picture. Italy shows only a small increase in skill mismatch until the early 1990s and a more sizeable increase since then though it is not as large as that seen in the UK and US. The Netherlands also shows some evidence of a rise in the late 1990s though no noticeable trend prior to that. Germany shows some evidence of an upward trend in the late 1980s but this reversed in the 1990s. And France does not have a noticeable trend in any part of the period. We have regressed our estimated coefficients ($\rho\mu_t$) for the period from 1984 (1983 for Netherlands) to 1995 on a linear trend (divided by 100). The estimated coefficients are respectively: .01 for France, -.26 for Germany, .55 for Italy, .29 for the Netherlands, .54 for the UK and .45 for the US.

Taken together, this suggests that there has been an increase in skill mismatch in the Anglo-Saxon countries during the 1980s but none (or at most a more modest one) in

[14] In this case equation (15) suggests a fall in $\rho\mu_t$ from 0.317 to 0.271.

Continental Europe. There is evidence, however, that some continental European countries 'catch up' with the Anglo-Saxon countries in the mid-1990s.

The different trend in skill mismatch in the US and UK from that in the Continental European countries can 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. In Table 4 we have estimated the trends in supply μ_{st} based on equation (14) (this is simply a numerical version of the data presented graphically in Figure 1). Again, we estimate the model by FGLS and we measure s as the maximum number of years of schooling correponsing to each educational group (see data Appendix). A few things are worth mentioning. First, Italy and France show comparatively low levels of education while Germany and Netherlands have higher levels. As far as the trends go, while there is a pronounced rise in the educational attainment of the population in France and Italy (between the mid 1980s and the mid 1990s this corresponds respectively to an average annual rise in the number of years of education of 0.26 and 0.19), a more modest rise is observed in the UK and the Netherlands (0.11 and 0.09) and an even slower rise in Germany and the US (0.03) and the US (0.04). Taken together, these data show no clear correlation between the estimated mismatch index in Table 3 and the change in relative supply in Table 416. This contrasts with the conclusion of Murphy, Riddell and Topel (1998) who compared Canada and the US and concluded that the data could be well-explained by a model in which the two countries had similar increases in the demand for skills but differed in their increases in the supply of skills.

One of the properties of our approach is that it derives a one-dimensional measure of skills that 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 $[\Phi^{-1}(B_{st})-\Phi^{-1}(A_{st})]$ to be identical across education categories. Figure 3 presents the evolution of

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[15] By the delta method, $var[\Phi^{-1}(B_t)]=D_{Bt}var(B_t)D_{Bt}$, where $D_{Bt} = diag(\phi^{-1}(B_t))$ and the $[var(B_t)]_{jk}=B_{jt}(1-B_{kt})/L_t$, $j<k$.

this difference for each country. There are persistent differences across education groups, notably the estimate of mismatch seems highest in the highest education group, which points to a failure of our model. As a more formal test we run a Breusch-Pagan test for the hypothesis that the residuals are uncorrelated over time within each education group. This is simply a LM test for the hypothesis of no random effects. The results of the test are reported in the bottom line of Table 3. We always reject the null hypothesis. However, this does not mean that our model is useless. It is reassuring that the trends in mismatch in Figure 3 seem similar for all education groups and we will see later that our restricted model predicts outcomes very similar to a model that 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. That is what we do next in Section 4.

4. Robustness Checks

The model is based on four main assumptions:

a. the variances of demand and supply are the same;
b. the correlation between education and skill is unchanged both over time and across countries;
c. the distribution of the demand and the supply of skills is normal;
d. the production function is Cobb-Douglas.

These assumptions have been made as much for analytical tractability as for realism: it is hard to relax them simultaneously without complicating the model greatly. So, we will relax each assumption individually.

a. Equality of variances

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16 Note that, while in Table 3 we estimate $\rho(\mu_{at}-\mu_{st})$, we are estimate μ_{st} in Table 4 so that the scale of

Suppose that the 'variances' of demand and supply are not the same. Let us assume in particular that:

(16) $\beta(h,t)=\phi((h-\mu_{st})/\sigma_h)$

where σ_h is the square root of the variance of supply relative to demand (which is standardized to be equal to one). In the technical appendix we show that in this case equation (15) rewrites as:

(17) $\Phi^{-1}(B_{st}) = \delta\Phi^{-1}(A_{st}) + \rho/\sigma_h \mu_t$

where $\delta=(1-\rho^2+\rho^2/\sigma_h^{\ 2})$. It is easy to see that if $\sigma_h=1$, $\delta=1$ and equation (17) specializes into (15). In order to test for the hypothesis that $\sigma_h=1$, one can then simply test for $\delta=1$ in equation (17) (assuming, at is seems plausible, that $\rho\neq0$). The estimates for this unrestricted model are reported in Table 5. One can easily see that although the model in (13) is rejected in favor of a less parsimonious model for all the Continental European countries in our model, the point estimates are not too far from one and the trends in mismatch are similar to the ones in Table 3 although somewhat more pronounced.

b. The Correlation between Education and Human Capital

The second check we run in this section regards identification of the parameter ρ. We have used estimates like those reported in Table 3 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 3 but $\rho\mu_t$. Only if ρ is constant over time can we use these estimates to make inferences about trends in skill mismatch and only if ρ is the same across countries can we use them to make cross-country comparisons. But, nothing that we have done so far allows us to estimate this parameter.[17]

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the estimated time-effects are not comparable.

[17]This is not a problem unique to our approach as most of the existing literature avoids it by making the convenient but wrong assumption that human capital and schooling are identical so that the correlation between them is perfect.

Suppose that the intercept in the in the labor supply equation can be expressed as a linear function of human capital $\log(\theta(F(h,t),t))=\lambda_0+\lambda_1 h$, suggesting that, at zero employment dispersion, log wages are some monotonic function of human capital and are normally distributed. Combining this expression with the expression for log D(F(h,t)) in (8) and using the expression for the equilibrium of the model (10a), it follows that wages are a linear function of human capital:

(18) $\log W=\beta_0+\beta_1 h+\eta$

where η picks up 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). Let R_{wh}^2 be the index of determination from this regression. Of course, a regression like (18) cannot be run on our data but Bound and Krueger (1991) provide an estimate that 20% of the observed variance in annual earnings in the CPS is error, which implies that $R_{wh}^2\approx.80$. [18] It is likely that this is a lower bound for measurement error in the other data sets.

Suppose now that we run a regression of log wages on schooling.

(19) $\log W=\delta_0+\delta_1 s+\varpi$

We can think of the index of determination from this regression, R_{ws}^2, 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^2 so that we have:

(19) $R_{ws}^2=R_{wh}^2\,\rho^2$

So, we can use information on the fraction of the variance of wages explained by education to estimate the correlation between human capital and education. Table 6 presents estimates of the square root of the correlation coefficient, R_{ws}, when an earnings function is estimated

[18] It should be remembered that, for most countries, we are using weekly earnings not annual earnings so that there results may not be strictly applicable to our data and we should think of the number used here as a 'best guess'.

using only education as controls.[19] We only have access to micro data for four countries so estimates for France and the Netherlands are not reported. Despite in theory we would like to have education as a continuous variable, we only have information on discrete educational categories so the grouping will mean that we are likely to underestimate R_{ws} to some degree. To try and account for this, for each country 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. The extent of the under-estimation 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 index of determination by that much. First, notice that the estimates are similar across countries and in the order of 0.40. Taking Bound's and Kruger's results, this implies a value of ρ in the order of 0.70. Second, if measurement error is more pronounced in other data sets than in the CPS, this implies that ρ is possibly lower in the US than in the other countries, so that the rise in μ_t appears even more pronounced in the US than in the European countries. Finally, across time there is evidence that in all countries R_{ws} increases modestly through time. Assuming that measurement error is constant over time, this implies that the correlation of human capital with schooling (ρ) is rising through time in all the countries. But changes are similar, across countries that should say that our basic conclusion about the relative performance of the US and UK vis a vis the other countries in the sample is not affected. Note also that by itself this is not able to explain the rise in the US

c. The Normality Assumption

Let us now consider the normality assumption. Suppose that, the demand function in (3) is given by $\alpha(h,t)=f_{\alpha}(h-\mu_{at})$ for some function $f_{\alpha}(.)$ which corresponds to a cumulative density function $F_{\alpha}(.)$ which is not necessarily normal. Suppose also that the supply of skills (1) has a

[19] Note that we positively do not want other variables in these regressions as our approach has conditioned solely

cumulative density $F_\beta(h-\mu_{st})$. 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 3. Since we found little evidence of ρ varying differentially across countries, we assume that $\rho=1$ which implies h=s (and $\sigma_h=1$). In this case, one can then straightforwardly derive the following equivalent of (13):

(20) $F_\beta^{-1}(B_{st})- F_\alpha^{-1}(A_{st})=\mu_t$

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

(21) $F_i^{-1}(x)=[x/(1-x)^{\lambda_i}-1]/\lambda_i$, $i=A, B$

we have a Box-Cox transformation of the wage bill and labor force shares. One attractive feature of this specification is that if $\lambda_i=0$, (21) implies that the distribution of A and B is logistic which we know is quite close to the normal. So (21) can be thought of as almost nesting our preferred specification. We estimated model (21) via maximum likelihood under the assumption that the error term is normal. Again, we use the expression for the theoretical variance of the inverse cumulative labor force share to weight our observations. Table 7 presents the results of estimating (21). 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. We find again evidence of no appreciable rise in mismatch in France and Germany while the UK and US show some pronounced rise. Italy and the Netherlands show some rise in the same order as the US but this rise in concentrated in the early 1990s. 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, US and Italy, the value of the statistic falls dramatically in all the countries suggesting that this model does quite a good job in fitting the data.

In Figure 6 we report the estimated mismatch index based on the estimates of model (20). One can clearly see that there is a rise in mismatch in the UK and US during the 1980s

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on education and all other variables are in the unexplained part of the skills distribution.

and early 1990s but virtually no change in France and Germany. Italy and the Netherlands show a flat trends up to the late 1980s but some rise in the early 1990s.

d. The Production Function

Finally, let us go briefly to the assumption about the production function. While there are some estimates suggesting that Cobb-Douglas is not a bad approximation (see Jackman et al, 1999; Manacorda and Petrongolo, 1999) others (e.g. Katz and Murphy, 1992) suggest a higher degree of substitutability and one might wonder how alternative choices of production functions would alter our results. The natural generalization is to a CES technology. This involves giving different weights to relative wages and relative employment rates in evaluating shifts in relative demand.[20] As most estimates suggest more substitution between labor of different skills than Cobb-Douglas would imply (see for example Katz and Murhpy, 1992), we should give greater weight to relative wage changes. For those countries where the increase in mismatch shows up largely through a rise in wage inequality this change would tend to increase measures of skill mismatch. So, moving away from a Cobb-Douglas production function would make the increase in skill mismatch in the US and the UK look even larger than in the other European countries.

5. Conclusions

In this paper we have proposed a conceptual framework for thinking about the labor market consequences of changes in relative demand and skills of different skills. We have used a simple model to show how a one-dimensional index of the gap between the demand and the supply of skills can be derived and computed and that 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 labor force shares, employment rates, relative wages by

[20] Note that equation (15) does not hold exactly if we have a CES production function, a bad but powerful reason for concentrating attention on a Cobb-Douglas production function.

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 since the early 19880s but not in the Germany and France. Our data show no rise in the Netherlands and Italy until the late 1980s but some subsequent increase in the 1990s .

How should we interpret these changes in the labor markets in US, UK and Continental Europe? The most conventional explanation of the UK and US findings is that there have been shifts in relative demand against the less-skilled either because of technology or trade. Presumably the same shifts have been occurring in Continental Europe so, if these countries show no evidence of increased skill mismatch it seems likely that the response of the supply of skills has been greater in Continental Europe. Recent evidence by Card and Lemiuex (2000) shows that the deceleration in the supply of college graduates which took place in the 1980s in the UK and US (as opposed to an acceleration in demand) is virtually able to explain all of the increase in the college wage gap over this period. This suggests that some further attention should be paid to different changes in labor supply on the two sides of the Atlantic if one wants to gauge some better understanding of the different performances of these labor markets.

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Technical Appendix

a. Equations (13) and (17)

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:

$$\alpha_s(s) = \int \alpha(h) f(s \mid h) dh$$

From (11) and (12) we have that:

$$s \mid h \sim N\left(\mu_s + \rho\sigma_s (h-\mu_s), \sigma_s^2(1-\rho^2)\right)$$

where ρ=corr(h,s)=$(\sigma_s+\rho_{s\varepsilon}+\sigma_\varepsilon)/\sigma_h$.

Assume now that:

$$\alpha(h,t)=\phi((h-\mu_{at})/\sigma_h)$$

where σ_h is the standard deviation of demand relative to supply. Note that for σ_h=1, this expression specializes in (3). It follows then:

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

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

$$(h-\mu_\alpha)^2 + \left(\frac{s-\mu_s-\rho\sigma_s/\sigma_h(h-\mu_s)}{\sigma_s\sqrt{1-\rho^2}}\right)^2 = (\delta_0 h-\delta_1)^2+\delta_2$$

Equating coefficients we have that:

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

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

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

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

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

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

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

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

Substituting for $(\delta_0,\delta_1,\delta_2)$, 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. This is the expression for the density function of a normal random variable. For $\sigma_h=1$, this expression specializes into (13).

Data Appendix

For each country we divide the labor force into four education groups. For each of these groups we collected data on the share of the labor force in each group, the unemployment rate and wages. Sources and definitions are listed for each country. In parenthesis after each educational group we report the maximum number of years of education that is necessary to achieve that level.

France: Data come from *Enquete Emploi*, 1982-1998 **XX**. The four groups are: up to primary school (*cep, be, beps*) (7), junior high school (*cap, bep*) (12), high school (*bac* or equivalent) (15), university education.

Germany: Data come from the German Socio Economic Panel, 1984-1997. The four groups are: without any vocational qualification and no higher education (12), with vocational qualification and no higher education (including apprenticeship) (15), with higher vocational education (16), with university degree. The wage variable is monthly income form labor. Data are weighted by cross-sectional weights.

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, 1993, 1995, 1998. Data on employment and unemployment come from the *Annuario statistico italiano*, ISTAT, various issues. The four groups are: up to primary school (7), junior high school (12), high school (15) 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 **XX**. Wage data come from *Tijdreeksee Arbeidsrekeningen*. The four groups are: up to primary school (8), junior high school (13), high school (16) and university degree or above. Earning concept: gross monthly wages.

UK: Data come from the General Household Survey for 1974-1997. The four groups are: those with no qualifications (9), those with O-levels (11) or equivalent qualification, those with A-levels (14) or equivalent qualification and university graduates. The wage variable is weekly earnings.

US: Data come from the Current Population Survey. Data for the period 1973-1977 are derived form the May Annual Files, while data for the period 1978-1997 come from the Outgoing Rotation Group. The four groups are high-school drop-outs (11), high-school graduates (12), those with 2 years of college (14) 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 by Education

	France				Germany				Italy				Netherlands				UK				US			
	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
73																					0.98	1.01	1.00	1.03
74																	0.99	1.01	1.01	1.01	0.98	1.01	1.00	1.03
75																	0.99	1.00	1.01	1.02	0.96	1.01	1.01	1.05
76																	0.99	1.01	1.02	1.02	0.97	1.01	1.01	1.04
77									1.03	0.98	0.93	1.00					0.99	1.00	1.02	1.03	0.96	1.01	1.01	1.04
78									1.03	0.98	0.93	1.00					0.99	0.99	1.02	1.03	0.96	1.01	1.01	1.04
79									1.03	0.97	0.93	1.01					0.99	1.00	1.02	1.03	0.96	1.00	1.01	1.03
80									1.04	0.98	0.94	1.02					0.99	1.00	1.02	1.03	0.95	1.00	1.01	1.05
81													0.96	0.99	1.02	1.03	0.97	1.01	1.05	1.06	0.94	1.00	1.02	1.05
82									1.04	0.97	0.94	1.03					0.96	0.99	1.05	1.08	0.93	1.00	1.02	1.07
83									1.05	0.97	0.94	1.04	0.92	0.97	1.04	1.05	0.96	1.00	1.04	1.08	0.92	1.00	1.02	1.07
84	0.98	1.00	1.02	1.07	0.98	1.00	1.02	1.04	1.05	0.97	0.94	1.05					0.96	1.00	1.04	1.05	0.93	1.00	1.02	1.05
85	0.98	1.00	1.03	1.07	0.97	1.00	1.03	1.05					0.91	0.98	1.03	1.04	0.95	0.99	1.04	1.07	0.93	1.00	1.02	1.05
86	0.97	1.00	1.04	1.07	0.97	1.00	1.03	1.03	1.04	0.98	0.96	1.06					0.95	1.00	1.03	1.06	0.93	1.00	1.01	1.04
87	0.97	1.00	1.04	1.07	0.97	1.01	1.02	1.04	1.04	0.98	0.96	1.07					0.96	1.00	1.02	1.05	0.94	1.00	1.01	1.04
88	0.97	1.00	1.04	1.07	0.97	1.01	1.02	1.03									0.96	1.01	1.02	1.04	0.94	1.00	1.01	1.03
89	0.97	1.01	1.03	1.07	0.98	1.00	1.01	1.04	1.04	0.98	0.96	1.07	0.92	0.98	1.01	1.01	0.96	1.01	1.02	1.04	0.95	1.00	1.01	1.02
90	0.97	1.01	1.03	1.06	0.98	1.01	1.00	1.03					0.92	0.99	1.02	1.02	0.97	1.00	1.02	1.04	0.95	1.00	1.01	1.02
91	0.97	1.01	1.02	1.05	0.98	1.01	1.01	1.03	1.04	0.99	0.97	1.06	0.93	0.99	1.01	1.01	0.95	1.00	1.03	1.04	0.94	1.00	1.01	1.03
92	0.96	1.01	1.03	1.05	0.96	1.02	1.02	1.04					0.91	0.98	1.01	1.02	0.96	1.00	1.01	1.05	0.93	1.00	1.01	1.03
93	0.97	1.01	1.01	1.05	0.97	1.01	1.02	1.03	1.03	0.98	0.98	1.06	0.90	0.98	1.02	1.02	0.94	0.99	1.02	1.05	0.93	1.00	1.01	1.03
94	0.96	1.01	1.01	1.06	0.96	1.01	1.01	1.05									0.96	1.00	1.01	1.04	0.93	1.00	1.01	1.03
95	0.96	1.01	1.02	1.05	0.95	1.02	1.01	1.05	1.02	0.99	0.99	1.05	0.91	0.98	1.01	1.02	0.96	1.00	1.01	1.03	0.93	1.00	1.01	1.03
96	0.95	1.01	1.02	1.05	0.95	1.01	1.01	1.04					0.91	0.98	1.01	1.02	0.95	1.00	1.02	1.05	0.93	1.00	1.01	1.03
97	0.95	1.02	1.01	1.05	0.93	1.02	1.01	1.07					0.92	0.98	1.01	1.02	0.93	1.01	1.01	1.06	0.93	1.00	1.01	1.03
98	0.95	1.01	1.01	1.05																				

Note: The Table reports the evolution of relative employment rates for 4 educational groups in 6 OECD countries. See also notes to Figure 1
.

Table 2
Trends in Relative Wages by Education

	France				Germany				Italy				Netherlands				UK				US			
	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
73																					0.77	0.97	1.02	1.55
74																	0.86	0.97	1.27	1.70	0.76	0.97	1.03	1.54
75																	0.86	0.93	1.25	1.73	0.73	0.96	1.02	1.53
76																	0.85	0.95	1.23	1.75	0.74	0.96	1.02	1.51
77									0.93	0.96	1.21	1.50					0.84	0.87	1.29	1.71	0.74	0.96	1.00	1.47
78									0.92	1.00	1.17	1.43					0.84	0.84	1.28	1.64	0.73	0.96	1.00	1.48
79									0.92	1.00	1.15	1.42					0.85	0.84	1.27	1.68	0.74	0.94	1.00	1.46
80									0.92	1.00	1.14	1.39					0.84	0.84	1.29	1.60	0.73	0.93	0.99	1.46
81													0.78	0.86	1.09	1.49	0.82	0.82	1.29	1.69	0.72	0.93	0.98	1.48
82									0.92	0.97	1.16	1.35					0.85	0.78	1.26	1.62	0.69	0.91	0.97	1.50
83									0.92	0.97	1.12	1.38	0.80	0.86	1.06	1.40	0.81	0.83	1.18	1.71	0.68	0.90	0.96	1.51
84	0.86	0.93	1.17	1.54	0.81	0.98	1.09	1.58	0.90	0.97	1.15	1.35					0.79	0.80	1.18	1.68	0.67	0.89	0.96	1.52
85	0.86	0.93	1.16	1.51	0.78	0.99	1.11	1.60					0.82	0.87	1.04	1.33	0.79	0.81	1.16	1.65	0.65	0.88	0.96	1.53
86	0.86	0.92	1.15	1.51	0.79	0.98	1.08	1.67	0.90	0.96	1.12	1.34					0.78	0.80	1.14	1.66	0.63	0.87	0.96	1.54
87	0.86	0.92	1.14	1.49	0.81	0.97	1.07	1.64	0.89	0.96	1.11	1.37					0.75	0.78	1.15	1.77	0.61	0.87	0.96	1.55
88	0.86	0.91	1.13	1.48	0.81	0.97	1.07	1.66									0.76	0.81	1.17	1.62	0.61	0.87	0.95	1.56
89	0.86	0.91	1.13	1.48	0.81	0.97	1.06	1.65	0.90	0.94	1.10	1.35					0.74	0.81	1.15	1.68	0.60	0.86	0.95	1.56
90	0.84	0.91	1.12	1.47	0.81	0.98	1.05	1.65					0.79	0.84	0.98	1.35	0.73	0.81	1.12	1.70	0.59	0.84	0.95	1.56
91	0.83	0.91	1.11	1.47	0.81	0.98	1.04	1.67	0.90	0.93	1.09	1.35	0.77	0.85	0.97	1.35	0.72	0.78	1.13	1.78	0.58	0.84	0.93	1.56
92	0.83	0.91	1.09	1.47	0.84	0.97	1.03	1.60					0.78	0.87	0.95	1.32	0.71	0.77	1.11	1.77	0.56	0.83	0.94	1.57
93	0.82	0.90	1.07	1.45	0.82	0.96	1.05	1.60	0.87	0.90	1.09	1.43	0.77	0.86	0.94	1.32	0.69	0.78	1.06	1.73	0.54	0.83	0.94	1.56
94	0.82	0.88	1.08	1.48	0.84	0.95	1.02	1.55									0.69	0.78	1.10	1.69	0.54	0.83	0.92	1.57
95	0.81	0.89	1.06	1.46	0.82	0.94	1.01	1.54	0.85	0.90	1.08	1.41	0.76	0.77	0.93	1.38	0.68	0.75	1.08	1.73	0.53	0.83	0.92	1.57
96	0.82	0.88	1.06	1.45	0.82	0.94	1.02	1.51					0.73	0.75	0.93	1.41	0.68	0.78	1.07	1.68	0.53	0.83	0.92	1.57
97	0.82	0.88	1.04	1.42	0.82	0.94	1.01	1.50					0.78	0.86	1.09	1.49	0.71	0.73	1.09	1.57	0.53	0.83	0.92	1.56
98	0.82	0.88	1.02	1.41																				

Note: The Table reports the evolution of relative wages for 4 educational groups in 6 OECD countries. See also notes to Figure 1

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

	France		Germany		Italy		NET		UK		US	
73												
74									0.227	(0.063)	0.290	(0.080)
75									0.227	(0.059)	0.291	(0.080)
76									0.236	(0.059)	0.322	(0.080)
77					0.091	(0.055)			0.261	(0.059)	0.305	(0.080)
78					0.089	(0.054)			0.256	(0.059)	0.304	(0.072)
79					0.086	(0.053)			0.254	(0.060)	0.305	(0.073)
80					0.084	(0.052)			0.261	(0.059)	0.253	(0.042)
81							0.206	(0.036)	0.304	(0.058)	0.263	(0.038)
82					0.087	(0.051)			0.276	(0.066)	0.269	(0.040)
83					0.079	(0.051)	0.210	(0.035)	0.302	(0.064)	0.301	(0.040)
84	0.255	(0.063)	0.219	(0.046)	0.093	(0.050)			0.306	(0.064)	0.310	(0.040)
85	0.245	(0.063)	0.253	(0.047)			0.189	(0.035)	0.309	(0.063)	0.307	(0.040)
86	0.248	(0.062)	0.250	(0.048)	0.100	(0.049)			0.309	(0.062)	0.320	(0.040)
87	0.247	(0.062)	0.235	(0.048)	0.109	(0.049)			0.335	(0.061)	0.327	(0.041)
88	0.249	(0.062)	0.239	(0.049)					0.307	(0.062)	0.333	(0.041)
89	0.251	(0.061)	0.224	(0.050)	0.105	(0.049)			0.324	(0.062)	0.331	(0.042)
90	0.254	(0.060)	0.225	(0.051)			0.219	(0.033)	0.328	(0.064)	0.331	(0.041)
91	0.258	(0.060)	0.226	(0.050)	0.104	(0.048)	0.218	(0.033)	0.353	(0.063)	0.344	(0.040)
92	0.266	(0.060)	0.212	(0.051)			0.204	(0.032)	0.354	(0.064)	0.349	(0.041)
93	0.260	(0.059)	0.218	(0.051)	0.149	(0.049)	0.214	(0.032)	0.359	(0.065)	0.361	(0.041)
94	0.238	(0.059)	0.210	(0.050)					0.345	(0.077)	0.363	(0.041)
95	0.240	(0.059)	0.222	(0.049)	0.155	(0.049)	0.251	(0.032)	0.364	(0.066)	0.343	(0.042)
96	0.236	(0.058)	0.215	(0.049)			0.261	(0.032)	0.354	(0.069)	0.344	(0.042)
97	0.230	(0.058)	0.231	(0.050)			0.279	(0.031)	0.341	(0.133)	0.343	(0.045)
98	0.220	(0.058)									0.342	(0.044)
R2	0.990		0.995		0.995		0.998		0.991		0.996	
LM	306.677	(0.00)	256.756	(0.00)	218.416	(0.00)	23.532	(0.00)	606.778	(0.00)	803.257	(0.00)

Notes: the table reports the estimates in mismatch using equation (15). Estimation method: FGLS. Standard errors in brackets. LM is a test a Lagrange multiplier test for random effects. Under the null (no random effects), the statistic is distributed as a chi-2 with 1 d.f. P-value in brackets. See also notes to Figure 1.

Table 4
Estimates of Shifts in Supply

	France		Germany		Italy		NET		UK		US	
73											11.501	(0.323)
74									8.455	(0.056)	11.593	(0.302)
75									8.693	(0.055)	11.677	(0.265)
76									8.785	(0.053)	11.740	(0.257)
77					6.528	(0.616)			8.835	(0.056)	11.790	(0.257)
78					6.874	(0.513)			9.030	(0.052)	11.835	(0.258)
79					7.181	(0.400)			8.963	(0.053)	11.996	(0.260)
80					7.483	(0.444)			9.169	(0.050)	12.058	(0.260)
81							12.283	(0.245)	9.244	(0.048)	12.100	(0.260)
82					8.034	(0.389)			9.377	(0.044)	12.159	(0.260)
83					8.280	(0.327)	12.558	(0.268)	9.749	(0.039)	12.225	(0.260)
84	6.419	(0.202)	13.117	(0.342)	8.500	(0.336)			9.991	(0.035)	12.272	(0.260)
85	6.579	(0.211)	13.133	(0.342)			12.833	(0.394)	10.103	(0.036)	12.316	(0.260)
86	6.867	(0.211)	13.121	(0.342)	8.937	(0.319)			10.300	(0.031)	12.353	(0.260)
87	7.153	(0.200)	13.115	(0.342)	9.142	(0.216)			10.284	(0.033)	12.381	(0.260)
88	7.379	(0.208)	13.100	(0.341)					10.369	(0.032)	12.407	(0.260)
89	7.470	(0.127)	13.146	(0.341)	9.506	(0.227)			10.478	(0.031)	12.449	(0.260)
90	7.900	(0.131)	13.153	(0.343)			13.348	(0.260)	10.558	(0.031)	12.490	(0.260)
91	8.178	(0.115)	13.176	(0.341)	9.872	(0.249)	13.443	(0.271)	10.550	(0.030)	12.524	(0.260)
92	8.423	(0.117)	13.210	(0.341)			13.594	(0.314)	10.743	(0.027)	12.561	(0.260)
93	8.749	(0.098)	13.270	(0.333)	10.267	(0.225)	13.742	(0.243)	10.968	(0.028)	12.603	(0.260)
94	8.956	(0.094)	13.408	(0.329)					10.935	(0.028)	12.643	(0.259)
95	9.169	(0.092)	13.509	(0.339)	10.631	(0.204)	13.902	(0.372)	10.992	(0.029)	12.674	(0.259)
96	9.315	(0.089)	13.584	(0.314)			14.004	(0.322)	11.043	(0.027)	12.670	(0.259)
97	9.565	(0.087)	13.627	(0.308)			14.065	(0.454)	11.233	(0.024)	12.680	(0.259)
98	9.745	(0.083)										
R2	0.994		0.884		0.881		0.892		0.906		0.741	

Notes: the table reports the estimates in the supply of education using equation (14). Estimation method: FGLS. Standard errors in brackets. See also notes to Table 1.

Table 5

Estimates of Shifts in Demand Relative to Supply: Unrestricted Model

	France		Germany		Italy		NET		UK		US	
δ	1.111	(0.005)	1.049	(0.010)	1.075	(0.003)	1.031	(0.007)	1.071	(0.011)	1.010	(0.009)
73											0.291	(0.080)
74									0.205	(0.046)	0.292	(0.080)
75									0.209	(0.043)	0.324	(0.080)
76									0.220	(0.043)	0.307	(0.080)
77					0.059	(0.010)			0.249	(0.043)	0.306	(0.072)
78					0.061	(0.009)			0.246	(0.043)	0.307	(0.073)
79					0.060	(0.009)			0.243	(0.044)	0.255	(0.042)
80					0.061	(0.009)			0.253	(0.043)	0.265	(0.038)
81							0.213	(0.026)	0.300	(0.042)	0.271	(0.039)
82					0.069	(0.009)			0.272	(0.047)	0.303	(0.040)
83					0.062	(0.009)	0.217	(0.026)	0.303	(0.046)	0.313	(0.040)
84	0.236	(0.016)	0.219	(0.034)	0.079	(0.009)			0.311	(0.047)	0.310	(0.040)
85	0.227	(0.015)	0.255	(0.035)			0.196	(0.025)	0.316	(0.046)	0.324	(0.040)
86	0.233	(0.015)	0.252	(0.036)	0.091	(0.009)			0.318	(0.044)	0.330	(0.041)
87	0.234	(0.015)	0.236	(0.036)	0.102	(0.009)			0.346	(0.044)	0.336	(0.041)
88	0.239	(0.015)	0.240	(0.037)					0.317	(0.045)	0.335	(0.042)
89	0.242	(0.015)	0.225	(0.037)	0.101	(0.008)			0.336	(0.045)	0.335	(0.041)
90	0.250	(0.015)	0.225	(0.038)			0.229	(0.024)	0.342	(0.046)	0.348	(0.040)
91	0.258	(0.015)	0.227	(0.037)	0.102	(0.008)	0.228	(0.024)	0.368	(0.046)	0.353	(0.041)
92	0.269	(0.015)	0.213	(0.038)			0.213	(0.024)	0.372	(0.046)	0.365	(0.041)
93	0.266	(0.015)	0.219	(0.038)	0.154	(0.009)	0.224	(0.023)	0.379	(0.047)	0.367	(0.041)
94	0.244	(0.014)	0.212	(0.037)					0.365	(0.056)	0.347	(0.042)
95	0.248	(0.014)	0.226	(0.036)	0.163	(0.009)	0.263	(0.023)	0.385	(0.048)	0.349	(0.042)
96	0.245	(0.014)	0.219	(0.037)			0.273	(0.023)	0.376	(0.050)	0.347	(0.045)
97	0.242	(0.014)	0.236	(0.037)			0.292	(0.023)	0.364	(0.096)	0.346	(0.044)
98	0.232	(0.014)										
R2	0.999		0.998		0.999		0.999		0.996		0.996	
LM	293.676	(0.00)	269.802	(0.00)	201.508	(0.00)	130.045	(0.00)	688.671	(0.00)	757.047	(0.00)

Notes: the table reports the estimates in mismatch using equation (17). Estimation method: FGLS. Standard errors in brackets. See also notes to Table 1.

Table 6

R from a Regression of Log Wages on Education

	Italy		Germany		UK		US	
73							0.32	0.34
74					0.30	0.35	0.34	0.36
75					0.30	0.34	0.34	0.37
76					0.32	0.36	0.34	0.37
77	0.30	0.31			0.36	0.40	0.33	0.35
78	0.27	0.29			0.35	0.40	0.34	0.36
79	0.28	0.28			0.35	0.39	0.32	0.35
80	0.28	0.31			0.35	0.39	0.33	0.35
81					0.37	0.41	0.33	0.35
82	0.30	0.30			0.38	0.42	0.34	0.36
83	0.30	0.30			0.35	0.39	0.34	0.36
84	0.30	0.32	0.33	0.36	0.36	0.40	0.35	0.37
85			0.34	0.37	0.35	0.41	0.36	0.38
86	0.30	0.31	0.35	0.38	0.36	0.41	0.38	0.40
87	0.33	0.33	0.35	0.39	0.39	0.42	0.39	0.41
88			0.37	0.39	0.35	0.40	0.39	0.41
89	0.33	0.33	0.35	0.38	0.37	0.42	0.40	0.42
90			0.35	0.39	0.38	0.42	0.41	0.42
91	0.33	0.33	0.36	0.38	0.39	0.42	0.41	0.42
92			0.43	0.45	0.39	0.43	0.41	0.44
93	0.35	0.35	0.44	0.48	0.37	0.41	0.42	0.44
94			0.41	0.45	0.39	0.42	0.43	0.44
95	0.33	0.33	0.42	0.47	0.38	0.41	0.43	0.45
96			0.42	0.47	0.35	0.40	0.43	0.45
97			0.46	0.50	0.37	0.41	0.43	0.45
98								

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 (18 for Germany, 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.

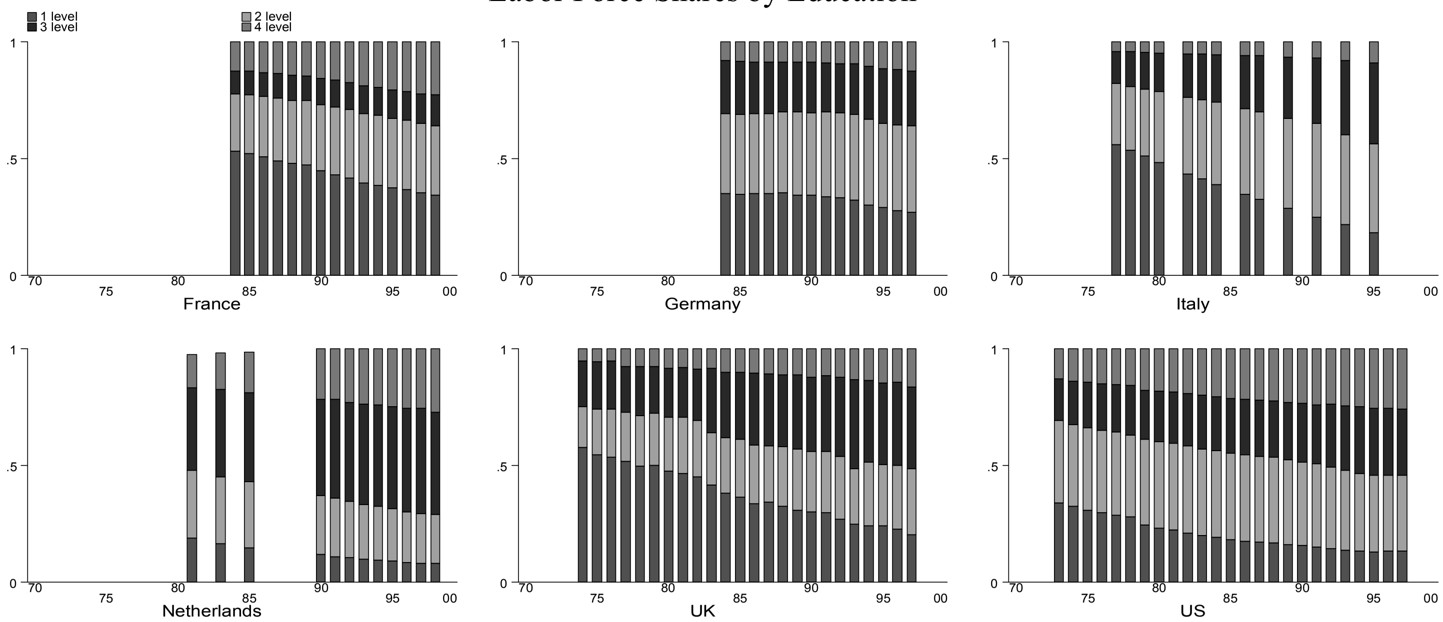
Table 7

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

	France		Germany		Italy		NET		UK		US	
λ_α	-0.326	(0.015)	-0.008	(0.013)	-0.384	(0.032)	-0.067	(0.014)	-0.188	(0.030)	-0.036	(0.005)
λ_β	-0.299	(0.009)	-0.122	(0.009)	-0.387	(0.027)	-0.083	(0.017)	-0.171	(0.022)	-0.182	(0.007)
											0.383	(0.028)
74									0.348	(0.116)	0.386	(0.032)
75									0.354	(0.064)	0.441	(0.028)
76									0.368	(0.092)	0.413	(0.027)
77					0.125	(0.015)			0.413	(0.095)	0.410	(0.028)
78					0.112	(0.015)			0.412	(0.054)	0.410	(0.028)
79					0.113	(0.016)			0.408	(0.063)	0.336	(0.020)
80					0.111	(0.016)			0.422	(0.054)	0.356	(0.017)
81							0.343	(0.030)	0.491	(0.066)	0.363	(0.017)
82					0.121	(0.015)			0.457	(0.117)	0.419	(0.017)
83					0.123	(0.015)	0.349	(0.030)	0.497	(0.115)	0.439	(0.020)
84	0.376	(0.016)	0.296	(0.018)	0.132	(0.016)			0.510	(0.113)	0.436	(0.022)
85	0.363	(0.015)	0.350	(0.018)			0.312	(0.030)	0.517	(0.110)	0.459	(0.022)
86	0.370	(0.015)	0.349	(0.018)	0.141	(0.015)			0.520	(0.066)	0.471	(0.022)
87	0.370	(0.015)	0.324	(0.019)	0.154	(0.015)			0.565	(0.065)	0.481	(0.022)
88	0.374	(0.014)	0.331	(0.019)					0.512	(0.113)	0.483	(0.023)
89	0.378	(0.015)	0.309	(0.018)	0.156	(0.015)			0.542	(0.110)	0.484	(0.023)
90	0.384	(0.015)	0.305	(0.019)			0.370	(0.027)	0.552	(0.106)	0.508	(0.022)
91	0.392	(0.015)	0.311	(0.018)	0.154	(0.015)	0.366	(0.027)	0.599	(0.099)	0.516	(0.021)
92	0.405	(0.015)	0.288	(0.019)			0.341	(0.027)	0.607	(0.093)	0.534	(0.022)
93	0.402	(0.015)	0.298	(0.019)	0.211	(0.016)	0.359	(0.027)	0.612	(0.091)	0.536	(0.022)
94	0.379	(0.015)	0.288	(0.019)					0.587	(0.078)	0.498	(0.022)
95	0.381	(0.015)	0.309	(0.019)	0.210	(0.017)	0.435	(0.027)	0.624	(0.086)	0.503	(0.021)
96	0.377	(0.016)	0.299	(0.019)			0.451	(0.026)	0.602	(0.076)	0.498	(0.022)
97	0.369	(0.015)	0.324	(0.019)			0.482	(0.026)	0.586	(0.118)	0.499	(0.022)
98	0.356	(0.015)										
R2	0.893	(0.34)	0.931	(0.33)	7.187	(0.01)	0.357	(0.55)	30.956	(0.00)	6.668	(0.00)

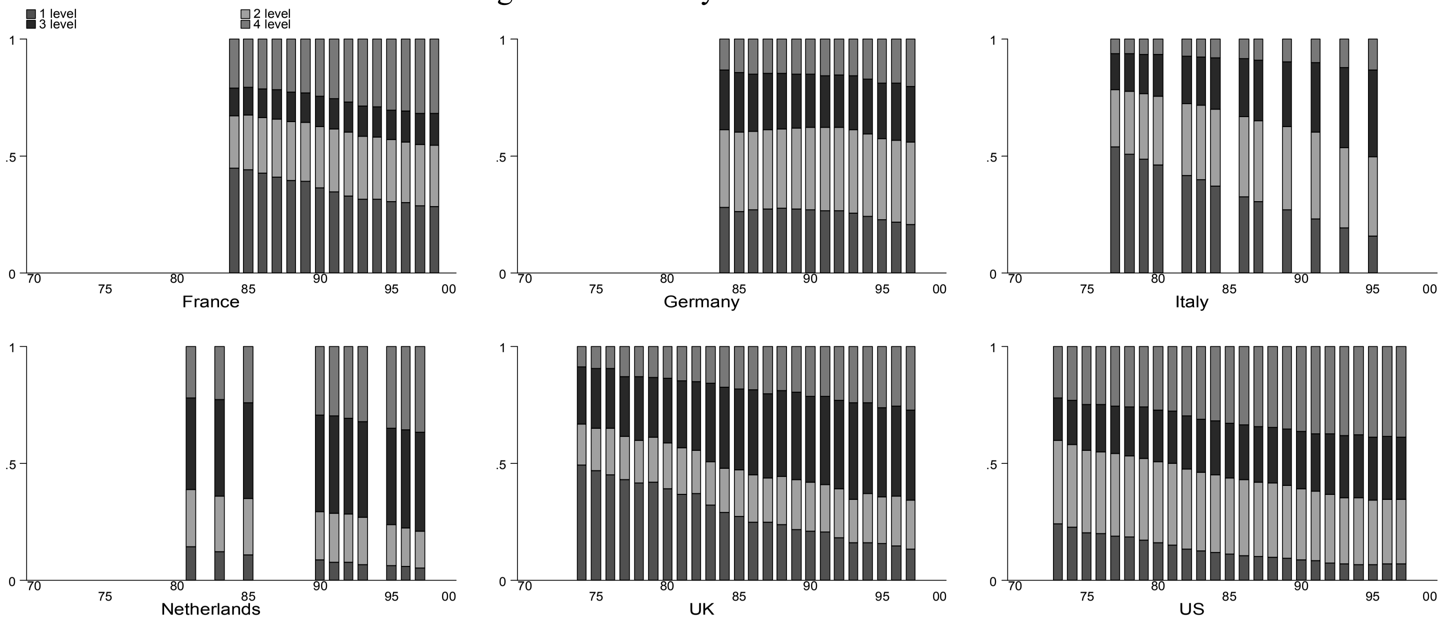
Notes: the table reports the estimates in mismatch using equation (20). Estimation method: FGLS. Standard errors in brackets. See also notes to Table 1.

Figure 1
Labor Force Shares by Education



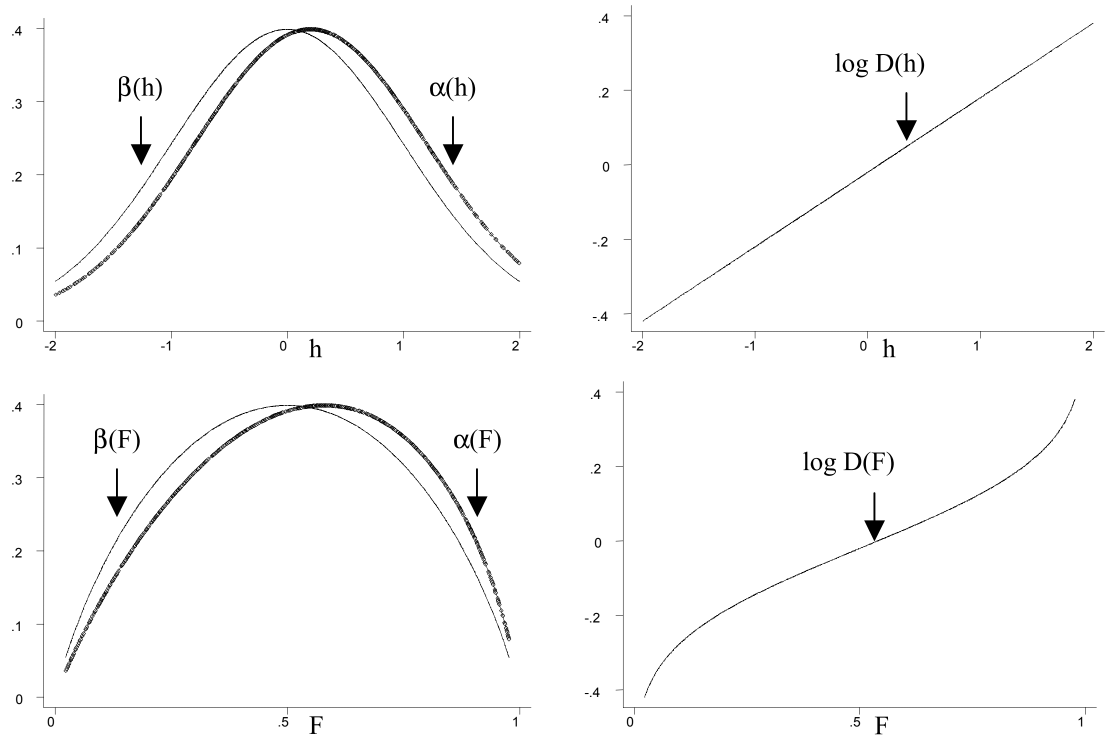
Note: The figure reports the evolution of the labor force share for 4 educational groups in 6 OECD countries. France, Netherlands, Germany, Italy. Level 1 is the lowest level of educational attainment, level 4 the highest. For sources and definition: see Data Appendix.

Figure 2
Wage Bill Shares by Education



Note: The figure reports the evolution of the wage bill share for 4 educational groups in 6 OECD countries. See also Notes to Figure 1.

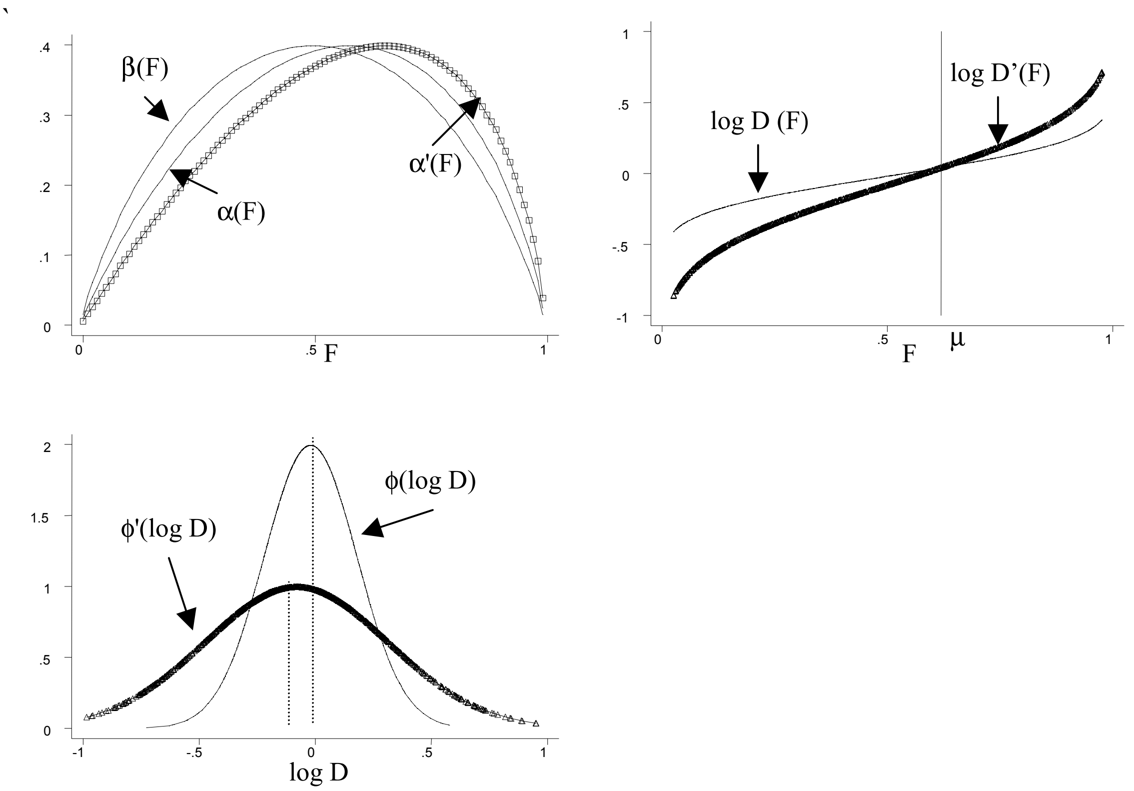
Figure 3
Simulated Imbalance Between Relative Demand and Relative Supply



Notes: In the top left-hand panel the figure reports the simulated distribution of relative demand and supply ($\alpha(h,t)$ and $\beta(h,t)$), assuming that $\mu_t=\mu_{at}-\mu_{st}=.2-0=.2$. In the to right-hand panel we have reported the index of imbalance between relative demand and relative supply $\log(D(h,t))=\log \alpha(h,t)/\beta(h,t)$. The bottom panels report the same series as a function of $F=\Phi(h-\mu_{st})$.

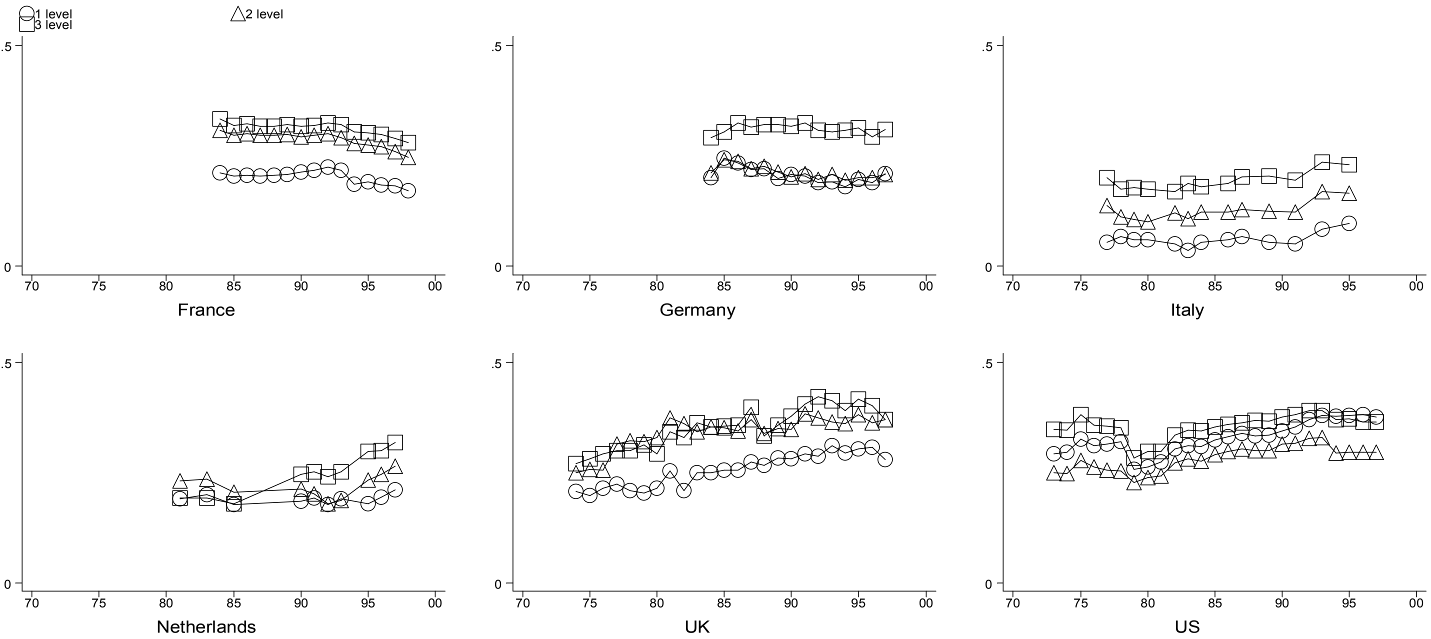
Figure 4

Simulated shift in relative demand



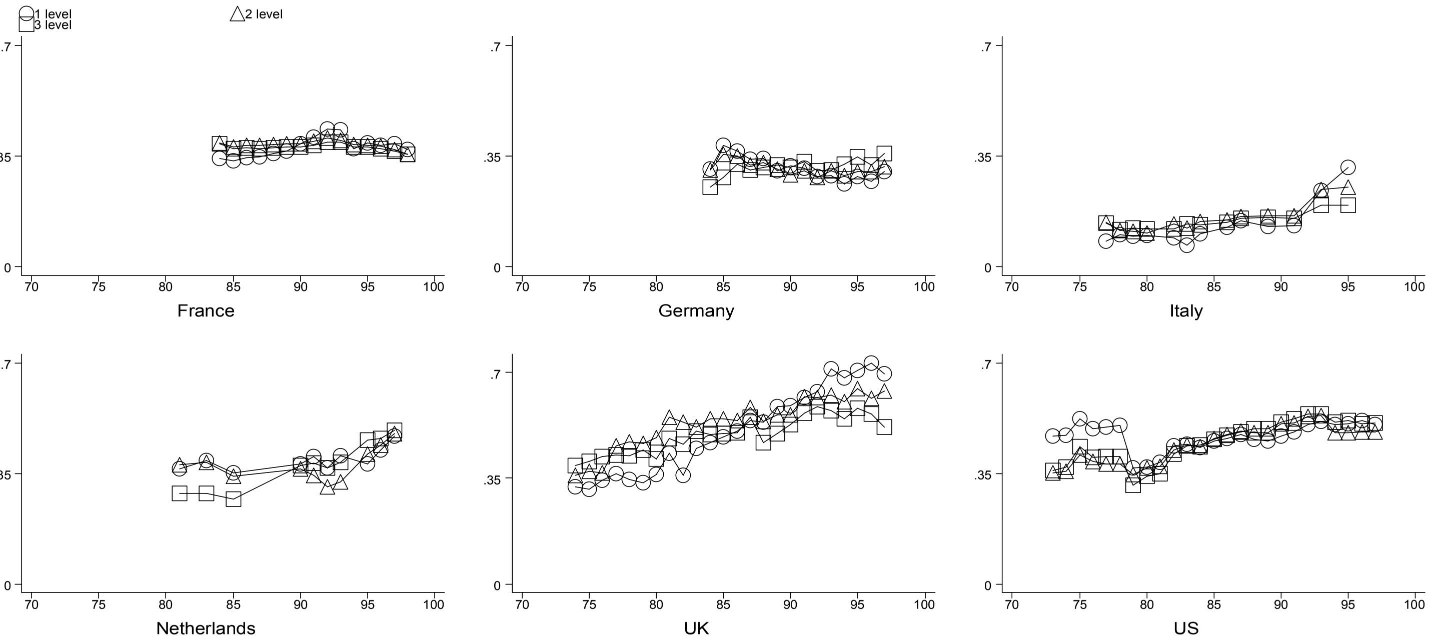
Notes: The figure reports a simulated increase in the imbalance between relative demand and relative supply from $\mu_t=\mu_{at}-\mu_{st}=.2-0=.2$ to $\mu_t=\mu_{at}-\mu_{st}=.4-0=.4$. The new distribution of demand is reported in bold in the top left-hand panel. The new value of the relative index of imbalance between demand and supply is reported in bold in the top right-hand panel. The bottom panels report the distribution of the index before and after the rise in relative demand.

Figure 5
Estimates of Skill Mismatch by Education Group.
Basic Model



Notes. The figure reports the evolution of our estimated measure of skills mismatch for in 6 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 6
Estimates of Skill Mismatch by Education Group.
Box-Cox Model



Notes. The figure reports the evolution of our estimated measure of skills mismatch for in 6 OECD countries based on the estimates in Table 7. The series are obtained by plotting $[(B_{st}/(1-B_{st}))^{\lambda\beta}-(A_{st}/(1-A_{st}))^{\lambda\alpha}]$ over time for each education group. See also notes to Figure 1.