Absorptive Capacity and Frontier Technology:

Evidence from OECD Manufacturing Industries

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Abstract

This paper investigates whether differences in absorptive capacity help to explain cross-country differences in the level of productivity. We utilise stochastic frontier analysis to investigate two potential sources of this inefficiency: differences in human capital and R&D for nine industries in twelve OECD countries over the period 1973-92. We find that inefficiency in production does indeed exist and it depends upon the level of human capital of the country's workforce. Evidence that the amount of R&D an industry undertakes is also important is less robust.

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1 Introduction

This paper investigates whether differences in absorptive capacity help to explain cross-country differences in the level of productivity. Absorptive capacity, as discussed by Arrow (1969), captures the idea that countries may differ in their effort and ability to adopt new technologies even if knowledge is global (Eaton and Kortum, 1996; Griffith, Redding and Van Reenen, 2000; Papageorgiou, 2000; Xu, 2000). Two formal approaches have been developed to model this mechanism: Abromovitz (1986) and Cohen and Levinthal (1989) model technical adoption as depending on the level of human capital, whereas Fagerberg (1988) and Verspagen (1991) develop models in which innovation improves the capacity to absorb foreign country technology.

Following this literature we examine the effect of human capital and of research and development (R&D), as determinants of absorptive capacity, on the inefficiency with which countries use frontier technology for a panel of nine manufacturing industries in twelve OECD countries over the period 1972 to 1992 using Stochastic Frontier Analysis (SFA). SFA allows the study of absorptive capacity in a framework that closely matches the idea of a technical frontier found in growth theory. In our framework, each industry faces the same production frontier – the maximum output for a given level of inputs. Differences in the level of absorptive capacity help explain deviations from this frontier through differences in inefficiency.

The use of R&D and human capital as determinants of absorptive capacity allows for the possibility that one or both have a dual effect on production: a direct effect and an effect through inefficiency. For this reason the paper is also concerned with the appropriate specification of the production function and the stock of frontier knowledge. We address these issues by focusing on alternative modelling strategies debated in the literature. Among these we consider the inclusion of human capital in the production function, the measurement of frontier knowledge, and the underlying functional form of the production function.

The study of absorptive capacity using SFA has a number of advantages over the alternative modelling strategies in the previous literature.[1] Griffith *et al*. (2000), Keller (2001a,b) and Kneller (2002) who also research the effects of R&D and human capital on productivity in OECD manufacturing industries, use a two stage modelling strategy.

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[1] The statistical advantages of using SFA are outlined in Koop *et al*. (2000).

In those paper estimates of productivity are generated as the residuals from a parameterised production function. Griffith *et al*. (2000) and Kneller (2002) then express these relative to the country within each industry with the highest level of TFP at each point in time. This relative productivity variable is regressed on a set of productivity determinants that includes human capital and R&D. The weakness of this methodology is that it assumes that the technical frontier is defined solely by the observations from this one country at each point in time and, therefore, that all changes in relative productivity in the remaining countries measures technical catch-up (reductions in inefficiency). Keller (2001a,b) in contrast, building on the work of Coe and Helpman (1995), studies the effect of foreign technology on domestic productivity. This approach assumes that productivity growth equates to technological change and therefore the restrictive assumption that all countries are completely efficient in their use of frontier technology. SFA allows the observations from more than one country to define the technical frontier and for productivity growth to be decomposed into changes in technology, inefficiency and statistical error. In this sense it allows us to clearly differentiate movements of and movements towards the technical frontier. Koop (2001) has previously used SFA for a similar sample in the decomposition of growth rates, although they did not consider the issue absorptive capacity.[2] This paper also differs in its treatment of human capital and its description of movements in the technical frontier from that paper.

We find from this study that there is strong evidence that countries differ in the efficiency with which they use frontier technology. The implied assumption of Coe and Helpman (1995), Keller (2001a,b) and others that countries are efficient in their use of frontier technology does not receive empirical support. Human capital plays a significant and quantitatively important role in explaining these differences in efficiency. There is also clear evidence that human capital affects production both directly and through an effect on productivity. For this reason we reject the Benhabib and Spiegel (1994) conclusion that human capital does not enter the production function directly. Like de la Fuente and Domènech (2000) we also raise concerns over data quality and argue against the use of Barro and Lee (2000) estimates of human capital.

[2] See also Färe *et al* (1994) Koop *et al* (1999, 2000) who use SFA and the related Data Envelopment Analysis (DEA) in the decomposition of growth rates at the cross-country level.

The results presented in this paper also lead us to conclude that the effect of R&D on production is primarily through its contribution to the stock of frontier knowledge in each industry. R&D is found to have only a quantitatively small effect on inefficiency and is not robust to all changes in specification. Spillovers from R&D on efficiency are not important for explaining differences in inefficiency. When we measure the stock of frontier knowledge with the R&D stock data from more than one country the absorptive capacity effect of R&D all but disappears. These results hold whether the stock of frontier technology is measured by the stock of R&D in the five largest OECD countries in the sample (France, Germany, Japan, UK and US); the remaining seven OECD countries in the sample (Canada, Denmark, Finland, Italy, Netherlands, Norway and Sweden); or the sum of the stock of R&D in these 12 countries. It would appear that the strong effects from R&D on productivity found in the previous literature are generated because of the strong assumptions made in those papers surrounding the measurement of the stock of frontier technology. This results leads us to suggest that careful consideration of how to measure the stock of frontier technology is important in future work.

Finally, Keller (2001a,b,c), Eaton and Kortum (1999) and others have argued that the source of new technology is typically not domestic but foreign. Eaton and Kortum (1999) estimate that even in the US, on average the most productive economy, around 40 per cent of productivity growth in 1988 was due to foreign R&D. This work suggests that the position of the technical frontier may differ across countries according to the international diffusion of technology at a given point in time. The position of the country specific industry frontier may lie inside the global industry frontier in the short-run. Following Keller (2001a,b) we test for this possibility by allowing the stock of frontier knowledge in each industry to depend on the physical distance from the source of new ideas. We find initial evidence to suggest that such factors may be important.

The rest of the paper is organised as follows. In section 2 we outline our model of production and empirical method, while section 3 discusses the data to be used. In section 4 we present results from our estimates, while Section 5 concludes.

2 A Model of Production

We assume in the paper that output, Y, is a function of the production technology set out in equation (1), where j indexes the industry, i country and t time.

$$Y_{ijt} = f_j\left(K_{ijt}, L_{ijt}, H_{ijt}, \overline{R}_{jt}\right)\eta_{ijt}\varepsilon_{ijt} \tag{1}$$

where K is the capital stock, L is the effective labour supply (number of workers adjusted for average hours per week), H is the stock of human capital, as measured by years of schooling, $\overline{R}_{jt}$ the stock of frontier technical knowledge in industry j at time t, η $(0 < \eta \leq 1)$ represents economic efficiency and ε reflects the random character of the frontier, due to measurement error or other effects not captured by the model. This last term is unique to the SFA approach. A detailed explanation of the estimation of SFA is outlined in Koop *et al*. (1999, 2000).

To account for possible complementarily between human capital and physical capital we follow Griliches (1969) and Mankiw, Romer and Weil (1992) and include human capital as a separate term in the production function.[3] We make this choice in order to recognise the possible dual role of human capital in the production function (both directly and through the efficiency term). We also consider the robustness of alternative specifications.

Aside from the usual set of factor inputs, output in Equation 1 is assumed to be a function of the total stock of knowledge in a given industry at time t, which following Griliches and Lichtenberg (1984) we assume to depend on the stock of R&D in each industry. Technological change therefore depends on growth in the stock of R&D. Koop (2001) and Koop *et al*. (1999, 2000) use an alternative assumption that technology growth depends on a quadratic time trend.

The question is how to measure the stock of industry knowledge. Two distinct methods have been used in the previous literature that might be useful in this regard. These might be labelled as the stock of accessible knowledge and the one-country frontier. The first measure of frontier technology used extensively in the previous literature has been the stock of technology accessible to the domestic economy. Under such a measure the size of the domestic R&D stock is combined with the stock of foreign R&D, where the latter is aggregated using the level of trade between the domestic and the foreign country as weights (Coe and Helpman, 1995; Coe, Helpman and Hoffmeister, 1997; Keller, 2000, 2001a,b). The stock of knowledge in a given country therefore differs according to the level of trade. This implies that the position of

[3] Koop (2001) does not include H in the production function or as a determinant of efficiency .

the technical frontier also differs across countries, frontier knowledge has not yet diffused identically to these countries. While this is a possibility that we explore below it also makes the restrictive assumption that countries are efficient in their use of the stock of accessible technology, an assumption that we do not follow. At the conceptual level this measure sits poorly with the idea of a common industry frontier found in growth theory (Howitt, 2000; Howitt and Mayer-Foulkes, 2002), and the empirical evidence that inefficiency helps to explain international differences in productivity (Prescott, 1998; Koop *et al*., 2000; Griffith *et al*., 2000).[4]

The problem of how to aggregate to total industry knowledge is simplified if the frontier level of knowledge is assumed to be approximated by the data from just one country. For example, Griffith *et al*, (2000) and Kneller (2002) both use the country with the highest level of productivity as the numeraire in a measure of relative productivity. However, such an approach has two obvious limitations in the context of this paper. First, it assumes that the reference country is on the technical frontier, indeed that it solely defines the frontier for all countries – no trivial assumption. Second, if a time dimension is added to the data then all technical progress is described by the observations from this sole country. If this is not the case then changes in technical progress from a follower country may be erroneously measured as catch-up to the productivity leader. Neither assumption holds unless the dispersion of knowledge across countries is instantaneous.

In the light of these issues we utilise an SFA approach in which the data is allowed to determine the position and the shape of the technical frontier. The stock of knowledge at the technical frontier is then assumed to equal the stock of R&D in the five countries that contribute most to the stock of R&D in the industry. The contribution of a unit of R&D to frontier knowledge from these countries is assumed to be identical. In the remaining countries R&D affects only their position relative to the technical frontier. A similar assumption is made in Keller (2001a). These assumptions appear reasonable in light of the fact that the five countries chosen, France, Germany, Japan, UK and US accounted for close to 90 per cent of the total measured stock of R&D in the 12 OECD sample countries in 1990. In addition Kneller (2002) finds evidence of an absorptive capacity effect of R&D, but no frontier effect when these five countries were excluded from the same sample. We test the robustness to the use of this measure below

[4] Kneller (2002) studies absorptive capacity and distance within the same empirical model.

by testing whether the results are affected by the exclusion of the five most intensive R&D countries and by allowing all countries to determine the stock of frontier knowledge.[5]

Equation (1) recognises that countries may differ in their level of productivity in each industry through the term η. If a country is 100% efficient (η = 1), it can utilise all frontier knowledge, otherwise impediments to absorption will cause the country to produce within the industry frontier. One of the implications of equation (1) is that it is possible for the R&D of a technical laggard country to contribute nothing to the stock of industry knowledge, but affect output through the efficiency term, η. Howitt and Mayer-Foulkes (2002) develop a theoretical model of growth that has similar properties.

Following Battese and Coelli (1995), the inefficiency effect is obtained by a truncation of the normal distribution $N(\mu_{it},\sigma^2)$. Inefficiency is modelled as dependent on the level of investment in R&D in industry j in country i at time t, the level of human capital and country-specific dummies to capture differences in institutional design and regulations across countries.[6] Given differences in the complexity of technology across industries the effect of human capital is allowed to vary by industry through industry specific interaction terms. The mean level of inefficiency is defined by

$$\mu_{ijt} = \delta_0 + \delta_1 r\&d_{ijt} + \delta_{20} h_{ijt} + \sum_{j=1}^{8} \delta_{2j} h_{ijt} ind_{j\neq 0} + \sum_{i=1}^{11} \delta_{3i} country_{i\neq 0} \tag{2}$$

where $r\&d$ is the (logarithm of) spending on R&D in the industry and $\sum_{j=1}^{8} \delta_{2j} h_{ijt} ind_{j\neq 0}$ is the (logarithm of) human capital interacted with industry dummies[7]. If human capital and R&D both promote the absorption of technology, we would expect to find negative coefficients on δ_1 and δ_{20}, i.e. they reduce the distance from the frontier.

The log-likelihood function for this model is presented in Battese and Coelli (1993), as are the first partial derivatives of the log-likelihood function with respect to the

[5] This measure of changes in the technical frontier might also be considered imperfect if there are significant cross-industry spillovers of R&D. We choose to leave alternative constructs of frontier knowledge that might include such spillovers for future research.

[6] Prescott (1998) and Parante and Prescott (2000) suggest that permanent differences in the design of institutions may be important.

[7] The baseline industry (j = 0) is 'basis metal industries'.

different parameters of the model[8]. The maximum likelihood estimators for the parameters in the model were obtained using the FRONTIER computer program (Coelli, 1996).

One of the parameters included with the tables of results in Sections 3 is the estimated the variance of the efficiency term relative to the variance of the total error:

$$\gamma = \frac{\sigma^2}{\sigma_\varepsilon^2 + \sigma^2} \tag{3}$$

The value of the γ parameter provides a useful test of the relative size of the inefficiency effects and lies between zero and one. If γ = 0, this indicates that deviations from the frontier are due entirely to noise, previous studies that use a standard (i.e. non-stochastic frontier) econometric methodology are entirely correct in their implicit assumption of economic efficiency. If γ= 1, however, this would indicate that all deviations are due entirely to economic inefficiency and hence the stochastic frontier model is not significantly different from the deterministic frontier model with no random error[9]. In practice we find γ to be in the range, 0.8 to 0.85 and statistically significant, questioning the validity of the findings from the non-SFA literature. The generalised likelihood-ratio test for the null hypothesis that the γ parameter and the δ parameters are jointly equal to zero is calculated by using the values of the log-likelihood function for estimating the full frontier model and that obtained from an OLS regression of the production function. This statistic has a mixed chi-square distribution.[10]

3 Data

The model outlined above is estimated for a sample of 9 manufacturing industries in 12 countries over the period 1973 to 1992. The total number of available observations is 1731 (the exact coverage for each industry and country is given in Table 1 below). The output (value added), capital stock and employment data are all taken from the OECD ISDB database. This data is available on an international comparable basis having been

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[8] This parameterisation originates in Battese and Corra (1977).

[9] Note that γ is not the proportion of the total error term explained (except at values of γ= 0 and γ= 1) (see footnote 7, page 188 of Coelli, Rao and Battese, 1999; Coelli, 1995).

deflated to 1985 prices and converted using measures of PPP to US$. As is usual in the literature we adjust the employment data for hours worked using OECD data in the manufacturing sector as a whole[11].

Table 1 Available data by country and industry

SIC / *Sector*	*31* *BMI*	*32* *CHE*	*33* *FOD*	*34* *MEQ*	*35* *MNM*	*36* *MOT*	*37* *PAP*	*38* *TEX*	*39* *WOD*	*Total*
Canada	73-90	73-90	73-90	73-90	73-90	73-90	73-90	73-90	73-90	162
Denmark	73-90	73-90	73-90	73-90	73-90	73-90	73-90	73-90	73-90	162
Finland	73-91	73-91	73-91	73-91	73-91	73-91	73-91	.	73-91	152
France	73-91	73-91	73-91	73-91	73-91	.	73-91	73-91	73-91	152
Germany	73-91	73-91	73-91	73-91	73-91	73-91	73-91	73-91	73-91	171
Italy	73-90	73-88	73-90	73-88	73-90	.	73-88	73-90	.	120
Japan	73-91	73-91	73-91	73-91	73-91	73-91	73-91	73-91	.	152
Neth.	73-90	.	73-90	.	.	.	73-90	73-89	.	71
Norway	73-91	73-91	73-91	.	73-91	73-91	.	73-91	73-91	133
Sweden	73-91	73-91	73-91	73-91	.	.	73-91	73-91	73-91	133
UK	73-91	73-91	73-91	73-91	73-91	73-91	73-91	73-91	.	152
US	73-91	73-91	73-91	73-91	73-91	73-91	73-91	73-91	73-91	171
Total	224	204	224	185	187	150	203	204	150	1731

Note: BMI = basis metal industries; CHE = chemicals etc; FOD = food, beverages and tobacco; MEQ = machinery & equipment; MNM = non-metallic mineral products; MOT = other manufacture industries; PAP = paper products; TEX = textiles, wearing apparel; WOD = wood products.

The absorptive capacity effect of R&D is measured using the flow of R&D investment made in each period from the OECD EBRD dataset for the period 1973 to 1992. Estimates of the stock of R&D (R_{ijt}) in each country, necessary for the construction of the stock of frontier knowledge in each industry, are generated by accumulating R&D expenditures using a perpetual inventory method (equation 4). The rate of depreciation (Δ) is set to equal 10 per cent in the equation, while the initial stock

[10] See Coelli and Battese (1996).

[11] Data for hours worked is available for Canada, Belgium, Denmark, France, Germany, Japan, Norway, Sweden U.K., U.S. The data for Germany, Belgium, Denmark, and Sweden is expressed as an index and was converted using information contained in O'Mahony (1999), where missing data was converted using the average of hours worked in the UK, France and Germany in the base year. Data for Italy and the Netherlands is unavailable in either data source and was instead generated as the average for all European countries.

of R&D is estimated in the usual way (where the term g^{RD} is the average annual growth rate of R&D over the period).

$$R_{ijt} = (1-\Delta)R_{ijt-1} + RD_{ijt-1}$$
$$R_{ij0} = \frac{RD_1}{(g^{RD}+\Delta)} \tag{4}$$

4 Results

To facilitate comparisons with the literature on the cross-country econometric estimation of the production function (Mankiw *et al*., 1992; Senhadji, 2000; Miller and Upadhyay, 2000) we assume in our initial specification that output in equation 1 is produced using Cobb-Douglas technology, which we write in log-linear form $f_j(\cdot)$ in Equation 5.

$$y_{ijt} = \beta_0 + \beta_1 k_{ijt} + \beta_2 l_{ijt} + \beta_3 h_{jt} + \beta_4 r_{jt} + \beta_5 d_j - \nu_{ijt} + \upsilon_{ijt} \tag{5}$$

where lower case letters represent logarithms ($\nu = \ln(\eta)$ and $\upsilon = \ln(\varepsilon)$). Koop (2001) also chooses to start from such a position. Given the objections to the assumption of C-D technology outlined in Duffy and Papageorgiou (2000) we test the robustness of the results to more flexible functional forms below.[12]

The results from the estimation of equations 2 and 5 are presented in Table 2. The top half of the Table refers to the production frontier and the bottom half the efficiency effects. Model (1) in the Table refers to our baseline specification (a Cobb-Douglas production function with industry dummies to account for variations in technology), while model (2) refers to the same form of production function, but does not allow for separate industry intercept terms. We omit the industry dummies from the top half of the Table however in order to conserve space, while we do the same for the country dummies in the bottom half of the Table.[13]

A comparison between models 1 and 2 illustrates the bias caused by excluding the industry effects. This bias is similar to that found from the assumption of identical initial productivity in the cross-country convergence literature (Islam, 1995; Caselli *et*

[12] The industry dummies in equation 4 allow the position of the technical frontier to differ across industries.
[13] These coefficients are available from the authors on request.

al., 1996; Evans, 1997). This bias is clearest in the case of the estimated parameter on human capital, *h.* In model 2 human capital has a significant negative effect – implying that countries with more years of average schooling actually have *lower* levels of output, *ceteris paribus*, whereas in model 1 the estimated relationship is significant and positive. The omission of industry dummies in turn leads to a bias in the estimated effect of human capital and R&D on inefficiency effects. The effect of R&D is insignificant in model 2, while many of the human capital interaction terms change sign. This would appear to be due to the fact that the latter is conflating differences in output due to economic inefficiency and differences in output explained by the technical relations of production – i.e. differences in the distance from the frontier with the frontier itself. For this reason we ignore model 2 from our discussion.

Table 2 Results from SFA base model

Number of observations: 1731, Time-periods: 19

Model No.	(1)*			(2)		
	Coef.	*s.e.*	*t*	*Coef.*	*s.e.*	*t*
Production Function						
l	0.708	0.014	49.9	0.722	0.019	40.0
k	0.301	0.013	23.2	0.301	0.017	17.6
$\bar{r}_5$	0.126	0.011	11.1	0.080	0.011	7.6
h	0.226	0.043	5.2	-0.238	0.085	2.8
Inefficiency Effects						
h	-1.170	0.406	2.9	-1.983	0.353	5.6
r&d	-0.035	0.014	2.5	-0.010	0.011	0.9
CHE×h	0.080	0.023	3.501	-0.034	0.024	-1.425
FOD×h	-0.079	0.025	-3.225	-0.185	0.019	-9.737
MEQ×h	-0.061	0.030	-2.008	0.079	0.034	2.313
MNM×h	-0.054	0.027	-2.013	-0.077	0.020	-3.880
MOT×h	-0.193	0.032	-6.062	-0.217	0.024	-8.860
PAP×h	0.010	0.025	0.415	-0.100	0.022	-4.656
TEX×h	-0.010	0.027	-0.360	0.069	0.021	3.276
WOD×h	-0.193	0.037	-5.214	-0.086	0.025	-3.452
σ^2	0.093	0.005	19.8	0.064	0.003	19.3
γ	0.863	0.012	69.3	0.898	0.021	41.9
Log likelihood function			379.33			236.71
LR test of the one-sided error			1237.2			1373.5

Notes:

- *Model 1 includes industry dummies within the production function.*
- *BMI = basis metal industries; CHE = chemicals etc; FOD = food, beverages and tobacco; MEQ = machinery & equipment; MNM = non-metallic mineral products; MOT = other manufacture industries; PAP = paper products; TEX = textiles, wearing apparel; WOD = wood products.*

Overall the impression from model 1 is that the estimated parameter values are close to those found from the previous literature. Indeed it is interesting to note that the results are consistent with several of the assumptions often used in the growth accounting. The elasticity of output with respect to physical capital is close to that implied by the National Accounts and the results are consistent with the assumption of constant returns to scale for physical capital and labour. The combined elasticity of output with respect to physical capital and human capital is 0.527. This is very close to the estimates for the OECD country sample in Mankiw *et al*. (1992) and just below the estimates made in Miller and Upadhyay (2000) and Bloom *et al*. (2002).

The estimated return to R&D found in model 1 is also plausible. According to the results a one percentage point increase in the stock of world technology increases output by 0.126 percentage points. This is within the range of results found elsewhere in the literature. For example, it is slightly higher than the estimates obtained from the import weighted measures of foreign R&D by Coe and Helpman (1995) and Keller (2001a,b), close to the frontier effect in Griffith *et al*. (2000) and slightly below the relative frontier variable used in Kneller (2002) .

Turning to the effect of the efficiency terms themselves, we can see in model 1 that human capital and R&D both have the expected negative sign. The two faces of R&D discussed by Griffith *et al*. (2001) and Kneller (2002) has empirical support even when using SFA. The estimated effect of R&D on domestic efficiency is smaller than the parameter estimates for domestic R&D found in Coe and Helpman (1995), Keller (2001a,b) and Kneller (2002) however. Indeed while R&D is found to be statistically important the point estimate in model 1 is small in absolute value, especially when compared to that on human capital. A one percentage point increase in R&D leads to a decrease in inefficiency in the order of just 0.035 percentage points. The evidence for spillovers from R&D on efficiency appears weak. Differences compared to those found using alternative modelling strategies may arise out of differences in the specification of the frontier.[14]

The results for human capital suggest strongly that improvements in education among OECD countries over the post-war period has contributed to increased level of efficiency. A one percentage point increase in human capital leads to a 1.17 percentage point reduction in productive inefficiency. These results are also supportive of evidence found in Griffith *et al*. (2000), Kneller (2002) and the discussion in Fagerberg (1994) that human capital is important for technology transfer. Fagerberg (1994) has previously argued, albeit for developed and developing countries, that the technology gap needs to be sufficiently small for human capital to significantly aid technology transfer. This does not appear to apply in this sample of OECD countries, but may suggest caution in generalising from these results to a broader sample of countries.

[14] The inclusion of an interaction term between R&D and human capital does not improve the results for R&D. All three terms, human capital, R&D and the interaction term, are found to be statistically insignificant in such a regression and the fit of the model, measured by the log-likelihood function, is weaker than that of model 1.

Several of the human capital interaction terms included in the efficiency equation are significantly different from zero. Despite their significance it is evident however, that the estimated parameters are actually quite small in magnitude, such that the contribution of human capital to absorptive capacity does not differ greatly in economic terms across industries. It is also evident from Table 2 that the pattern of the coefficients on the industry/human capital interaction terms do not match the usual *a-priori* perceptions about cross-industry differences in skill intensity.

The mean and standard deviation of the efficiency score for each country in each industry is presented in Table A1 of the Appendix. The industry and country specific averages are reported in weighted and in un-weighted forms, where average output figures over the sample periods are used as weights.

4.1 The Role of Human Capital

Little agreement exists in the literature as to the appropriate treatment of human capital in the production function and to its measurement. Mankiw, Romer and Weil (1992), Miller and Upadhyay (2000) and Bloom Canning and Sevilla (2002) allow human capital to affect production technology directly, whereas Benhabib and Speigel (1994), Pritchett (1996) and Islam (1995) find evidence to suggest that human capital affects the level of total factor productivity and has no direct effect on output. An interesting explanation for this lack of consensus is given in de la Fuente and Domènech (2000). They conclude that the Benhabib and Speigel (1994), Islam (1995) and Pritchett (1996) results are generated by poor quality data, namely from the use of the Barro and Lee (2000) and World Bank datasets. We address this modelling issue using SFA.

Thus far our results point to a dual effect on production. We consider the robustness of these results by re-estimating equations 2 and 5 using data from Barro and Lee (2000) (labelled model 3), and by excluding human capital from the production function, but using the de la Fuente and Domènech (2000) estimates of human capital to capture any indirect effects (model 4). If data quality is not an issue then we would expect the results in model 3, using the Barro and Lee (2000) data, to be similar to those found using the de la Fuente and Domènech (2000) data in model 1. We test whether omitting human capital from the production function is appropriate through a comparison of the estimates of the log-likelihood function in model 1 and model 4.

We find from model 3 that we can replicate the general conclusion of de la Fuente and Domènech (2000). The Benhabib and Spiegel (1994) results do indeed appear to be sensitive to the use of the Barro and Lee measures of human capital. Therefore, if the de la Fuente and Domènech (2000) data are an improvement over the Barro and Lee (2000) estimates, it is important that the former are used. The direct effect of human capital on the production function estimated in model 3 is close to that estimated in model 1, but unlike in model 1 there is no longer evidence that human capital affects the level of efficiency. Indeed if anything the point estimate on human capital suggests increased levels of human capital lowers the level of efficiency. This provides an interesting contrast with the result of Benhabib and Speigel (1994). Like them, when we use Barro and Lee data we find evidence that human capital affects production only through one channel, but unlike those authors we find that this effect on production is direct and not through productivity.

The evidence from model 4 leads to a clear rejection of the assumption that human capital can be safely excluded from the production function. A comparison of the estimates of the log-likelihood function shows that the fit of model 4 is much weaker than that of model 1. The log likelihood function is 379.34 in model 1 and 83.34 in model 4. The exclusion of human capital from the production function also has a interesting impact on the estimated parameters. The coefficient on physical capital rises from 0.3 to 0.4, but is no longer statistically significant at conventional levels. Somewhat surprisingly the effect of human capital on efficiency is also much lower in model 4 and is no longer statistically significant. Indeed a 1 percentage point increase in human capital now leads to a 0.09 percentage point decrease in the level of inefficiency.

Table 3 The inclusion of Human Capital in the Production Function

Number of observations: 1731, Time-periods: 19

Model No.	(3)[a]			(4)		
	Coef.	*s.e.*	*t*	*Coef.*	*s.e.*	*t*
Production Function						
l	0.687	0.014	47.6	0.690	0.275	2.507
k	0.293	0.014	21.7	0.404	0.246	1.641
$\bar{r}_5$	0.135	0.011	11.8	0.159	0.124	1.284
H	0.233	0.032	7.3	-	-	-
Inefficiency Effects						
h	0.35	0.208	1.7	-0.091	0.858	-0.106
$r\&d$	-0.046	0.014	3.4	0.012	0.610	0.020
$CHE\times h$	0.498	0.152	3.3	0.041	0.997	0.041
$FOD\times h$	0.985	0.124	8.0	-0.115	0.999	-0.115
$MEQ\times h$	1.63	0.169	9.6	-0.074	0.998	-0.074
$MNM\times h$	2.38	0.116	20.5	-0.054	0.997	-0.054
$MOT\times h$	1.58	0.135	11.7	0.013	0.999	0.013
$PAP\times h$	2.46	0.123	20.0	0.100	0.995	0.100
$TEX\times h$	2.23	0.113	19.7	0.077	0.993	0.077
$WOD\times h$	2.00	0.112	17.8	-0.153	0.999	-0.153
σ^2	0.084	0.005	15.9	0.143	0.436	0.329
γ	0.862	0.014	62.5	0.869	0.413	2.107
Log likelihood function			379.34			83.34
LR test of the one-sided error			1214.5			785.25

Notes:

- *Model 3 uses Barro and Lee (2000) data.*
- *BMI = basis metal industries; CHE = chemicals etc; FOD = food, beverages and tobacco; MEQ = machinery & equipment; MNM = non-metallic mineral products; MOT = other manufacture industries; PAP = paper products; TEX = textiles, wearing apparel; WOD = wood products.*

4.2 Measurement of the Technical Frontier

Evidence about the difference between the direct and efficiency effects of R&D might be inferred if, as seems likely, the innovative aspect of R&D is less important for the smaller OECD economies. In model 5 we therefore consider the effect on the results of excluding France, Germany, Japan, UK and US countries from the sample. The R&D data from the remaining countries are used to determine the level of frontier knowledge.[15] A similar approach is utilised in Kneller (2002). Given the results from

[15] Similar results are found when we use the stock of industry knowledge from model 1, but still exclude France, Germany, Japan, UK and US from the sample.

this exercise we also report the results from a model in which all OECD countries contribute to the level of frontier technology (model 6).

Our final test in this section considers differences in the position of the technical frontier across countries. Evidence presented in Coe and Helpman (1995), Keller (2001a,b) and Eaton and Kortum (1999) suggests that international technology transfer is important for explaining differences in productivity. The question in SFA is whether this should be modelled as an effect on the position of the technical frontier or the distance from the frontier. In this paper we assume absorptive capacity determines the efficiency with which the stock of accessible technologies issued, where the stock of accessible knowledge depends on technology transfer. This implies that the position of the country specific industry frontier may lie inside the global industry frontier at a given point in time. In the long-run we would expect the two frontiers to coincide.

Following Keller (2001a,b) and Kneller (2002) we assume technology transfer depends on the physical distance from the source of new ideas. Physical distance has been previously identified as an important determinant of a number of the transmission mechanisms of knowledge transfer, such as international trade, FDI and human contact (see Keller, 2001c for a review). The effect of distance on industry knowledge is captured by adding to equation 5 an interaction term between R&D and physical distance, shown in equation 6 below. The term D_{if} measures the physical distance between country i and country f (where f is one of France, Germany, Japan, UK and US). The interaction term is increasing in distance such that the expected coefficient on β_5 is negative.[16] If this holds then the stock of R&D in country f accessible in country i is decreasing in the physical distance between the two countries.

$$y_{ijt} = \beta_0 + \beta_1 k_{ijt} + \beta_2 l_{ijt} + \beta_3 h_{jt} + \beta_4 r_{jt} + \beta_5 r_{jt} D_{if} + \beta_6 d_j - \nu_{ijt} + \upsilon_{ijt} \tag{6}$$

[16] Equation 6 restricts the effects of distance on technology transfer to be log-linear. We use the results from this specification to indicate that the position of the industry frontier may differ across countries at a given point in time and leave a more advanced treatment of this issue to future research.

Table 4: Measurement of the Technical Frontier

Model No.	*No. of obs:933 Time-periods: 19* (5)			*No of obs: 1731 Time-periods: 19* (6)			*No of obs: 1731 Time-periods: 19* (7)		
	Coef.	*s.e.*	*t*	*Coef.*	*s.e.*	*t*	*Coef.*	*s.e.*	*t*
Production Function									
l	0.752	0.019	40.383	0.706	0.015	48.505	0.701	0.013	53.698
k	0.183	0.016	11.204	0.303	0.013	23.317	0.289	0.013	22.524
$\bar{r}_{fj}$	0.132	0.013	10.503	0.093	0.009	9.874	0.214	0.017	12.693
$\bar{r}_{fj}\, D_{if}$							-0.078	0.011	-7.334
H	-1.291	0.106	-12.200	0.204	0.045	4.515	0.093	0.047	1.989
Inefficiency Effects									
h	-2.989	0.330	-9.058	-1.399	0.411	-3.403	-1.338	0.390	-3.430
$r\&d$	-0.025	0.009	-2.721	-0.032	0.014	-2.229	-0.024	0.014	-1.719
$CHE\times h$	-0.108	0.024	-4.410	0.072	0.026	2.708	0.059	0.026	2.264
$FOD\times h$	-0.016	0.023	-0.709	-0.086	0.027	-3.208	-0.073	0.027	-2.765
$MEQ\times h$	0.030	0.026	1.157	-0.071	0.033	-2.124	-0.086	0.034	-2.556
$MNM\times h$	0.073	0.029	2.544	-0.060	0.026	-2.298	-0.067	0.026	-2.549
$MOT\times h$	-0.183	0.025	-7.233	-0.200	0.032	-6.187	-0.207	0.032	-6.392
$PAP\times h$	-0.134	0.021	-6.367	0.002	0.025	0.093	-0.023	0.025	-0.923
$TEX\times h$	-0.071	0.026	-2.695	-0.018	0.027	-0.674	-0.017	0.027	-0.619
$WOD\times h$	-0.135	0.024	-5.714	-0.197	0.042	-4.655	-0.201	0.042	-4.734
σ^2	0.039	0.002	18.998	0.094	0.005	17.633	0.084	0.005	16.975
γ	0.918	0.021	44.647	0.872	0.010	89.693	0.884	0.011	80.435
Log likelihood function			345.44			375.75			396.44
LR test of the one-sided error			676.93			1236.0			1244.2

Notes:

- *In model 5 f is defined by the sum of the stock of R&D in Canada, Denmark, Finland, Italy, Netherlands, Norway and Sweden.*
- *In model 6 f is defined as the sum of the stock of R&D in all 12 OECD countries included in the sample.*
- *In model 7 f is defined as the sum of the stock of R&D in France, Germany, Japan, UK and US.*
- *BMI = basis metal industries; CHE = chemicals etc; FOD = food, beverages and tobacco; MEQ = machinery & equipment; MNM = non-metallic mineral products; MOT = other manufacture industries; PAP = paper products; TEX = textiles, wearing apparel; WOD = wood products.*

The results from these three exercises are presented in Table 4. Unlike Kneller (2002) we find that when we exclude from the data the five largest R&D countries the dual effect of R&D on production identified in Griffith *et al*. (2001) remains. Indeed the estimated effect of R&D on the frontier and the level of efficiency are very similar in magnitude to those found from model 1. Given this result it is no surprise that in model 6 when we allow all OECD countries to determine movements in the technical frontier in each industry the results are largely unaffected. Once again R&D affects the production function directly as well as through the level of efficiency, but the spillovers from R&D on efficiency are again estimated to be small in size. Finally according to the results from model 7 the stock of frontier technology does indeed decline with the physical distance from the source of new ideas. The interaction term is negative as expected and statistically significant.

5 Functional Form of the Production Function

Duffy and Papageorgiou (2000) argue that the Cobb-Douglas form of the production function typically assumed when econometric estimation of the production function is undertaken is misspecified. They argue instead in favour of the less restrictive CES functional form, although they do restrict how human capital enters the production function. In model 8 we report the results for a semi-translog specification (i.e. translog in *n* and *k*), which provides a good first-order approximation to a broader class of production functions, including the CES. Following the results in model 7, in model 9 we allow the effect of R&D on the frontier to vary according to the physical distance from the source of new ideas.

The additional parameters in the translog production function are significant, confirming Duffy and Papageorgiou (2000)'s result that the Cobb-Douglas functional is unduly restrictive given the data. The results for the translog would also appear to confirm the questions over the absorptive capacity effects of R&D. The stock of industry R&D is found to affect the production function, but there is no evidence that the level of R&D contributes to lower efficiency. Finally, model 9 suggests that the interaction term between physical distance and R&D has explanatory power even in this more flexible production function. The coefficient on the R&D and distance interaction term is negative and statistically significant. The physical distance from the source of new ideas is important.

Table 5 Sensitivity to Changes in the Production Function

Number of observations: 1731, Time-periods: 19

Model No.	**(8)**			**(9)***		
	Coef.	*s.e.*	*t*	*Coef.*	*s.e.*	*t*
Production Function						
l	1.97	0.178	11.1	1.877	0.186	10.083
k	-0.336	0.15	2.2	-0.276	0.156	-1.764
l^2	-0.052	0.008	6.5	-0.048	0.008	-5.819
k^2	0.003	0.007	0.4	0.004	0.007	0.593
lk	0.053	0.014	3.8	0.048	0.014	3.324
$\bar{r}_5$	0.084	0.014	6.1	0.123	0.021	5.835
$\bar{r}_5 D_{if}$				-0.032	0.014	-2.331
h	0.347	0.056	6.2	0.309	0.058	5.310
Inefficiency Effects						
h	-1.91	0.37	5.2	-1.860	0.379	-4.907
$r\&d$	-0.019	0.016	1.2	-0.017	0.014	-1.189
$CHE \times h$	-0.232	0.034	6.8	-0.228	0.031	-7.268
$FOD \times h$	-0.597	0.04	15.1	-0.572	0.043	-13.176
$MEQ \times h$	-0.377	0.043	8.9	-0.380	0.039	-9.776
$MNM \times h$	-0.324	0.033	9.8	-0.314	0.034	-9.150
$MOT \times h$	-0.385	0.038	10.2	-0.390	0.038	-10.242
$PAP \times h$	-0.197	0.031	6.3	-0.187	0.029	-6.404
$TEX \times h$	-0.235	0.032	7.3	-0.232	0.032	-7.291
$WOD \times h$	-0.981	0.116	8.5	-0.970	0.115	-8.408
σ^2	0.08	0.01	16.4	0.08	0.00	17.40
γ	0.81	0.01	56.7	0.81	0.01	58.85
Log likelihood function			395.29			
LR test of the one-sided error			986.28			

Notes:

BMI = basis metal industries; CHE = chemicals etc; FOD = food, beverages and tobacco; MEQ = machinery & equipment; MNM = non-metallic mineral products; MOT = other manufacture industries; PAP = paper products; TEX = textiles, wearing apparel; WOD = wood products.

6 Conclusions

In this paper we have tested whether differences in absorptive capacity help to explain differences in the level of technical efficiency for a panel of nine manufacturing industries in twelve OECD countries over the period 1972 to 1992 using Stochastic Frontier Analysis (SFA). One of the advantages of a stochastic frontier-based methodology is that is promotes strong links with the economic theory underlying it.

Technology does not merely determine a unique maximum potential output per unit of input, but rather it defines a whole set of potential maxima associated with any given vector of inputs. Moreover, technology is not merely ‘the part of output that we cannot explain’, but rather the result of an ongoing process of research and innovation.

From our analysis we find that absorptive capacity does appear to be important for the level of efficiency. Of the two determinants of absorptive capacity considered, human capital and R&D, both are statistically significant but R&D is not always quantitatively important. The spillovers from R&D on efficiency do not appear to explain much of the cross-country variation in productivity. These findings contrast in some important ways with those previously found by Griffith *et al*. (2001), Keller (2001a,b) and Kneller (2002) also for OECD manufacturing industries. These differences in part reflect the restrictive assumptions made in those papers that either all productivity growth reflects changes in inefficiency or technical progress, but also by allowing the observations from more than one country to determine the stock of frontier knowledge.

While the results from this paper provide a useful test of the robustness of the results from the previous literature we also use SFA to readdress several modelling issues debated in the literature. We find strong evidence to suggest that the R&D from all of the OECD countries in the sample contribute to the stock of frontier technology within each industry, although the results are not sensitive to changes in the measurement of this variable. but the results for R&D are not robust to changes in the function form of the production function. We find however initial evidence that suggests that the position of the industry frontier is not identical across countries at a given point in time. The physical distance from the source of new ideas appears to matter.

We are also able to conclude from our analysis that the result of Benhabib and Spiegel (1994) that human capital affects the production function only through productivity is not supported by the data. We find that human capital affects production both directly and indirectly through inefficiency. Instead we conclude like de la Fuente and Domènech (2000) that the Barro and Lee human capital estimates should not, despite their popularity, be used. Finally we find evidence that the translog, rather than the C-D production function, is a better fit of the underlying data. In this model R&D is found to have a small and insignificant effect on efficiency.

While further investigation of these issues is clearly warranted we might use the results from this paper as initial evidence that differences in productivity across countries both because the stock of available technology differs across countries and because countries differ in the efficiency with which they use this technology.

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Table A1: Mean Efficiency Levels and Standard Deviation, by country and industry.

Country		*Industry*										
		BMI	**CHE**	**FOD**	**MEQ**	**MNM**	**MOT**	**PAP**	**TEX**	**WOD**	***Unwtd. ALL***	***Wtd. ALL***
CAN	*Mean*	0.785	0.583	0.865	0.925	0.881	0.884	0.737	0.868	0.861	*0.818*	*0.828*
	s.d.	0.079	0.027	0.040	0.014	0.064	0.039	0.048	0.040	0.051	*0.115*	*0.036*
DEN	*Mean*	0.536	0.602	0.655	0.711	0.674	0.893	0.698	0.668	0.705	*0.684*	*0.681*
	s.d.	0.125	0.059	0.055	0.056	0.065	0.045	0.063	0.074	0.045	*0.112*	*0.058*
FIN	*Mean*	0.402	0.601	0.623	0.638	0.624	0.690	0.636		0.759	*0.622*	*0.629*
	s.d.	0.117	0.058	0.018	0.106	0.064	0.120	0.066		0.047	*0.125*	*0.075*
FRA	*Mean*	0.887	0.950	0.943	0.948	0.946	0.958	0.943	0.954	0.936	*0.938*	*0.944*
	s.d.	0.047	0.011	0.010	0.012	0.012	0.001	0.008	0.008	0.017	*0.028*	*0.013*
GERM	*Mean*	0.887	0.934	0.901	0.947	0.922	0.948	0.874	0.876	0.947	*0.915*	*0.927*
	s.d.	0.033	0.010	0.012	0.005	0.016	0.013	0.018	0.041	0.012	*0.036*	*0.012*
ITL	*Mean*	0.789	0.747	0.915	0.887	0.894		0.864	0.906		*0.859*	*0.871*
	s.d.	0.111	0.103	0.049	0.061	0.046		0.067	0.056		*0.094*	*0.065*
JAP	*Mean*	0.912	0.577	0.842	0.685	0.634	0.781	0.299	0.314		*0.630*	*0.692*
	s.d.	0.039	0.064	0.087	0.144	0.054	0.053	0.015	0.044		*0.225*	*0.102*
NETH	*Mean*	0.953		0.758				0.920	0.900		*0.882*	*0.855*
	s.d.	0.016		0.051				0.011	0.044		*0.083*	*0.032*
NOR	*Mean*	0.683	0.325	0.532		0.393	0.683		0.499	0.693	*0.544*	*0.534*
	s.d.	0.061	0.041	0.060		0.037	0.120		0.018	0.069	*0.153*	*0.055*
SWE	*Mean*	0.564	0.628	0.570	0.692			0.586	0.706	0.789	*0.648*	*0.657*
	s.d.	0.099	0.061	0.022	0.053			0.039	0.029	0.061	*0.096*	*0.051*
UK	*Mean*	0.602	0.632	0.941	0.793	0.798	0.721	0.864	0.699		*0.756*	*0.792*
	s.d.	0.150	0.062	0.005	0.041	0.045	0.068	0.033	0.028		*0.127*	*0.041*
US	*Mean*	0.955	0.959	0.969	0.967	0.966	0.966	0.965	0.952	0.977	*0.964*	*0.965*
	s.d.	0.016	0.005	0.004	0.007	0.005	0.011	0.007	0.017	0.002	*0.012*	*0.007*
Unwtd. ALL	*Mean*	*0.745*	*0.685*	*0.793*	*0.818*	*0.773*	*0.820*	*0.761*	*0.756*	*0.834*	*0.772*	-
	s.d.	*0.197*	*0.196*	*0.158*	*0.140*	*0.183*	*0.130*	*0.197*	*0.202*	*0.114*	*0.179*	
Wtd. ALL	*Mean*	*0.889*	*0.848*	*0.908*	*0.879*	*0.860*	*0.862*	*0.867*	*0.848*	*0.947*	-	*0.877*
	s.d.	*0.042*	*0.026*	*0.028*	*0.043*	*0.028*	*0.037*	*0.019*	*0.032*	*0.011*	-	*0.034*