Certified and uncertified skills and productivity growth performance: cross-country evidence at industry level

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Abstract

We analyse the relationship between human capital and productivity growth using a five-country multi-industry dataset together with a measure of human capital which accounts for both certified skills (educational qualifications) and uncertified skills acquired through on-the-job training and experience. We find evidence of positive human capital effects on growth in average labour productivity, particularly when using our composite human capital measure. We also find some tentative evidence that multi-factor productivity (MFP) growth is positively related to the use of high-skilled labour. However, externalities of this kind are largely confined to industries which make intensive use of university graduates.

Key words: human capital, productivity, catching-up, spillovers.

JEL classification: C23, J24, O47.

1. Introduction [1]

Research on the impact of human capital on productivity growth at country level has encountered many difficulties over the years. In a survey of the econometric literature in this area, Sianesi and van Reenen (2003) concluded that, while the evidence of a positive effect for human capital was 'compelling', the empirical evidence was nonetheless 'still weak at various crucial points' (ibid: 192). In particular, they emphasised the many methodological issues that remained unresolved in this field such as how best to measure skills and how to model possible channels of influence of skills on economic performance.

Only a few years later considerable progress has been made in respect of both skills measurement and modeling the potential contribution of skills to performance. For example, de la Fuente and Domenech (2006) have developed new estimates of educational attainments for 21 OECD countries which take care to avoid sharp breaks and implausible changes in measured skill levels over very short periods of time that often derive from changes in primary data collection methods. At the same time Vandenbussche, Aghion and Meghir (2006) have built on previous work by Nelson and Phelps (1966) and endogenous growth theorists such as Romer (1990) and Aghion and Howitt (1992) to develop a model in which human capital contributes to multi-factor productivity (MFP) growth in different ways depending on how close countries are to the technological frontier.

However, these positive developments have hardly eliminated all the problems associated with measuring the impact of human capital on economic performance at country level. Skill measures based on certified educational attainments are unable to take account of uncertified skills acquired through employment-based training and learning. And, in a recent critique of Vandenbussche et al. (2006), Inklaar, Timmer and van Ark (2008) suggest that any positive

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correlation between human capital and MFP growth at country level disappears if due account is taken in the estimation of MFP of inter-country differences in labour quality and in the number of hours worked.

In this paper we present new evidence on the relationship between human capital and productivity growth at industry level, making use of measures of human capital which take account of uncertified as well as certified skills, and which are fully incorporated into quality-adjusted measures of labour inputs. While the construction of quality-adjusted indices of labour is a common practice in growth accounting studies, their use within an econometric framework has been less common[2]. Here we use panel methods to estimate models of productivity growth that specify the potential channels of influence by which skills might be expected to influence performance.

Our analysis makes use of a cross-country industry-level dataset which contains annual series for output, capital, labour input and workforce skills for 26 industries in five countries (UK, US, France, Germany and the Netherlands) over the period 1979-2000. Using industry-level data for a small number of advanced industrialised countries enables us to work with a more homogenous sample than many previous cross-national studies of human capital which pooled together countries that were very different in terms of economic development. The difficulties inherent in this approach are discussed by Temple (2001) who also highlights potential differences in the quality of schooling across a wide range of countries. Although educational institutions differ in the countries included in the present study, we show below that we can minimise the effects of such differences in the construction of our human capital variable.

Throughout our analysis we undertake a systematic comparison of how our quality-adjusted measure of labour inputs (reflecting uncertified skills as well as certified skills) compares with

[2] Griliches and Regev (1995) use a quality adjusted measure of labour in the estimation of a production function using Israeli data, and others have followed this approach particularly in work based on agricultural data (see Jamison and Lau 1982 for a survey). See O'Mahony and Vecchi (2005) for a more recent example of the use of quality-adjusted labour measures in regression analysis.

other measures of human capital based solely on certified skills. Our main findings can be summarised as follows: we find strong evidence of the impact of human capital on average labour productivity, both in the long and in the short run. In the short-run, the analysis needs to allow for a more complex dynamic specification that accounts for the stock of human capital and the distance of countries from the technological frontier. We also find some limited evidence of spillovers onto MFP growth from the use of high-level skills. However, we do not find any support for the argument that such externalities are stronger in countries/industries that are close to the technological frontier.

The paper is ordered as follows. In Section 2 we discuss skills measurement issues in detail and outline the theoretical framework underlying the main hypotheses to be tested regarding the impact of human capital on relative labour productivity and MFP growth rates at country/industry level. Section 3 describes our dataset and our benchmark model. Sections 4-6 report our results and discuss our main findings on the impact of human capital on productivity growth at country/industry level. Section 7 concludes the paper.

2. Measurement and theoretical issues

2.1 Measurement of certified and uncertified skills

As an intangible asset, human capital is notoriously difficult to measure. Typically, use is made of proxy measures of skill such as educational level, occupation and wages. Discussions in this area are sometimes hampered by the use of terms like 'attainments' (an output concept) to refer to input measures such as years of completed schooling – a measure of attendance rather than attainment. Education output measures such as formal qualifications (diplomas) have the advantage of capturing something of what has actually been learned while undergoing education, rather than just signifying attendance. However, they have the disadvantage of being hard to compare across countries with different education systems and, like the years of schooling measure, they ignore skills acquired in the workplace without formal certification.

Hanushek and Kimko (2000) address concerns about the comparability of formal qualifications by constructing a new measure of labour force quality based on student performance in international tests of academic achievement in mathematics and science. This measure is found to be significantly and positively related to growth in per capita GDP in several countries, observed over the period 1960-1990. By contrast, in this analysis, years of schooling measures based on Barro and Lee (1993) estimates prove to be statistically insignificant when the test-based indicator of labour force quality is included.

More recently, the importance of uncertified skills has been noted by Ingram and Neumann (2006) who attribute increasing variation in wage income within formal qualification groups in the US to unobserved skill heterogeneity within those educational categories. They report evidence that other measures of skill such as mathematical ability or hand-eye coordination (derived from analysis of job characteristics) contribute substantially to the increase in wage dispersion among workers in different formal qualification groups.

At the same time, there are good reasons to believe that uncertified skills which are developed through employment-based training and experience may in some ways be complementary to certified skills. One of the great regularities in empirical research on employer-provided training is that highly-educated employees typically receive more training than do employees with few or no formal qualifications. Economic theory points to three main reasons why this outcome should be expected. First, high levels of ability (as signified by educational qualifications) are likely to contribute to higher (and quicker) returns to training provision by employers (Booth, 1991; Green, 1993; Lynch and Black, 1998; Acemoglu and Pischke, 1998). Second, highly-qualified workers are more able to co-invest in their own education and training as they tend to be less credit-constrained than low-qualified workers. Third, in some institutional and labour market settings, 'compressed' wage structures may develop such that wages increase more slowly than productivity as skills increase, thus providing further incentives to employers to support further training for workers who are already well-qualified (Acemoglu and Pischke, 1999; Booth and Zoega, 2004).

In this context our objective in this study is to develop measures of skill at country level which take full account of both certified and uncertified skills and any complementarities between them. Accordingly, we build on quality-adjusted skills measures developed for growth accounting purposes, as in Jorgenson et al. (2005), which make use of education output data (formal qualifications) combined with relative earnings data in order to capture differences in relative productivity between different qualification groups. Since individual productivity reflects the possession of uncertified skills as well as certified educational attainments, we expect this approach to help to produce better skill measures than those which are based solely on formal qualifications.

The use of relative earnings data for this purpose rests on the assumption of perfectly competitive markets in which a firm will hire an additional hour of labour up to the point where that worker's marginal productivity equals his/her marginal cost. Under this assumption, a measure of quality-adjusted total labour input can be obtained by weighting each different type of labour input (as signified by qualification levels) by its relative wage rate or the share that each type of labour occupies in total labour compensation. In fact, of course, employee wages may deviate from their marginal products due to imperfect labour market conditions and the operations of country-specific labour market institutions such as collective bargaining procedures and minimum wage legislation. Nonetheless, wage-based measures of relative labour quality go further than any other type of available measure towards capturing variations in relative marginal products across different qualification groups in each country.

Another problem in measuring skills is that even formal qualification categories may be hard to match across countries. In particular, there are pronounced inter-country differences in institutional arrangements for education and training which cause a lack of clear equivalence between intermediate qualification groups in different countries such as A levels in the UK, the Baccalaureate in France and high school graduates in the US. Hence, in this paper our approach is to benchmark on unskilled workers and then use ratios of mean wages in other qualification categories to unskilled wages in each country as indicators of labour quality differences between the respective qualification groups. This avoids having to try and classify non-comparable vocational and secondary education qualifications from different education systems into categories such as 'intermediate' qualifications. At the same time, all hours worked by skilled and highly-educated workers can be calculated as 'effective units of labour' relative to the unskilled category.

One alternative to this approach would be to benchmark on the highest skills category -- university graduates – which might be seen as more internationally comparable than any other qualification group. This issue is discussed further in Appendix B where we report evidence that our preferred measure of quality-adjusted labour calculated relative to an unskilled base is significantly positively correlated with an alternative graduate-based measure of effective units of labour.

2.2 Modelling the impact of human capital on productivity growth

Although economic growth theory allocates an important role to human capital, empirical evidence at country level often fails to confirm theoretical predictions. While human capital is often found to have positive and significant effects on relative productivity levels at country level (see Mankiw et al., 1992), many researchers have found no systematic links between human capital and relative productivity growth rates (for example, De Gregorio, 1992; Knight et al., 1993; Islam, 1995; Hamilton and Monteagudo, 1998). These negative findings have been variously attributed to misspecification of the production function, delays in any impact of human capital on productivity growth and shortcomings in the way that the impact of human capital has been modelled.

In retrospect, key insights in this area were provided by Nelson and Phelps (1966) who suggested that simply including an index of education or human capital as an additional input in a production function would represent a gross misspecification of the productive process because it did not account for complementarities between human capital and technology diffusion. Specifically, in Nelson and Phelps's theoretical model, human capital is not simply another factor of production but one that enhances the ability of a country to adopt and develop innovations and thus contribute to MFP growth

Following Nelson and Phelps's suggestion, Benhabib and Spiegel (1994) proposed a different model that allows human capital to affect growth through two channels: by increasing a country's ability to innovate and by facilitating the adoption and diffusion of foreign technology which may help technologically lagging countries to catch up with technology leaders. In this model, therefore, productivity growth may be positively related to a country's distance from the technology frontier so long as it has sufficient levels of human capital to identify and make use of knowledge and technologies generated elsewhere. Thus, countries that are technologically distant from the leader country and have relatively low levels of human capital by world standards may nonetheless, as a result of the catching-up effect, experience relatively high rates of productivity growth compared to countries that are closer to the leader in terms of human capital and technology levels.

Research on innovation has identified a number of different mechanisms by which this catching-up process may be linked to skills. Examples include the transfer of knowledge between firms, industries and countries through collaboration on R&D and technical problem-solving among skilled workers involved in supply-chains (Lundvall, 1992) and the mobility of highly-qualified engineers and scientists between firms (Mason et al., 2004). Furthermore, in order for firms in each country to identify and make effective use of knowledge, ideas and technologies that become available through spillovers, what is required is 'absorptive capacity' which may be developed through organisations' own investments in R&D and more generally through the development or acquisition of high levels of workforce skills (Cohen and Levinthal, 1989).

Thus in the Benhabib and Spiegel (1994) analysis described above, they find that human capital stocks are positively associated with individual countries' ability to narrow the gap between themselves and the world-leading nation in terms of productivity. Eaton and Kortum (1996) find that inward technology diffusion increases with a country's human capital. Xu (2000) provides evidence suggesting that the reason why relatively rich countries benefit more than poorer countries from hosting US multinational subsidiaries may be due to higher threshold levels of human capital in rich host countries. In a cross-country analysis at industry level between 1974 and 1990, Griffith et al. (2004) find that both R&D and workforce skills help to stimulate productivity growth via their effects on innovation and absorptive capacity.

In a further development of this line of investigation, Vandenbussche et al. (2006) have developed a theoretical model in which high-level skills contribute more to productivity the closer a country is to the technological frontier. They argue that more advanced countries are more likely to engage in innovation (requiring high-level skills) than they are in imitation (requiring lower levels of skills) because advanced countries have fewer opportunities for imitation than less advanced countries. This approach focuses attention on the composition of human capital and the possibility that different mixes of skills have different effects on productivity depending on the distance to the technological frontier. Vandenbussche et al.'s empirical results suggest that MFP growth is indeed positively related to the proportion of highly-skilled (tertiary-educated) workers at country level. The use of MFP on the left hand side of their model implies that the focus is on the externality effect rather than the internal returns to human capital. In addition to this externality effect, MFP growth is negatively related to proximity to the technological frontier but positively related to the interaction between proximity and skilled human capital. The latter effect implies that highly skilled workers are more important for those countries closer to the frontier.

However, as noted in Section 1, this result has recently been challenged by Inklaar et al. (2008) who show that, using a similar modelling framework, externalities from the use of high-level skills can only be found when MFP is computed without any adjustment for inter-country differences in the quality of labour inputs used in the production process. When such adjustment is carried out, any evidence of skills externalities disappears.

These prior contributions provide a rich background for our own investigation of the relationship between human capital and productivity growth at country/industry level. Making use of our new quality-adjusted measure of human capital (which takes account of both certified and uncertified skills), we propose to submit the following hypotheses to a number of empirical tests:

H1: All else being equal, changes in average labour productivity (ALP) at country/industry level are positively related to changes in human capital.

H2: All else being equal, changes in MFP at country/industry level are positively related to changes in human capital (positive human capital externalities or spillover effects).

H3: All else being equal, the impact of human capital on growth rates in ALP and MFP at country/industry level is greater, the closer each country/industry is to the technology frontier.

3. Benchmark model and data description

Our analysis of the relationship between skills and productivity starts with a general production function where output (Y) is expressed as a function of total capital (K), the total number of hours worked (L) and a measure of human capital (HC):

(1) $$Y_{ijt} = A_{ijt} F(K_{ijt}, L_{ijt}, HC_{ijt})$$

where A is a technology shift parameter and i, j and t denote industries, countries and time respectively. Assuming a Cobb-Douglas production function and constant returns to scale, we can define a per capita production function that expresses average labour productivity (ALP) as a function of average skills and average capital per worker, as follows:

(2) $$\ln(Y/L)_{ijt} = \alpha + \beta_1 ln(K/L)_{ijt} + \beta_2 ln(HC/L)_{ijt} + \varepsilon_{ijt}$$

Our analysis is based on the Employment Prospects in the Knowledge Economy (EPKE) growth accounting database which was built up from national accounts and production census data for five countries. [3] It contains data for 26 industries in the UK, France, Germany, the Netherlands and the US, observed over the period 1979-2000. The industry coverage includes 13 manufacturing industries and 9 service industries as well as agriculture, mining, utilities and construction. A list of all industries is presented in Appendix Table A1. Our measure of output is gross value added. Values at constant prices in national currencies are converted to US$ using industry-specific purchasing power parity exchange rates. Labour input is measured as hours worked defined as the total number of persons engaged (employed plus self-employed) times the average number of hours worked per year. A particular advantage of this dataset, compared to other existing industry

[3] Available at http://www.niesr.ac.uk/research/epke/database.html

level data, is that it provides detailed information on workforce qualifications and wages across different countries and industries, as shown in Appendix Table A2. [4]

Capital input is measured by capital service flows and is constructed using information on investment in current and constant prices from six asset types: computers, communication equipment and software (ICT capital), transport equipment, other non-ICT machinery and equipment and non-residential structures (non-ICT capital). Total capital is derived by aggregating ICT and non-ICT capital using a Tornqvist index formula where the weights are provided by the average over two consecutive years of the share of each asset in total capital compensation.

As outlined in Section 2.1, our measure of human capital is benchmarked on unskilled labour in each country. We first derive a measure of quality-adjusted labour (QAL) by aggregating employment by qualification levels multiplied by the wage relative to the unskilled category. For each country and industry we compute the following index:

(3) $$QAL_{ij} = \sum_{1}^{\Theta} l_{ij\theta} * \frac{w_{ij\theta}}{w_{ij\_unsk}},$$

where $l_{ij\theta}$ is the total number of hours worked by qualification group θ in industry i and country j, Θ is the total number of qualification groups, $w_{ij\theta}$ is the average wage of workers in qualification group θ and w_{ij_unsk} is the average wage of unskilled workers. The time subscript is dropped for simplicity. Following this analysis we derive a measure of certified and uncertified skills in industry i and country j by taking the ratio of quality-adjusted labour inputs to the total number of hours worked (L_{ij}):

(4) $$skills_{ij} = \left(\frac{QAL_{ij}}{L_{ij}} \right)$$

[4] In general, the labour input information in the EPKE dataset is more disaggregated than that available in more recent cross-country industry-level data sets such as EUKLEMS. The latter provides information for three groups of skilled workers (low, medium and high) without fully accounting for differences in the qualifications systems in each country. As discussed in O'Mahony et al (2008), such aggregation can result in a loss of information and produce misleading estimates.

This measure of human capital, which takes account of both certified and uncertified skills, is then systematically compared in our analysis against two other skill measures which only take account of certified skills. These are $higher_{ij}$, defined as the number of hours worked by persons with Bachelor degree qualifications or postgraduate university qualifications (L_{ij_high}), divided by the total number of hours worked (L_{ij});[5] and $highinter_{ij}$, defined as the proportion of the worker-hours with either certified high-level skills (L_{ij_high}) or certified intermediate level skills (L_{ij_inter}) such as Associate degrees in the US and technician- and craft-level qualifications in the European countries:[6]

$$higher_{ij} = (L_{ij\_high}/L_{ij}) \tag{5}$$

$$highinter_{ij} = [(L_{ij\_high}+L_{ij\_inter})/L_{ij}] \tag{6}$$

Descriptive statistics for our measures of output, hours worked, capital services and certified and uncertified skills in each country are shown in Appendix Table A3.

[5] Similar measures of high-level skills are used by Vandenbussche et al. (2006) and Inklaar et al. (2008).
[6] See Appendix A for further details of the classification of qualifications in each country and the national data sources on qualifications.

4. Assessing the direct impact of human capital on relative productivity performance

We begin our analysis by estimating Equation (2) and comparing the coefficient estimates for the different human capital measures. Results are presented in Table 1. All estimates are carried out using panel data methods to account for cross sectional heterogeneity. The first three columns of Table 1 present estimates based on the Fixed Effect (FE) estimator, while columns 4-6 present the estimates based on the First Difference (FD) estimator. Time dummies are included in all specifications and country dummies are included in the specification in first differences[7]. Many previous cross-country studies of productivity and growth have assumed cross sectional homogeneity and have estimated relationships similar to Equation (2) for groups of countries characterised by marked differences in, for example, income levels, standard of living, education systems and institutional frameworks (Mankiw et al., 1992; Benhabib and Spiegel, 1994). Although we are analysing a fairly homogenous group of countries, country-specific effects reflecting institutional differences are still likely to play an important role and to affect our estimates. Indeed the Pooled Ordinary Least Squares model was rejected by our data[8].

As discussed in Sianesi and Van Reenen (2003), earlier studies on human capital and productivity assumed independence between the explanatory variables and the error term, i.e. all variables were treated as exogenous. However, if this assumption is not met, the FE and the FD estimators produce biased and inconsistent coefficient estimates. Therefore, at each stage of our analysis we addressed endogeneity issues by comparing estimates based on OLS methods, and Instrumental Variable (IV) methods. Since the results suggested the presence of endogeneity, all tables show the estimates based on a Generalised Method of Moments (GMM) estimator, with lagged values of explanatory variables used as instruments (Hayashi, 2000; Baum et al., 2003).

[7] Country dummies are not included in the FE estimation because any variable that does not have a time dimension is automatically dropped when the data is expressed in deviation from their mean over time. In the FD model country dummies have been included after taking first differences of the rest of the data.
[8] Results based on the Pooled OLS estimator are available from the authors on request.

Instrumental variable estimation produces consistent estimates under the hypotheses that all instrumental variables are relevant, i.e. correlated with the endogenous variables, and they are orthogonal with the error term. For all IV estimates we report the Kleibergen-Paap (2006) test of under-identification and the Hansen-J (1982) test of instrument validity. The results, presented at the bottom of each table, show that our models are correctly identified and that the instruments satisfy the orthogonality conditions.

Results in Table 1, column 1, show that our indicator of certified and uncertified skills (*skills*) has a positive and significant impact on ALP implying that, at a given rate of physical capital intensity, a 1% increase in this skills measure increases ALP by approximately 0.3%. The coefficient on certified high level skills (*higher*) is also positive and significant but it is half the size of the *skills* variable, suggesting an elasticity of 0.12% (Column 2). By contrast, the coefficient on high and intermediate skill levels (*highinter*) is not statistically significant (Column 3). This shows that our measure of certified and uncertified skills leads to a stronger role for human capital in determining ALP. In all specifications the underlying capital and labour elasticities with respect to ALP are generally consistent with existing estimates and prior expectations of factor shares.

[TABLE 1 HERE]

The second half of Table 1 (Columns 4-6) presents the results of estimating Equation (2) in log first differences. The coefficient estimates for all three measures of human capital turn out to be either negatively signed or not significantly different from zero. This is a common problem in related studies and it has been discussed in length in Islam (1995), Barro and Sala-i-Martin (1995), Benhabib and Spiegel (1994) and De La Fuente (2011) among others. The problem can be the result of two main causes: measurement error and misspecification of the dynamic relationship between ALP and human capital. Compared to the FE, the FD estimator is particularly sensitive to measurement errors (Wooldridge 2002) and this can lead to underestimation of the strength of the relationship between variables of interest (De La Fuente, 2011). In addition, the specification in levels can be considered as depicting a long run relationship between variables[9], while the first difference specification looks at such relationship in the short run. Under this perspective, results in the second half of table 1 suggest that to explain the impact of human capital on the short-run variations in ALP we need a different specification. We investigate this issue in the next session.

5. Human capital and productivity growth: the missing link

In order to explore the links between human capital and productivity growth rates in more detail, we now extend our production function specification in first differences, following the framework suggested by Benhabib and Spiegel (1994), and recently extended by Vandenbussche, Aghion and Meguir (2006), which takes account of the potential role of skills in assisting productivity follower countries to catch up with countries on or near the technology frontier. This model has often been used for the analysis of human capital spillovers (see next section), but we believe that its implementation for the assessment of internal returns of human capital could provide a better understanding of the short run relationship between human capital and ALP. In this model we allow for the stock of human capital, rather than its rate of change, to affect growth, accounting for the proximity of a country to the technology frontier:

$$\text{(7)} \qquad \Delta \ln\left(\frac{Y}{L}\right)_{ijt} = a + \alpha \Delta \ln\left(\frac{K}{L}\right)_{ijt} + \beta \ln\left(\frac{HC}{L}\right)_{ijt-1} + \gamma \operatorname{Pr} ox_{ijt-1} + \mu_{ijt}$$

where hc_{ijt-1} is the lagged level of human capital, $Prox_{ijt-1}$ identifies the proximity to the frontier and μ_{ijt} is an error term. As in the previous section, we check the sensitivity of our results to our three human capital measures (*skills, higher, highinter*). Equation (7) can be expanded to allow for

[9] To test for the presence of a stationary long run relationship between productivity and its determinants we run a set of panel unit root tests on the residuals of the specifications in levels (Maddala and Wu 1999). The null hypothesis of a unit root could always be rejected at the 1% significance level, implying the validity of the long-run relationship.

the interaction between human capital and the proximity measure to test whether the impact of human capital on labour productivity growth increases when an industry gets closer to the frontier:

$$(8) \qquad \Delta \ln\left(\frac{Y}{L}\right)_{ijt} = a + \alpha\Delta\left(\frac{K}{L}\right)_{ijt} + \beta \ln\left(\frac{HC}{L}\right)_{ijt-1} + \gamma \Pr ox_{ijt-1} + \phi \ln\left(\frac{HC}{L}\right)_{ijt-1} * \Pr ox_{ijt-1} + \mu_{ijt}$$

A positive and significant coefficient on the interaction term implies that investing in human capital is more important when an industry is closer to the frontier.

As proxy measures of the potential catching-up effect available to productivity follower countries, we use two indicators of proximity: the lagged value of ALP and the lagged levels of relative Multi Factor Productivity (MFP). Levels of MFP are estimated residually as that portion of value added per capita which cannot be accounted for by per capita physical capital, divided by the respective geometric averages across all industries:

$$(9) \quad MFP_{ijt} = \exp\left[\ln\left(\frac{Y_{ijt}/L_{ijt}}{\overline{Y}_{it}/\overline{L}_{it}}\right) - \tilde{\kappa}\ln\left(\frac{K_{ijt}/L_{ijt}}{\overline{K}_{it}/\overline{L}_{it}}\right)\right],$$

where a bar over a variable indicates the cross country average. The variable $\tilde{\kappa}_{ijt} = 1/2(\alpha_{ijt} + \bar{\alpha}_t)$ is the average capital-labour share in country i, industry j, and the geometric mean capital -labour share[10].

The frontier is the country with the highest MFP ($MFPf_{ijt}$) relative to the base measure in each industry *i* at time *t*. The proximity of each country/industry to the frontier is first computed by subtracting MFP in each country/industry from the frontier MFP. In order to facilitate the interpretation of our results, we take the exponent of the negative MFP gap, which gives us the proximity of each country/industry's MFP relative to the frontier:

[10] For a detailed description of the methodology, see Griffith et al. 2004.

(10) $\quad MFPprox_{ijt} = \mathrm{e}^{-(MFPf_{ijt} - MFP_{ijt})}$

Larger values of *MFPprox* mean that the country/industry is closer to the frontier.

The results of Fixed Effects GMM estimates of equation (7) are presented in Table 2[11]. As expected, the coefficients on the proximity variables are negatively-signed and statistically significant in all specifications. Looking at the three measures of human capital in turn, the coefficient on our quality-adjusted measure (*skills)* is positively and statistically significant. In the same specifications the coefficient on *higher* is also positive and statistically significant, although it predicts a smaller effect of human capital than does the *skills* measure and it loses its significance when using a different proximity measure. On the other hand, the variable *highinter*, which denotes a combination of certified high-level and intermediate skills, is negatively signed and not significantly different from zero in all specifications (Columns 3, 6 and 9).

[TABLE 2 HERE]

In table 3 we present the results from the estimation of equation (8), where we interact human capital with the proximity measure. All specifications yield a negative and significant coefficient on the two proximity measures, consistently with our expectations. However, the interaction term does not play any effect and its introduction substantially reduces the significance of the human capital stocks. For example, the coefficient on skills although positive and substantially higher compared to the results in table 2, is no longer statistically significant.

Taken together our results in sections 4 and 5 suggest that there is strong support for Hypothesis 1 which posited that, all else being equal, changes in ALP at country/industry level are positively related to changes in human capital. The estimated elasticity is higher when we use a measure of human capital that accounts for both certified and uncertified skills as compared to measures of human capital that only account for certified skills. However, we reject the hypothesis of a stronger human capital effect when an industry is closer to the frontier.

[11] We also run equation (7) excluding the proximity measure but this specification did not yield any significant human capital effects.

Our results so far have shown that industries' investments in human capital significantly improve their productivity performance. However, the theoretical and empirical literature has often posited the existence of human capital spillovers, whereby industries benefit from the technology and the investments in human capital occurring elsewhere (Lucas 1988). We address this issue in the following session.

[TABLE 3 HERE]

6. MFP growth rates, proximity to the technology frontier and human capital spillovers

We now go on to test Hypothesis 2, which assumes a positive relationship between measures of human capital and multi-factor productivity growth (ΔMFP), and Hypothesis 3, which posits that this relationship is stronger the closer a country/sector is to the technology frontier. To test these hypotheses we apply the framework discussed in the previous section (i.e. equations 7 and 8) to the analysis of MFP growth as originally carried out by Vandenbussche et al. (2006). Therefore, our analysis in this section is based on the following specification:

$$(11) \quad \Delta MFP_{ijt} = \alpha + \beta_1 \ln\left(\frac{HC}{L}\right)_{ij,t-1} + \beta_2 MFPprox_{ij,t-1} + \beta_3 MFPprox_{ij,t-1} * \ln\left(\frac{HC}{L}\right)_{ij,t-1} + \mu_{ijt}$$

The use of ΔMFP on the left hand side of the equation enables us to examine the extent of any spillover effects of human capital, that is, positive effects on growth performance over and above the direct effect of human capital on individual productivity. The estimation of human capital spillovers based on equation (11) has generated a contradicting set of results. Vandenbussche et al. (2006) find that MFP growth rates are positively related to both the proportion of high-skilled (ie, tertiary-educated) labour and to the interaction of proximity to the technology frontier with the proportion of high-skilled labour. However, Inklaar et al. (2008) note that Vandenbussche et al.'s estimates of residual MFP growth make no allowance for inter-country differences in hours worked per employee or in labour quality (educational attainment). When such adjustments are undertaken the evidence of human capital spillovers vanishes and neither the human capital variable nor the interaction term between proximity and high-skilled labour are statistically significant. Hence Inklaar et al.'s results provide no evidence of externalities from employing high-skilled workers.

Drawing on our own multi-country sector-level dataset, our analysis will contribute to this important debate using our three human capital measures. We also acknowledge the fact that to correctly asses the importance of human capital spillovers we must control for the industry's own human capital investments by following Inklaar et al. (2008) in constructing a *sophisticated* MFP in levels and in growth rates:

$$MFP^{*}_{ijt} = \exp\left[\ln\left(\frac{Y_{ijt}}{\bar{Y}_{jt}}\right) - \kappa_{ijt}\left(\frac{K_{ijt}}{\bar{K}_{jt}}\right) - (1-\kappa_{ijt})\ln\left(\frac{Skills_{ijt}}{\overline{Skills}_{jt}}\right)\right] \tag{12}$$

$$\Delta MFP*_{ijt} = \Delta\ln\left(\frac{Y_{ijt}}{L_{ijt}}\right) - \alpha\Delta\ln\left(\frac{K_{ijt}}{L_{ijt}}\right) - (1-\alpha)\Delta\ln\left(Skills_{ijt}\right) \tag{13}$$

As in section 5, a bar over a variable indicates the cross country mean and an '*' indicates the *sophisticated* measure.

Table 4 shows the results of the estimation of equation 11 using our three definitions of human capital. All estimates are carried out using FE GMM methods, taking lagged values of the independent variables as instruments. Time dummies are included in all specifications. As expected, the coefficients on the technological proximity measure are negative and significant in all equations, providing further support for the idea that productivity laggards have greater scope for catching up with productivity leaders through successful absorption of knowledge and technologies generated elsewhere. Our composite *skills* variable is not statistically significant in this specification, irrespective of whether we include the interaction between proximity and human capital (Columns 1 and 2). However we find some evidence of spillovers from certified high-skilled labour (*higher*), but only in the absence of the interaction term (Column 3). This provides partial support for Hypothesis 2 which posited a positive impact of human capital on MFP growth and also constitutes further evidence of possible externalities to the use of high-skilled labour. Similar to previous results, the coefficient of *highinter* is never statistically significant (Columns 5-6).

[TABLE 4 HERE]

The coefficient on the term interacting the technology gap with human capital is insignificant in all specifications shown in Table 4. Thus we find no support for Hypothesis 3 derived from Vandenbussche et al.'s argument that the contribution of high-skilled labour to MFP growth is higher, the closer the country is to the technological frontier.

In order to examine the robustness of these findings, we re-estimate equation (11) for groups of industries that we can think of as being characterised by some common features, under the assumption that spillovers are more likely to arise among industries that are technologically similar (Jaffe 1986, 1989). We use only certified higher level skills as our human capital measure, given that this is the only measure suggesting spillovers in table 4[12]. Table 5 presents results for respectively manufacturing, market services, ICT-intensive and graduate-intensive industries. The classification of industries as ICT-intensive follows the taxonomy developed by van Ark et al. (2002) while graduate-intensive industries are defined as those where the average graduate share of employment is 15% or more in all five countries in the last five years of the time period under consideration.

In 3 out of 4 groups of industries, the coefficient on the interaction term is negatively-signed. In the case of manufacturing, market services and ICT-intensive industries, this coefficient is not statistically significant (Table 4, Columns 2, 4 and 6) but in the case of graduate-intensive

[12] We performed a similar exercise using the other two measures of human capital but the results were never statistically significant.

industries this negative effect is weakly significant (Column 8). Thus – for this group of countries in this time period – we continue to find no support for Vandenbussche et al.'s (2006) argument that the impact of high-level skills increases, the closer a country is to the technology frontier.

These robustness tests suggest that our finding of externalities to high-level skills is largely confined to the industries which we have defined as graduate-intensive (Table 5, Columns 7-8) and to a lesser extent to market services (Column 4). Across the whole economy, the marginal effect of an increase in high-level skills on MFP growth is relatively small (Table 4, Column 3). Therefore, we conclude that our evidence of the presence of externalities deriving from certified high-level skills is best described as tentative.

[TABLE 5 HERE]

7. Summary and assessment

In this paper we have undertaken a detailed analysis of the relationship between human capital and productivity growth using a five-country multi-industry dataset together with a measure of human capital which accounts for both certified skills (educational attainments) and uncertified skills acquired through on-the-job training and experience. Our analysis finds evidence of positive human capital effects on average labour productivity, and also shows that our human capital measure outperforms traditional ones based solely on educational attainment.

This work contributes to recent debates about the presence of human capital spillovers and whether such spillovers are stronger in countries closer to the technological frontier. Using a measure of technological proximity which makes appropriate adjustments for inter-country differences in the quality of labour inputs, we find that spillovers from the use of certified high-level skills onto MFP growth are mainly confined to industries which make intensive use of university-educated labour. On the other hand, and in contrast to some other researchers, we find no evidence that the contribution of high-skilled labour to MFP growth is higher, the closer the country is to the technological frontier. It should be noted that our results are based on a relatively homogeneous group of advanced industrial countries and this may partly explain differences from other analyses which include a more diverse set of countries. In addition, our analysis is based on industry data and this level of aggregation might be too high to capture externality effects. Further research would be useful to examine whether the same inferences about human capital externalities emerge from studies based on different units of analysis, such as firm or plant level data, and different specification of the way human capital spillovers affect productivity.

Appendix A

[TABLE A1 HERE]

[TABLE A2 HERE]

[TABLE A3 HERE]

Appendix B

Measurement of certified and uncertified skills: benchmarking on different skill categories

In Section 2.1 we argue the case for benchmarking on unskilled workers and then using ratios of mean wages in other qualification categories to unskilled wages in each country as indicators of labour quality differences between the respective qualification groups. Our aim is to calculate all hours worked by skilled and highly-educated workers as 'effective units of labour' relative to the unskilled category.

An alternative approach would be to benchmark on the highest skills category (university graduates) and then use ratios of mean wages in non-graduate categories to mean graduate wages in each country as indicators of labour quality differences between the respective qualification groups. This approach has the attraction that university graduates are notably more mobile across national borders than those in other qualification groups and there is widespread acceptance by employers in the US and Western Europe of graduate-level qualifications from overseas.

Recall that in Section 3 we compute the following index of quality-adjusted labour (QAL) to an unskilled base:

(B1) $$QAL_{ij} = \sum_{1}^{\Theta} L_{ij\theta} * \frac{w_{ij\theta}}{w_{ij\_unsk}},$$

where $L_{ij\theta}$ is the total number of hours worked by qualification group θ in industry i and country j, Θ is the total number of qualification groups, $w_{ij\theta}$ is the average wage of workers in qualification group θ and w_{ij_unsk} is the average wage of unskilled workers.

Following Hellerstein et al (1999), this measure of QAL can be decomposed between unskilled and skilled labour as follows:

(B2) $$QAL_{unsk} = L_{unsk} + \sum_{p=1}^{n} (\sigma_{\mathrm{p}} + 1) L_p$$

where L_{unsk} is the total number of hours worked by unskilled workers, there are n different skilled worker groups and $(\sigma_{\mathrm{p}} + 1)$ is the marginal product of worker group p relative to the unskilled worker group, which in competitive labour markets is assumed to equate to $(wage_p/wage_{unsk})$

An equivalent index of quality-adjusted labour to a graduate base can be computed as follows:

(B3) $$QAL_{grad} = L_{grad} + \sum_{ng=1}^{n} (\sigma_{\mathrm{ng}} + 1) L_{ng}$$

where L_{grad} is the total number of hours worked by graduates, there are n different non-graduate worker groups and $(\sigma_{ng} + 1)$ is the marginal product of non-graduate worker group ng relative to graduates which is assumed to equate to $(wage_{ng}/wage_{grad})$

Since QAL_{grad} cannot be decomposed between total unskilled hours and total skilled hours in the same way as QAL_{unsk} , we prefer to carry out the main part of our analysis taking unskilled workers as the base category. However, as a sensitivity test, we check the extent to which the two different measures of quality-adjusted labour inputs are correlated with each other. The results indicate that, conditional on total hours worked[13], there is a high degree of correlation between QAL_{grad} and QAL_{unsk} (correlation = 0.724; p-value = 0.05). This finding gives some confidence that our main analysis is robust to the use of alternative measures of quality-adjusted labour with effective labour calculated to a graduate base.

[TABLE B.1 HERE]

[13] Note that, without the control for total hours worked, the correlation would be dominated by the size element of the quality-adjusted labour input measures.

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Table 1. Generalised Method of Moments (GMM) estimation of the impact of certified and uncertified skills on Average Labour Productivity (ALP)

	Specification in levels			*Specification in first differences*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
ln $(K/L)_t$	0.395***	0.372***	0.382***	0.415***	0.426***	0.446***
	(0.077)	(0.075)	(0.076)	(0.082)	(0.086)	(0.080)
Ln $(\text{skills})_t$	0.291***			-0.035**		
	(0.145)			(0.017)		
Ln $(\text{higher})_t$		0.123**			-0.035**	
		(0.060)			(0.016)	
Ln $(\text{highinter})_t$			0.085			-0.043
			(0.103)			(0.049)
Hansen J test	4.257	3.979	4.486	0.063	2.258	2.696
(P value)	(0.119)	(0.137)	(0.106)	(0.802)	(0.133)	(0.260)
Kleibergen-Paap	43.38	30.78	42.24	11.06	5.84	8.00
(P value)	(<0.001)	(<0.001)	(<0.001)	(0.004)	(0.054)	(0.046)
R-squared	0.571	0.573	0.577	0.103	0.080	0.097
Observations	2338	2338	2338	2288	2288	2186

Notes: ***= significant at 1%, **= significant at 5%, *= significant at 10%.
Fixed effects (FE) estimates in Columns 1-3; First difference (FD) estimates in Columns 4-6. The dependent variable is log average labour productivity (ALP), defined as average value added per hour worked. Heteroscedasticity-robust standard errors, shown in brackets, are corrected for clustering of observations at the country/industry level. All independent variables have been instrumented with their own values at time t-1 and t-2. All equations include year dummies. Country dummies are included in the FD models. In the presence of heteroscedasticity, the Hansen J statistic is an appropriate test of the null hypothesis of instrument validity. The Kleibergen-Paap LM statistic tests the null hypothesis that the matrix of reduced-form coefficients in the first-stage regression is under-identified.

Table 2. Fixed effects GMM estimates of the determinants of Average Labour Productivity (ALP): accounting for human capital stock and proximity to the frontier

Dependent variable: ΔALP	*Human capital measure: skills*		*Human capital measure: higher*		*Human capital measure: highinter*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
$\Delta\ln(K/L)_t$	0.365***	0.345***	0.361***	0.324***	0.370***	0.351***
	(0.098)	(0.108)	(0.103)	(0.109)	(0.101)	(0.109)
$Ln(HC/L)_{t-1}$	0.044**	0.031*	0.021*	0.014	-0.010	-0.008
	(0.021)	(0.018)	(0.012)	(0.011)	(0.018)	(0.015)
Proximity: ALP_{t-1}	-0.052**		-0.055**		-0.043*	
	(0.022)		(0.023)		(0.023)	
Proximity: MFP_{t-1}		-0.130***		-		-
		(0.032)		0.130***		0.126***
				(0.032)		(0.032)
Hansen J test	0.418	0.094	2.491	2.709	0.593	0.292
(P value)	(0.811)	(0.759)	(0.288)	(0.099)	(0.744)	(0.589)
Kleibergen-Paap	39.34	34.96	36.08	36.00	31.30	31.06
(P value)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Observations	2313	2313	2313	2313	2313	2313
R-squared	0.098	0.108	0.098	0.108	0.097	0.107

Notes: ***= significant at 1%, **= significant at 5%, *= significant at 10%. The dependent variable is the first difference of log average labour productivity (ΔALP), defined as average value added per hour worked. Heteroscedasticity-robust standard errors, shown in brackets, are corrected for clustering of observations at the country/industry level. All independent variables have been instrumented with their own values at time t-1 and t-2. All equations include year dummies. For details of test statistics, see notes to Table 1.

Table 3. Fixed effects GMM estimates of the determinants of Average Labour Productivity (ALP): accounting for human capital stock and proximity to the frontier, extended specification

Dependent variable: ΔALP	*Human capital measure: skills*		*Human capital measure: higher*		*Human capital measure: highinter*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
$\Delta \ln(K/L)_t$	0.364***	0.362***	0.360***	0.308***	0.364***	0.352***
	(0.102)	(0.107)	(0.103)	(0.109)	(0.104)	(0.109)
$\ln(HC/L)_{t-1}$	0.137	0.110	0.049	0.035	-0.008	-0.005
	(0.206)	(0.118)	(0.088)	(0.036)	(0.020)	(0.034)
Proximity: ALP_{t-1}	-0.043*		-0.073*		-0.038*	
	(0.022)		(0.065)		(0.022)	
Proximity: MFP_{t-1}		-0.098**		-0.205*		-
		(0.047)		(0.106)		0.130***
						(0.048)
Proximity*$\ln(HC/L)_{t-1}$	-0.027	-0.130	-0.009	-0.028	-0.000	-0.005
	(0.054)	(0.170)	(0.024)	(0.036)	(0.000)	(0.042)
Hansen J test	0.375	0.204	2.548	2.553	0.627	0.289
(P value)	0.829	0.651	0.280	0.110	(0.731)	0.591
Kleibergen-Paap	11.33	4.507	13.34	18.52	31.80	31.78
(P value)	(0.010)	(0.105)	(<0.001)	9.50e-05	(<0.001)	(<0.001)
Observations	2313	2313	2313	2313	2313	2313
R-squared	0.091	0.101	0.099	0.108	0.097	0.107

Notes: ***= significant at 1%, **= significant at 5%, *= significant at 10%. The dependent variable is the first difference of log average labour productivity (ΔALP), defined as average value added per hour worked. Heteroscedasticity-robust standard errors, shown in brackets, are corrected for clustering of observations at the country/industry level. All independent variables have been instrumented with their own values at time t-1 and t-2. All equations include year dummies. For details of test statistics, see notes to Table 1.

Table 4. Fixed effects GMM estimates of the determinants of MFP growth rates: estimation of human capital spillovers.

Dependent variable: ΔMFP*	*Human capital measure: skills*		*Human capital measure: higher*		*Human capital measure: highinter*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Proximity$_{t-1}$	-0.162***	-0.102***	-0.090***	-0.068	-0.093***	-0.135**
	(0.048)	(0.036)	(0.031)	(0.085)	(0.034)	(0.053)
Ln (HC/L)$_{t-1}$	-0.023	-0.019	0.037**	0.031	0.002	0.034
	(0.023)	(0.067)	(0.018)	(0.025)	(0.019)	(0.030)
Ln (HC/L)$_{t-1}$ * Proximity$_{t-1}$		0.023		0.008		-0.057
		(0.126)		(0.029)		(0.046)
Hansen J test	0.107	0.002	3.740	4.201	0.060	0.001
(P value)	(0.744)	(0.965)	(0.154)	(0.122)	(0.970)	(0.972)
Kleibergen-Paap LM statistic	24.784	10.125	32.745	33.932	45.000	42.326
(P value)	(<0.001)	(0.006)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
R-squared	0.026	0.035	0.046	0.047	0.035	0.036
Observations	1,875	1,875	1,875	1,875	1,875	1,875

Notes: ***= significant at 1%, **= significant at 5%, *= significant at 10%. The dependent variable is the sophisticated MFP growth, defined in equation (13). The measure of proximity to the technology frontier is based on 'sophisticated' MFP estimates described in the main text, equation (12). For other details of estimation procedure see notes to Table 2.

Table 5: Fixed effects GMM estimates of the impact of high-level skills on MFP growth rates: robustness tests

Dependent variable: ΔMFP*	*Manufacturing industries*		*Market services industries*		*ICT-intensive industries*[(a)]		*Graduate-intensive industries*[(b)]	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Proximity_{t-1}	-0.080**	-0.029	-0.065	-0.248**	-0.074*	-0.133	-0.096	-0.251*
	(0.040)	(0.127)	(0.061)	(0.106)	(0.042)	(0.122)	(0.066)	(0.136)
Ln (higher)_{t-1}	0.020	0.005	0.019	0.070*	0.028	0.047	0.128***	0.118***
	(0.029]	(0.034)	(0.030]	(0.041]	(0.029)	(0.048)	(0.046)	(0.038)
Ln (higher)_{t-1} * Proximity_{t-1}		0.021		-0.056		-0.033		-0.074*
		(0.042)		(0.038)		(0.045)		(0.043)
Hansen J test	2.296	2.394	5.125	4.709	1.961	3.649	3.617	6.132
(P value)	(0.317)	(0.302)	(0.077)	(0.194)	(0.375)	(0.302)	(0.164)	(0.105)
Kleibergen-Paap LM statistic	16.11	18.35	14.42	15.02	19.97	20.75	15.83	15.15
P value	(0.001)	(<0.001)	(0.002)	(0.005)	(<0.001)	(<0.001)	(0.001)	(0.004)
R-squared	0.061	0.059	0.065	0.086	0.066	0.067	0.029	0.052
Observations	975	975	600	600	750	750	750	750

Notes: ***= significant at 1%, **= significant at 5%, *= significant at 10%. The dependent variable is the sophisticated MFP growth, defined in equation (13). The measure of proximity to the technology frontier is also based on 'sophisticated' MFP estimates described in the main text, equation (12). For other details of estimation procedure see notes to Table 2. (a) ICT-intensive industries comprise: Pulp, paper and paper products, printing and publishing; Mechanical engineering; Electronic engineering; Transport equipment; Furniture and miscellaneous manufacturing; Wholesale trade; Retail trade; Communications; Financial services; Business services

(b) Graduate-intensive industries comprise: Oil refining, Chemicals, Electronic engineering, Pulp, paper and paper products, printing and publishing, Utilities, Communications, Financial services, Business services, Other services and Non-market services.

Table A1

Classification of EPKE industries

EPKE Industry	Industry Name	SIC 1992 Codes
1	Agriculture, forestry and fishing	01-05
2	Mining and quarrying	10-14
3	Food, drink and tobacco manufacturing	15-16
4	Textiles, leather, footwear and clothing manufacturing	17-19
5	Wood and wood products	20
6	Pulp, paper and paper products, printing and publishing	21-22
7	Oil refining, coke and nuclear fuel	23
8	Chemicals	24
9	Rubber and plastics	25
10	Non-metallic mineral products	26
11	Basic metals and fabricated metal products	27-28
12	Mechanical engineering	29
13	Electrical & electronic equipment and instruments	30-33
14	Transport equipment	34-35
15	Furniture and miscellaneous manufacturing; recycling	36-37
16	Electricity, gas and water	40-41
17	Construction	45
18	Repairs and wholesale trade	50-51
19	Retail trade	52
20	Hotels and catering	55
21	Transport	60-63
22	Communications	64
23	Financial services	65-67
24	Business services	71-74
25	Other private services	90-99
26	Non-market services	75-85

Table A2

Qualification categories employed in the measurement of human capital quality

Country	Qualification group	Description
USA	1	Bachelor degrees and above
	2	Associate degree
	3	Some college, no degree
	4	High school graduate
	5	Did not complete high school
UK	1	First degree and above
	2	Other NVQ4
	3	NVQ3
	4	NVQ2 & NVQ1
	5	No formal qualification
France	1	Bachelor degree and above
	2	Baccalaureate plus 2 years college
	3	Baccalaureate
	4	Vocational (CAP, BEP or similar)
	5	General Education (BEPC)
	6	No formal qualification
Germany	1	Higher education (16+ years of education)
	2	Vocational degree
	3	No degree
Netherlands	1	Master degree and above
	2	HBO*
	3	HAVO/VWO**
	4	MAVO**
	5	MBO***
	6	LBO/VBO***
	7	Primary education or below

Data sources:
US: Current Population Survey; UK: Labour Force Survey; France: Enquête-Emploi; Germany: Mikrozensus and Socio-Economic Panel; Netherlands: Labour Force Sample Survey and Labour Force Survey
Notes:
*HBO is tertiary education, of a vocational type. **HAVO/VWO/MAVO is general education which normally leads to entry into a higher level, taking up to 4 to 6 years of study after primary school. *** LBO/VBO and MBO are vocational schooling, taking up to a maximum of 4 to 6 years after primary school (O'Mahony and Van Ark, *EU productivity and competitiveness: an industry perspective*, European Communities 2003).

Table A.3

Descriptive statistics

	Obs.	Mean	Std. Dev.	Min	Max
(a) Gross value added (US$, millions, constant prices)					
US	572	212.0	277.0	10.6	1560.0
UK	572	28.6	30.6	2.2	173.0
France	572	30.9	36.7	1.7	225.0
Germany	572	47.0	51.2	2.0	290.0
Netherlands	572	11.0	15.9	0.5	89.6
(b) Total hours worked (thousands)					
US	572	8219.5	10700.0	255.0	62500.0
UK	572	1774.6	1919.7	62.4	9577.1
France	572	1446.0	1750.3	40.0	9262.5
Germany	572	2097.9	2152.6	35.2	11600.0
Netherlands	572	353.4	442.0	11.2	2232.3
(c)Total capital services (US$, millions, constant prices)					
US	546	51.6	43.7	2.4	245.0
UK	546	8.5	8.1	0.7	53.5
France	546	14.3	18.4	0.1	97.8
Germany	546	18.1	14.2	1.3	58.8
Netherlands	546	3.0	2.8	0.1	15.2
(d) Certified and uncertified skills (ratio of quality-adjusted labour inputs, unskilled base, to total hours worked)					
US	572	1.46	0.29	1.03	2.43
UK	572	1.36	0.44	1.00	6.39
France	475	1.23	0.18	1.00	2.35
Germany	500	1.44	0.32	1.09	3.12
Netherlands	550	1.18	0.11	1.02	1.64
(e) High-qualified hours worked as proportion of total hours worked					
US	572	0.18	0.09	0.04	0.42
UK	572	0.09	0.07	0.02	0.35
France	475	0.07	0.06	0.0001	0.32
Germany	500	0.05	0.04	0.003	0.15
Netherlands	550	0.15	0.11	0.02	0.47
(f) High- and intermediate-qualified hours worked as proportion of total hours worked					
US	572	0.37	0.15	0.10	0.76
UK	572	0.42	0.14	0.12	0.73
France	475	0.59	0.13	0.25	0.93
Germany	500	0.67	0.10	0.41	0.91
Netherlands	550	0.28	0.12	0.10	0.61

Table B.1

OLS regression of quality-adjusted labour inputs (unskilled base) on quality-adjusted labour inputs (graduate base)

Explanatory variables	(1)
Quality-adjusted labour inputs (graduate base)	0.7242*
Total hours worked	1.3140***
	(0.3014]
Observations	2669
Adj R2	0.9601

Notes: ***= significant at 1%, **= significant at 5%, *= significant at 10%.
The dependent variable is quality-adjusted labour inputs (unskilled base). Robust standard errors in parentheses are corrected for clustering of observations at the country/industry level. Year dummies are included.