Distance to Which Frontier?

Evidence on Productivity Convergence from International Firm-level Data*

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Abstract

An extensive literature on the convergence of productivity between countries examines whether productivity is pulled towards the frontier country, perhaps due to learning and knowledge spillovers. More recently, studies that acknowledge the wide dispersion of productivity across firms in an industry explore the convergence of firms to the national frontier. This paper combines the two approaches by merging an improved measure of the global frontier, built up from firm-level data, into a firm-level dataset. We find that the national frontier exerts a stronger pull on domestic firms than does the global frontier. However, the pull from the global frontier falls with technological distance, while the pull from the national frontier does not. This result suggests that firms might lag so far technologically that they cannot learn from the global frontier, while they still are able to benefit from domestic, non-technological, knowledge.

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1 Introduction

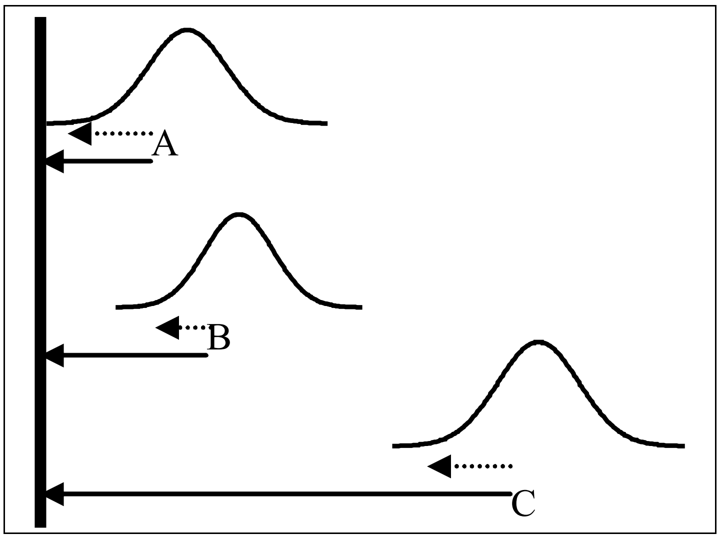
Productivity plays a key role not only in the prosperity of countries but also in the success of firms. Not surprisingly, there is an extensive literature on productivity levels and convergence between countries and an emerging literature on convergence between firms. The theoretical construct underlying the process of convergence is that of knowledge spillovers emanating from the most productive, or frontier, technology. To the extent that knowledge is non-rival and not fully appropriable, countries below the frontier can potentially improve performance by learning from the best, subject of course to various constraints affecting the process.

Investigations of these issues typically proceed in one of two ways. The 'macro' method is to identify the productivity of the global frontier country (for a specific industry), using country (or country-industry) panel data, and test whether productivity growth in other countries is related to their productivity gap to the global frontier (see e.g. Quah, 1996, and Sala-i-Martin, 1996, for discussions). A second, more recent, approach is to use micro data for an individual country (Griffith, Redding, and Simpson, 2003; Sabirianova, Svejnar, and Terrell 2005; Nishimura, Nakajima, and Kiyota, 2005). Here, one identifies a national frontier that reflects the best technology in the country and assesses whether other firms within the country catch up to that frontier.

There are however some conceptual and practical problems with this literature. Take the macro literature first. In this approach, it is implicitly assumed that within a country all firms in a particular industry have the same productivity. Thus if productivity in country A is above that in country B (for industry j) it is assumed that all firms in country B lie below the frontier and so potentially have scope to learn and catch up to all firms in A. The firm-level productivity literature, however, clearly points to large and persistent dispersion in productivity across firms in many countries (Bartelsman and Doms, 2000, Bartelsman, Halitwanger and Scarpetta 2004). The recent micro approach to convergence addresses this problem by allowing micro-level heterogeneity in productivity. Unfortunately, the frontier firms in a country may not be related to the global technology frontier that is the hypothesized source of knowledge spillovers.

A simple illustration highlights the problem associated with that the fact that industries in a country are populated by firms displaying a wide dispersion of productivity. Figure 1 shows spreads of productivity in, say, three countries A (the US) and B and C (two EU countries say). The US has the globally best firm on the frontier indicated by the heavy line on the left.

Figure 1 Productivity Spreads



As the diagram shows, the US is above the EU *on average*. But at least *some* EU firms are better than both the US average and the US laggards. Cross-country regressions will look at the convergence of the country average to the US average. While this econometric practice is standard in the literature because the averages are the only cross-country productivity indicators readily available, the averages hide very interesting underlying learning and convergence dynamics. For example, it seems unlikely that the best EU firms are learning from the average US firm; more likely they are learning from the leading US firms, or conceivably, the leading US firms are learning from them. Indeed, quite apart from productivity growth, it would be interesting to know just as a matter of fact which country has the leading firms for a particular industry. Country or country-industry data cannot tell us this.

The figure also highlights another issue that arises if one further assumes that firms differ in their absorptive capacity for knowledge. Suppose now that country C is a less-developed country, whose average and frontier firms are both below the global frontier. A simple catch-up model assumes that all firms in country C converge to the frontier via learning. Perhaps a more natural assumption is that low productivity firms are less able to absorb knowledge, so that, perhaps, poor firms within a country converge to the national frontier, but better firms are influenced by the global frontier. This carries the interesting implication that if the national frontier is too far from the global frontier then "convergence clubs" emerge; firms converge to the national frontier, but the national frontier is too far away from the global frontier for the topmost firms to converge to the global frontier. If however, the topmost national frontier firms are close enough to the global frontier then they converge to it and in turn spread knowledge to the firms below the national frontier. If this knowledge spreading is indeed an externality, this raises potentially interesting policy issues.[1]

To investigate these issues we clearly need micro data; while country or country-industry data are an important first step, they provide a poor proxy for the frontier and thus for the process by which firms absorb knowledge and catch up. The problem here is that while micro data within a single country, say B, can address firm-level heterogeneity and are potentially helpful for shedding light on whether convergence effects differ for different firm types, they may not identify the correct frontier either. In terms of Figure 1, for example, they impose that the best firms in country B are converging to country B's frontier, whereas they in fact might be converging to A's frontier.[2]

Thus to examine these issues we need micro data for all (potentially relevant) countries. Using indicators derived from country-specific firm-level data we first measure where the global frontier is. We then use single country micro data to construct distances of each firm to both the global and national frontier. Finally, we assess how productivity growth of the firms is influenced, if at all, by these two distances.

Until recently, such international micro data have not been available. The innovative contributions of this paper, we believe, are therefore three fold. First, we use

[1] For example, countries might wish decide that this externality is sufficient to justify creating or subsidising "world-class" firms within the country from whom domestic firms can learn (or subsidising infant-industries so they can either have a chance to learn or become world class).
[2] Of course, if A and B's frontier are moving at the same rate then there might be circumstances where econometrically one can estimate marginal impacts of changes in the frontier using only country data. As we show below, the assumptions required for this are rather strong and do not seem to hold in our data at least.

information on the productivity distribution from a database built up from firm-level sources in as many relevant countries as possible, convert them into internationally comparable measures and calculate an indicator of the global frontier for each industry. Second, we measure, using micro productivity data for a particular country, the distance of each firm to both the global and national frontiers. Third, we apply tools from the convergence literature, to see if firms converge to the national or the global frontier, or a combination of both, and what affects the extent of convergence.

To preview our results we find the following. First, as a matter of data, we find that the top firms in the US lead in many, although, not all industries, but that leadership does change over time. Britain is a notable laggard in all industries. Second, as a consequence, individual firms in the UK have quite different gaps between the global and national frontier. Third, we find that the convergence patterns of UK firms to the global and national frontiers are quite different. The national frontier exerts a stronger pull on domestic firms than does the global frontier. However, the pull from the global frontier falls with technological distance, while the pull from the national frontier does not. This result suggests that some UK firms might lag so far technologically that they cannot learn from the global frontier, while they still are able to benefit from domestic, non-technological, knowledge.

The plan of the rest of this paper is as follows. Section 2 sets out the theory, section 3 the data, section 4 the estimation of convergence and robustness checks and section 5 concludes.

2 Theoretical Framework

We suppose there is a conventional output production function which relates real physical output Y to a given state of knowledge capital A, and real physical inputs Z

$$Y_i = A_i F(Z_i) \tag{0.1}$$

where i indexes firm or country as appropriate. Following Grilliches (1979), just as production of physical goods arises from inputs, we suppose that the output of knowledge production arises from inputs. Changes in knowledge ΔA, are captured by the ideas, or innovation production function:

$$\Delta A = f(X, Z^{KNOW}) \tag{2}$$

In (2), X are the physical inputs into the ideas process (i.e. the numbers of scientists, laboratories, test tubes, the efficiency of the ideas production organisation). Z^{KNOW} are the knowledge inputs into the ideas process. Z^{KNOW} are potentially transferable and non-rival within and across organisations (unlike laboratory inputs). Thus we may write the knowledge inputs as those originating from the knowledge stock at the company i itself and those from outside company *i*

$$\Delta A_i = f(X, A_i, A_{\_i}) \tag{3}$$

Log linearising this gives

$$\Delta \ln A_i = \alpha_1 \ln X_i + (\alpha_2 - \alpha_3) \ln A_i + \alpha_3 \ln\left(\frac{A_{\_i}}{A_i}\right) \tag{4}$$

where it is usual to impose α_2=α_3, so the overall growth of A only depends on the relative levels of $A_{\_i}$ and A_i. For simplicity of exposition we shall do this in what follows, but test for it empirically below. In both the macro and firm-level convergence literature, one identifies $A_{\_i}$ as the productivity level in the "leading" entity. If for example, *i* indexes firms in a country, this may be the productivity level of the leading firm (or the average of firms within some high percentile range to avoid problems of measurement error, or the level of an estimated frontier). With country data, $A_{\_i}$ would be the productivity of the leading country. In addition, , the convergence speed, α_3, may be interacted with variables of interest that differ across firms, such as absorptive capacity of the firm or the magnitude of the gap itself.

We take the first step in bridging these two strands of the literature. We extend the firm-level single-country studies by adding information on the global frontier. Viewed from the other strand, we extend the cross-country literature, by distinguishing average versus frontier productivity in each country and by taking into account productivity movements of each firm in the productivity distribution of a reference country. Data limitations do not yet allow the logical step of studying convergence in a cross-country firm-level panel.

Our theoretical construct will be explained as an extension to single-country firm-level studies. For the given country there are some firms on the national frontier, who we shall denote as having productivity A_N. Other firms in the country have a knowledge gap with these frontier firms and can potentially learn from them. But the national firms also may have a knowledge gap with firms at the global frontier and so presumably could learn from them as well. Thus a more complete description of the sources of knowledge spillovers stocks might be

$$\Delta \ln A_i = \alpha_1 \ln X_i + \alpha_{2N} \ln\left(\frac{A_N}{A_i}\right) + \alpha_{2G} \ln\left(\frac{A_G}{A_i}\right) \tag{5}$$

where A_G is the global knowledge stock. Equation (5) raises a number of interesting issues.

First, why might A_G differs from A_N? In the knowledge production function framework, A_i represents non-rival knowledge available to the firms. Often, this is taken to be the technology of the frontier firm. That would argue that only A_G is relevant.[3] However, the knowledge may be embodied in labor, capital, or intermediates, in which case labor immobility, frictions in capital markets, or trade restrictions may differentiate the ability to absorb knowledge from national or global frontier firms. Indeed, in Sabirianova et al., it is found that spillovers from FDI to domestic firms varies with competitiveness and openness of the national economy. Further, the knowledge that is relevant for a firm's productivity may not be solely technological in nature, but may also include knowledge about local markets and institutions. In that case, possibly much can be learned from the domestic frontier as well.

Second, if A_G differs from A_N, but is omitted from the equation, then the estimate of the pull of the national frontier, α_{2N} , will be biased. If A_N and A_G move together then α_{2N} is upwardly biased: we find this below.

Further, it might be that α_{2N} and α_{3N} differ from each other in magnitude, and differ in different ways with characteristics of firms e.g. the pull from the global frontier may be higher for firms that are R&D intensive. The absorptive capacity literature suggests that firms differ in their ability to learn from others with, for example, the skill at the firm, the amount of R&D, geographical presence etc.[4] We shall account for this empirically in a number of ways.

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[3] Of course, the global frontier could happen to be the technology of the best national firm. This is a matter of data that we will explore.

[4] We interpret the absorptive capacity literature as describing how different firms learn from the same stock of knowledge. One might think of the rationale for including global and national knowledge separately in (5)as saying that A_G and A_N are different stocks of knowledge.

First, in a reduced form approach, we simply allow α_{2N} and α_{2G} to be functions of the gaps themselves. One way of implementing this empirically is to divide the distance up into quartiles and allow each quartile to have its own coefficient

$$\Delta \ln A_i = \alpha_1 \ln X_i + \sum_{q=1}^{4} \alpha_{2N}^{q} \ln\left(\frac{A_N}{A_i}\right)_q + \sum_{q=1}^{4} \alpha_{2G}^{q} \ln\left(\frac{A_G}{A_i}\right)_q \qquad (6)$$

where q denotes quartile. A second method is to simply let α_{2G} vary depending on whether the firm is a "global" or "national" firm, with global firms defined as those with productivity at or above the national frontier and national as the rest. Thus we may write

$$\Delta \ln A_i = \alpha_1 \ln X_i + \alpha_{2N} \ln\left(\frac{A_N}{A_i}\right) + \alpha_{2G}^{TOP} \ln\left(\frac{A_G}{A_i}\right)\Bigg|_{A_i > A_N} + \alpha_{2G}^{BOT} \ln\left(\frac{A_G}{A_i}\right)\Bigg|_{A_i < A_N} \qquad (7)$$

A third method is to simply let α_{2N} and α_{2G} vary linearly by the (log) distance itself giving

$$\Delta \ln A_i = \alpha_1 \ln X_i + \alpha_{2N}^{1} \ln\left(\frac{A_N}{A_i}\right) + \alpha_{2N}^{2} \ln\left(\frac{A_N}{A_i}\right)^2 + \alpha_{2G}^{1} \ln\left(\frac{A_G}{A_i}\right) + \alpha_{2G}^{2} \ln\left(\frac{A_G}{A_i}\right)^2 \qquad (8)$$

A second broad approach is to let α_{2N} and α_{2G} to be functions not of the distances but of economically interesting variables such as whether the firm is an MNE, whether it does R&D etc. We shall try both these approaches below.

3 Data, measurement, and stylized facts

This section describes the data sources used and delves into some of the measurement issues. Further, descriptive statistics are provided on the productivity dispersion in the sample countries, on the global frontier, and on the position of firms in the U.K. relative to the global frontier.

3.1 Data sources

The Global Frontier

The global productivity frontier, by industry and time, cannot readily be found without a dataset of all firms world-wide. A work-around is to find estimates of national productivity frontiers for all countries. The global frontier in industry *i* is then measured as the frontier productivity in the country with the highest frontier in that industry:

$$A_{Git} = Sup_N \left\{ A_{Nit} \right\} \tag{9}$$

Of course, internationally comparable estimates of the national productivity frontier for all countries also are difficult to find. The strategy in this paper, is to convert available indicators of the productivity of the top quartile of firms in a selection of countries into comparable units using industry-of-origin PPPs from the Groningen Growth and Development Center, ICOP Database 1997 Benchmark. (henceforth called, ICOP PPPs, or PPPs; see e.g. O'Mahoney and van Ark 2003). The indicators of top-quartile productivity were computed using so-called distributed micro-data analysis [see Bartelsman, Haltiwanger and Scarpetta 2004, 2005, henceforth BHS]. Owing to the unavailability of the required business statistics in many countries, restrictions on use of confidential business data in others, and resource constraints, the indicators exist only for a subset of countries, namely Finland (FIN), France (FRA), Great Britain (GBR), the Netherlands (NLD), Sweden (SWE) and the USA.[5] This is of course a selected group (we have no data from Japan or China for example) but it does cover the major developed countries that are regarded as likely to have the global productivity leaders. Importantly, we do have the USA, which in most studies of 'average' industry productivity, is the global productivity leader. If a country with the global frontier firms is omitted, and those firms behave in ways uncorrelated with our measured frontier, our results are of course biased. Research into this question awaits assembling micro-based indicators for more countries.

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[5] These are the countries for which the distribution of value added per worker could be computed. The list is expanded to include (West) Germany, and Portugal for measure of gross output per worker. TFP measures only were available for a smaller subset of countries. The BHS dataset also contains estimates from a host of Transition economies and some countries in Southeast Asia and Latin America. These were not used to locate the global frontier.

Details of the method of distributed micro-data analysis are found in BHS, but in short, an attempt is made to obtain indicators derived from firm-level data from each country in as consistent a way as possible. This is a major task since countries differ substantially in how their business registers are compiled, whether their production statistics are based on a survey or a census etc. To improve comparability, common code was sent out to process the data in all countries. This code arranges the data in a consistent way and then carries out identical calculations for all countries, using the same industry definitions, cutting out outliers in the same way, deflating in the same way etc. Some problems remain, for example, not all countries have all data for all years. In particular the US data is every five years (ending in 2 and 7). In addition, the data presently are restricted to manufacturing for the selected OECD countries. Thus our data consist of the years 1992 to 1997 inclusive, where the USA data are interpolated across these years and other countries are present for all or some of the years. At present, the estimation is done for a measure of labor productivity, specifically, value added per worker.[6]

In the BHS dataset, the distribution of productivity across firms in each country and industry was split into quartiles, and for each quartile the unweighted average of (log) productivity was computed.

$$\Pi_t^q = \sum_{i \in \{Q_q\}} \ln(\pi_{it}) / N_q \tag{10}$$

where Q_q, q={1,2,3,4} is the subset of firms in the qth quartile of the productivity distribution, consisting of N_q firms, and π_{it} is a measure of productivity of firm *i,* in year *t*. The average productivity of the top quartile from the BHS dataset, $\Pi^1_{c,i,t}$ ---varying by country, industry and time --- was converted into an internationally comparable national frontier, using ICOP PPPs.

The details of the conversion differ between labor productivity and TFP measures. Beginning with labour productivity, the numerator of the firm-level productivity measure is calculated in local currencies in nominal terms. In the BHS procedures, these are converted into real local currency terms using deflators that vary by industry, but not by

[6] . In a later draft, estimation may be done with a measure of TFP and a global frontier drawn from Fin, Fra,

firm. The average log productivity of the top quartile measure is then converted from these real local currency units (per worker) into a common currency unit using PPP exchange rates.[7] We use country/industry-specific ICOP PPPs. Denoting the conversion rate for country N, industry *i*, into US$ by $PPP_{it}^{N\$}$ we have:

$$A_{Nit} = \Pi_{Nit}^{1} - \ln(PPP_{it}^{N\$}) \tag{11}$$

For converting total factor productivity (TFP) using PPPs, a further complication arises from having capital stock in the denominator (suppose, without loss of generality that we are calculating value added and the only inputs are labour and capital). To convert firm-level TFP for country N into a measure comparable to US TFP,

$$TFP_{Nit}^{\$} = \frac{V_{it}^{real} / PPP_{t}^{N\$}}{(K_{it}^{real} / PPP_{K,t}^{N\$})^{\alpha_K} L^{\alpha_M}} = \frac{(PPP_{K,t}^{N\$})^{\alpha_K}}{PPP_{t}^{N\$}} TFP_{it} \tag{12}$$

Where V is value added, and K is real capital input, measured in constant local currency units. Thus the following points are worth noting. First, note that domestic TFP has to be converted by a ratio of the PPP of value added to the PPP of capital, with the PPP of capital raised to a power. Second, note that even if the same PPP is used, the conversion still requires knowledge of α_K. Third, if the conversions are to be transitive then α_K cannot be country-specific in which case one is faced with the choice of country, or averages of country for the α_K. Fourth, note this formula is for Cobb Douglas which may be restrictive.

Finally, note that in the BHS dataset, only industry averages are available that were not converted to a common currency before calculating TFP measures. Thus the averages must be calculated on log TFP values so that the factor required to transform the mean values into different currency units becomes a linear of the mean of the factor shares. Otherwise there would be no way to make the transformation (exactly) without knowledge of the factor shares at the firm level. Thus for the moment, we cannot do TFP comparisons with all countries. Since we have access to the UK micro data, we can however convert the UK micro data to US$ and then carry out a TFP analysis with

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Gbr, Ita, Nld, and USA

[7] For example, the suppose price of a Big Mac in the UK is £3.49 and in the US $1.27. The exchange rate that makes these two equivalent is 3.29/1.27=2.6 pounds per dollar. The actual exchange rate is, say 1.8 pounds per dollar. Thus the relation between the two is 2.6/1.8=1.4

respect to the US. Since other work suggests that the US is the global leader on average in many industries when using TFP and they are leaders in the top quintile for many industries using labour productivity, we believe this exercise to be of interest.

The U.K. Firm-level data (ABI data)

While the method above generates estimates of the global and national frontiers, it does not provide the direct ability to estimate (5) using data for firms in all countries simultaneously, owing to confidentiality of the underlying firm-level data. At present, the study will consist of the industry and time-specific indicators of the global frontier merged into micro data only for UK firms.

Our UK data comes from the UK business register, the Inter-Departmental Business Register (IDBR), that contains the addresses of businesses and some information about their structure (including their domestic and foreign ownership) based on accounting and tax records, Dun and Bradstreet data and data from other surveys. The IDBR holds data on about 4 million businesses. However, productivity cannot be calculated reliably from the IDBR since it rarely holds output and employment data independently.8 Thus we rely on the information from the Annual Business Inquiry (ABI), an annual inquiry based on the IDBR covering manufacturing and other sectors and asking for information on output and inputs. There are two important points about the ABI however. First, to reduce reporting burdens, multi-plant firms are allowed to report, if they wish, on plants jointly. In practice most firms amalgamate to the firm level (with conglomerate or multi-industry firms typically reporting for each firm in each industry). Whilst by number most of our observations are plants, by employment, most are firms. To simplify the terminology we refer to our observational units in the reminder of this paper as a "firm". Second, reporting burdens are further reduced by requiring only firms above a certain employment threshold to complete an ABI form every year. In our data from 1992-97, typically all firms over 100 were sampled and fractions of firms less than that. In sum, the usable ABI manufacturing data consist of just over 10,000 units (firms or plants) per year. We have six years of data for this study (1992-7 inclusive) and a firm has to appear

[8] It mostly hold output data, from turnover collected for tax purposes and the employment data is interpolated.

at least twice in adjacent years to form the dependent variable. Thus our final sample size is 27,582.

We calculate labour productivity direct from the ABI which asks for value added and employment. Employment is asked for as year averages and value added is sales less materials costs, adjusted for inventory growth and insurance claims.

We use other data to calculate multi-national enterprise (MNE) status and R&D intensity. Regarding MNEs, the IDBR has a foreign ownership marker that is updated every year. We denote a firm as an MNE if it is foreign owned. The problem is that this marker does not show if a domestic firm is an MNE or not. To derive this we must use another data set, the Annual Inquiry into Foreign Direct Investment (AFDI). This tracks when UK firms are MNEs according to their investments abroad. However, the ADFI data is only for 1996 to 2001. Thus for consistency we allocated MNE status to firms between 1992 and 1997 if they were domestic or foreign MNEs at any point in 1996 or 1997. Finally, a number of firms are designated as foreign-owned in a number of locations that have tax advantages (e.g. the Channel Islands, British Virgin Island, Bermuda and Luxembourg). We did not classify a firm as an MNE if they were coded as located in these countries.

Regarding R&D we used the firm-specific survey on Business Enterprise R&D, (BERD), which is the official UK R&D survey designed to capture the universe of R&D performers. This survey asks for R&D current and capital expenditure, both intramurally and extramurally. We use all current intra and extramural expenditure normalised on sales.

3.2 Measurement Issues

The choice of global frontier might be inaccurate for a number of reasons, relating to methodological choices, to the quality of the underlying national data, or to methods to convert productivity into internationally comparable units. First, using the average productivity of the top quartile of firms was a practical choice. While it might be correct to discount the uppermost firms since they are more likely to have been subject to positive measurement error, the average of the top decile, or some econometric estimate of a stochastic frontier, might be a better indicator. We cannot obtain these data without asking each country to rerun an amended program which is a costly task. At the moment we shall stick with the indicators of country and industry productivity as collected by BHS.

Second, international differentials in industry productivity usually are calculated from national accounts data. In most countries, national accounts output measures derive from industry surveys and employment derives from labour force surveys. In our exercise, industry output and employment in each country come from the same survey or census. Thus industry productivity may differ between the two approaches, depending upon how the national accountants integrate the underlying microdata sources to generate the industry output and employment measures. An alternative approach to defining a global frontier, therefore, is to set the *average* of each industry-year observation of productivity in each country to be equal to the industry-year observations from national accounts sources, such as from the OECD STAN dataset or the GGDC productivity dataset (O'Mahoney and van Ark (2003) CD-ROM), while allowing the industry-year quartile-spreads to be generated from our quartile-industry-year data benchmarked to the GGDC average. As a robustness check, we recalculate the global frontiers using this approach.[9]

Finally, the global frontier may also be mismeasured owing to the difficulty in converting currency units of the national frontiers. A large literature exists with suggestions and data to cope with this problem (cite best ref: Feenstra, OECD, WB, Groningen?) We use industry-of-origin PPPs that are designed to convert the output units of manufacturing firms into a common currency (usually US$). Remaining errors in the PPPs will affect our measured gaps, but likely will not affect our econometric results since any static differences for example in output baskets will be subsumed into the industry dummies.

3.3 Some Stylized Facts

Before moving to the econometric results we display the international productivity differentials, at the mean and different quartiles of the country specific distributions.

[9] For a detailed discussion of differences between industry productivity from firm-level versus national accounts sources, see Bartelsman and Bouwmeester 2005.

Industry average productivity

Figure 1 shows measures of value added per worker in manufacturing for a selection of countries, in thousands of 1997 US$ per year. The indicators of nominal value added per worker are the sum of firm-level value added divided by the sum of workers across firms, and are available at the industry level from the BHS database. The indicators are deflated and converted to US dollars using the GGDC value added deflators and PPPs.. As may be seen from figure, the US is at the frontier in 1992, and shows considerable growth between 1992 and 1997. Table 1 shows the distance of the productivity measure in each country to that of the U.S., both for the BHS data, and the GGDC data. Columns 1 and 2 show the data for 1992 and 1997 for total manufacturing as in Figure 1. Columns 3 and 4 show the 1992 and 1997 gaps as calculated by GGDC. While the exact gaps differ, the two sources are reasonably similar. Data from Sweden is almost exactly the same and is very close in the case of the U.K. The differences between the two sets of columns result from differences in employment and nominal output data, because we use GGDC deflators and PPPs for both sets. As mentioned, differences in survey coverage, and methods of integration by national accounts are the source of differences between the two. However, because the patterns are not too different, our main results will use frontier indicators from BHS, while results of indicators benchmarked to GGDC will be left for the appendix (available on request).

Cross-country productivity distributions

We now move to indicators of the productivity distributions. In Figure 3, we show the internationally comparable measures of value added per worker in manufacturing (in thousand 1997 US$ per worker per year) for each of the four quartiles. The left-hand panel shows indicators for 1992, the right-hand panel for 1997.[10] In both panels, the US is ahead of the other countries in the top quartile. However, in the bottom quartile, the ranking across countries is different, with the US dropping a few notches. The relative ranking of the other countries does not vary as dramatically by quartile.

[10] Note, that each point is (the anti-log) of the unweighted average of (log) productivity at the quartile, so that the average over the quartiles will not equal the average productivity of figure 1.

Table 2 shows internationally comparable information on the top quartile broken down by industry, with the BHS indicators converted using sector specific ICOP PPPs. The table shows the identity of the top ranked country for the top quartile, as well as the second and third ranked countries. The 4th and 5th columns show the ratios of the top-quartile productivity in the second country to that in the top country, and the ratio of the third country to the top. There are some notable differences to the patterns seen in Figure 3. While the US is the highest ranking country in the top quartile in most industries in 1992, it gives up ground to Sweden and the Netherlands by 1997. Next, the distance between top quartiles across countries often is larger than the cross-country distance of productivity averages. Especially for the US, the average is held down by relatively poor performance in the bottom quartile, while often the top quartile is quite excellent. These data speak to the "long tail" hypothesis that is a popular explanation for the poor performance of UK productivity (namely a "long tail" of poor performers) and equally an explanation for the relatively good performance of French productivity (namely a "short tail" of poor performers, due to e.g. high minimum wages in France). For the purposes of this paper, looking at the role of knowledge spillovers in boosting productivity, it is clear that average productivity levels are a poor proxy for the position of the best firms constituting the knowledge frontier.

The distribution of distance-to-the-global-frontier in the U.K.

Figure 4 sets out a histogram of the productivity gap of U.K. firms to the (industry specific) global frontier for each STAN industry. In some industries, there is a large mass at gap zero, denoting that these firms are at the global frontier. In actuality, some of the U.K. firms may lie above the average of the top quartile of firms from the country with the highest top quartile, However, the firm-specific distance-to-the-frontier (DTF) measure is truncated as shown below:

$$\begin{aligned} DTF_{Git} &= A_{Gt} - \ln(\pi_{it}), if\ \ln(\pi_{it}) < A_{Gt} \\ DTF_{Git} &= 0, otherwise \end{aligned} \qquad (13)$$

A number of interesting facts emerge from Figure 4. First, the distributions of (log) productivity appear bell-shaped, with wide spreads, consistent with findings from the literature (Bartelsman and Doms, 2000). Next, in some UK industries, there are firms at the global frontier, for example in basic metals, rubber, or wood products, while other sectors only have few firms near the global frontier. Table 3 explores this using UK data for 1997. Column 1 shows the industry and column 2 and 3 the share of firms and employment in the UK that are above the national frontier. The table shows that the share of employment of these firms is greater than the share of firms, suggesting the best firms are larger than average. The industries with the largest share of employment above the national frontier are Motor Vehicles, Pharmaceuticals, Basic metals and wood.

Columns 4 and 5 show the average distance to the national and global frontier. The distance is measured as the average of the log of productivity at the national, or global, frontier, less the log of the productivity level of each UK firm. A value of 1.13 for the distance of Food and Tobacco firms from the national frontier means that the average firm is 113% below the global frontier i.e. average firm productivity is less than half that of the global firm. Some points are worth making. First, the distance from the global frontier is greater than that from the national, since in no case is an UK industry at the global frontier. Next, the gaps vary quite a lot across industries, ranging from 57% in Basic Metals to 113%. Third, as mentioned, there is a tendency for more productive firms to be larger, on average, so that a weighted average distance to frontier always is smaller than the unweighted average distance.

4 Estimates of Convergence

4.1 Econometric specification

The version of (5) that forms the baseline specification for estimation is given by:

$$\Delta \ln A_{it} = \alpha + \beta DTF_{i,t-1} + \gamma X_{it} + \varepsilon_{it}, \tag{14}$$

In estimation, α represents a constant, as well as industry and time dummies. The β's measure the pull from the frontiers, while the γ's represent the effect of firm actions and firm and industry characteristics on firm-level productivity growth. Relative to (5), it is assumed for now that firm-level growth is homogeneous of degree zero in the level of global, national, and firm-specific knowledge. This will be relaxed in various robustness checks, below.

The first X variable in (14) is the R&D to sales ratio of the firm. R&D expenditures are a natural proxy for investment in knowledge-creation, or the firm-specific factor X driving productivity growth. However, our measure is of firm expenditures on R&D conducted in the UK. Because many multinational enterprises (MNEs) do R&D abroad, but use that knowledge domestically, we include an MNE dummy as an X variable as well. Finally, the growth potential of the industry is added as an X variable. The growth potential is measured as the lagged growth rate of the global frontier for the relevant industry, ΔA_{GIt-1}. With this term, we capture the fact that e.g. companies in the pencils industry might have different potential growth rates than companies in the computer industry.

The distance-to-the-frontier component of (14) varies across specifications. First, only DTF_N is included, to provide a direct comparison to the firm-specific convergence literature.[11] Next, DTF_G is used instead, and finally both frontiers are included. To further explore how the pull from the frontier varies across firms and by frontier, the parameter is allowed to depend on the distance itself by using linear and squared terms for DTF. Alternatively, the parameter is allowed to vary between firms that are above the national frontier and those below. Further, the specification is expanded, with the pull varying by location of the firm in the distribution of the relevant DTF, for example the firm's quartile rank in the distribution. Finally, in the robustness checks, the pull is estimated for different groups of firms, e.g. those that are R&D intensive or for MNEs, separately.

4.2 Results

Table 4 presents some baseline results. The first column reports a standard regression of productivity growth on the distance from the national frontier, the R&D/Sales ratio, an MNE dummy and the lagged growth of the global frontier (as above, to proxy warranted productivity growth), as well as year and industry dummies. The marginal pull from the national frontier is 0.32. Column 2 enters instead the distance from the global frontier. This shows a rather similar marginal effect, 0.29, suggesting that since the two frontiers move reasonably similarly together, the effect of each in isolation is rather similar.

[11] DTF_N is constructed analogously to DTF_G , with truncation value zero for those firms whose productivity is above the mean of the top quartile.

Column 3 enters them both together. Here main finding of interest is that the marginal impact of the global frontier on UK productivity growth is less than that of the national frontier (0.1and 0.2 respectively).

Table 5 goes on to explore how much the DTF effects vary with distance. We do this in three main ways, and then inspect the robustness to other methods etc. in the following table. The first way we allow the marginal impact to vary with distance is to assign quartile dummies for both DFT measures (assigned by year and industry) and interact the DFT measure with each dummy separately, thus allowing the marginal effect of different distances to vary according to quartile-location of distance. In column 2 we show the results if we simply enter the national quartiles without any global measure. Here the DTF_N effect declines with the distance to the frontier (although the drop-off levels off for the furthest distance quartile. Column 3 adds the four DTF_G terms. It is notable that first, all the DTF_G coefficients are lower than the DTF_N coefficients, reflecting the basic results as above. Second, it is also notable that the DTF_N coefficients are now more or less flat, with some pick up at for the final distance, whereas the DTF_G coefficients are declining, with the furthest distance statistically insignificant.

The second way we let the marginal impact vary is to interact DTF_G with a dummy signifying whether firms are above or below the national frontier. The results of this are shown in column 4. To fix ideas, the marginal effect from DTF_N is 0.20. The marginal effect from DTF_G for firms above the national frontier is very similar at 0.18, whereas the 0.12 is marginal effect from DTF_G for firms below the national frontier (the difference between the two is statistically significant). One might imagine that for firms above the national frontier the global frontier is, in a sense their "national frontier" and the coefficients suggest this. Put more formally, for these "global" firms, positioned above the national country frontier, their learning flows are such that the impact of global changes in the productivity frontier look similar to the impact of national changes in the productivity frontier on "national" firms.

The final way that we allow the marginal impact of DTF to vary is by simply allowing the marginal impact to vary linearly with DTF, which implies entering a linear and squared term. As column 3 shows, the effect of DTF_N is increasing with distance, with a negative linear and positive squared term. The effect of DTF_G is decreasing with distance, with a positive linear and negative (although statistically insignificant) squared term.

In sum, all these results suggest two findings. First, the marginal effect of DTF_G is less than that of DTF_N and second, the marginal effect of DTF_G declines as DTF_G increases. In future extensions, we will assess whether pull from the national frontier falls with spatial distance to the frontier.

4.3 Robustness Checks

Industry dummies

As set out above, DTF_G and DTF_N vary by industry and time. Thus the variation that allows us to identify the effects of DTF_G and DTF_N separately is the industry and time variation in these variables. In the regressions above we have used industry dummies. Thus, if the global and national frontiers tend to move closely together over time then it will be hard to differentiate the effects of DTF_G and DTF_N. In our regression sample the correlation between $(A_G - A_i)$ and $(A_N - A_i)$ is 0.86 and an analysis of variance for these two distances on industry and year effects returns R2=0.10, suggesting that much of the variation is over time within industries. Thus the levels of these variables are highly correlated but changes over time less so. To check the robustness of our results to this, we re-ran the regression with DTF_G and DTF_N , as in column 3 of Table 4 but without industry dummies. The DTF_N effect hardly changes, but the DTF_G effect falls to 0.035 (t=5.12). Note that DTF_N is still higher than the DTF_G effect. If, following column 4 of Table 5 we further divide the DTF_G effect for the "top" and "bottom" firms and drop the industry dummies we get the same qualitative result i.e. that the respective effects are 0.065(t=4.22) and 0.033 (t=-4.74) i.e. both less than DTF_N with the more distant firms having a smaller marginal effect.

Other checks

Table 6 contains some other robustness checks to the specification of column 4 of Table 5. Columns 1 and 2 run separate regressions for MNEs and non-MNEs. As the columns show, the marginal effects of the DTF terms are quite similar. The same is true in columns 3 and 4 which run separate regressions for firms performing R&D and those not. Column 5 adds the change in the log capital/labor ratio to inspect robustness to including other input terms that would be expected to affect changes in labor productivity. Interestingly the DTF_N and the DTF_{G_top} coefficients are now equal at 0.169, suggesting, as above that for the top firms the "pull" of the global frontier is like the "pull" of the domestic frontier. Also, the DTF_{G_bot} term is both less than the DTF_{G_top} coefficient and the DTF_N term, consistent with what we found above. So whilst a fuller analysis of TFP would have to use the global and national TFP frontiers, the former of which we are not currently in a position to calculate, this check does at least suggest that our labor productivity results are robust to including this term.

Column 6 of Table 5 adds a lagged labor productivity term. This is statistically significant but does not affect the DTF_N term too much. It does however reduce the coefficients and precision of the DTF_{G_top} and DTF_{G_bot} terms, which is perhaps not surprising given the colinearity between all these terms. At least in terms of point estimates however, the DTF_{G_top} and DTF_{G_bot} terms show a consistent pattern with above, namely quantitatively less than the DTF_N term and with the DTF_{G_top} greater than the DTF_{G_bot} term.

Column 7 of Table 5 uses DTF_G and DTF_N measures that are not truncated at zero when a firm's productivity is above the global and national frontiers, respectively. This carries the strong implication that if firms have productivity above each frontier then their productivity falls towards the frontier. Whilst the relative effect of DTF_{G_top} still exceeds that of DTF_{G_bot}, as above, both terms are now higher than the DTF_N term. We are not clear how to interpret these results.

Column 8 of Table 5 shows a long-difference specification (i.e. just the cross-section formed by the 1997-1992 difference). Long differences lower measurement error relative to year-by-year differences but they exacerbate selection bias since only surviving firms are included. As the results show, the relative effect of DTF_{G_top} still exceeds that of DTF_{G_bot}, as above, and both terms are below $DTF_{N.}$ This result was robust to a number of other ways of controlling for measurement error. [12] Note that

[12] We also obtained similar results by: averaging the observations over adjacent pairs of years, which should reduce the measurement error in productivity, giving a three period panel, and then took differences

although DTF_G is lower than DTF_N , the DTF_G term for the lower firms draws closer to that for top firms. This could be due to selection, since only firms who survive for a long time are included for those long differences. For the “bottom” firms, these survivors are likely those who were closer to the global frontier in the base period, since those further away would likely have not survived.

5 Conclusions

This paper has used new indicators from cross-country micro data to explore which countries and industries are at the productivity frontier and how the frontier affects the productivity growth of UK firms. First, we have used cross-country micro data to measure productivity at different quartiles of each country-industry. This helps us locate where the global frontier is and represents an advance on existing country or country-industry data, since there is wide dispersion of productivity in industries. Second, we have used UK micro data to assess how the productivity growth of the UK firms is influenced, if at all, by the global and the national frontiers. This is an advance on existing micro studies since they have not been able to use both frontier measures in their work.

We find the following. First, as a matter of data, we find that the US leads in many, although, not all industries, but that leadership has changed over time. Britain is a notable laggard in all industries. Second, as a consequence, individual firms in the UK have quite different gaps between the global and national frontier. Third, we find that the convergence patterns of UK firms to the global and national frontiers are quite different. The national frontier exerts a stronger pull on domestic firms than the global frontier. However, the pull from the global frontier falls with technological distance, while the pull from the national frontier does not.

Our results have, we believe, at least two interesting implications for future work. First, the fact that the convergence rate is low for firms who are a distance from the global frontier would suggest that economies without any firms near to the global frontier

giving a two differenced cross-sections: instead a two year averaging that moves through the data, giving five successive periods of two year averages and so four differenced cross-sections and a long difference between the first and last pairs of cross-sections years of the panel.

may never catch up. However, if the national frontier firms are close enough to the global frontier, such economies might eventually catch up. Second, a number of recent Schumpeterian growth theories have been developed with interesting implications for growth and the influence of the frontier. The current paper merely documents some facts in the data, but future work could use these data to test some of the implications form recent theoretical work on the importance of distance-to-the-frontier.

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Figure 2 Value Added per Worker (1997 US$ 000s)

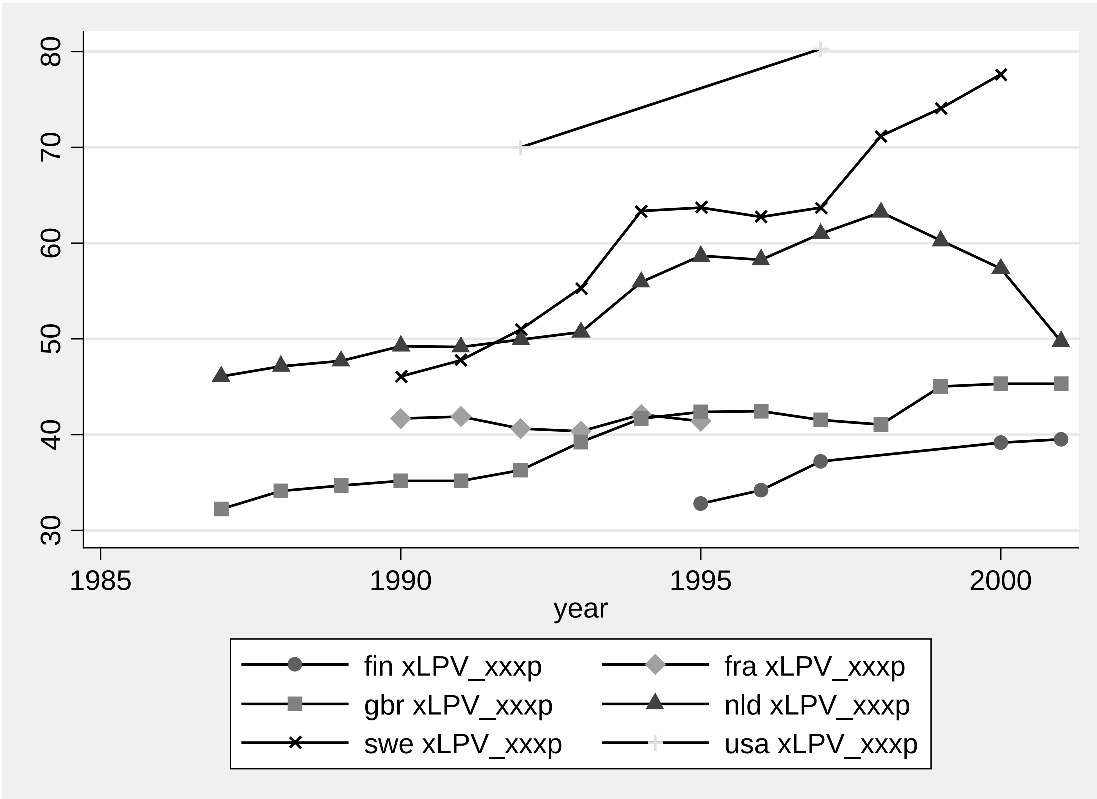

Table 1 Relative VA per Worker (USA=1)

	BHS		GGDC	
country	1992	1997	1992	1997
usa	1.00	1.00	1.00	1.00
swe	0.73	0.79	0.72	0.82
nld	0.71	0.76	0.81	0.79
gbr	0.52	0.52	0.59	0.52
fra	0.58		0.79	0.79
fin		0.46	0.75	0.84

Figure 3 Value added per worker (1997 US$ 000s); by quartile

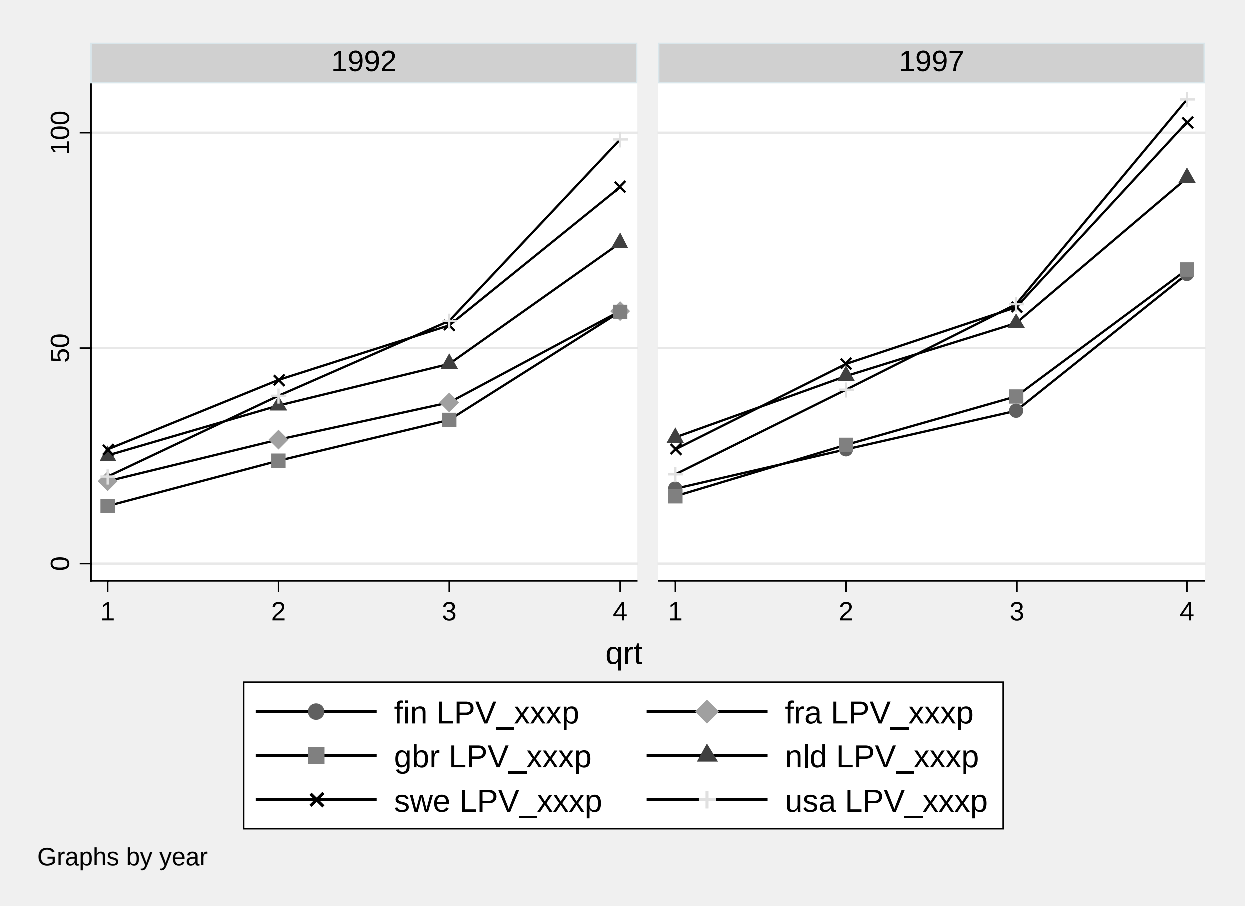

Table 2 Country Productivity Rankings; by Industry

Industry	1st	2nd	3rd	Π_2/Π_1	Π_3/Π_1	1st	2nd	3rd	Π_2/Π_1	Π_3/Π_1
15a6	usa	swe	nld	0.89	0.79	usa	nld	swe	0.97	0.92
17t9	usa	fra	swe	0.61	0.61	usa	nld	swe	0.77	0.69
20	usa	swe	fra	0.96	0.62	swe	usa	fin	0.73	0.51
21a2	usa	swe	fra	0.95	0.78	swe	usa	fin	0.65	0.64
2423	usa	fra	nld	0.51	0.49	usa	nld	fin	0.60	0.57
24x2423	usa	swe	nld	0.91	0.84	usa	swe	nld	0.91	0.81
25	swe	nld	usa	0.97	0.96	nld	swe	usa	0.93	0.89
26	nld	swe	usa	0.92	0.77	nld	usa	fin	0.73	0.68
27	usa	nld	swe	0.78	0.73	swe	usa	nld	0.83	0.66
28	swe	usa	nld	0.90	0.87	swe	usa	nld	0.99	0.97
29	swe	usa	nld	0.99	0.90	usa	swe	nld	0.72	0.67
30	usa	swe	gbr	0.81	0.52	usa	swe	nld	0.83	0.52
31	usa	swe	nld	0.83	0.55	usa	swe	gbr	0.51	0.41
32	usa	swe	nld	0.70	0.62	swe	usa	gbr	0.36	0.24
33	usa	swe	gbr	0.82	0.52	swe	usa	gbr	0.92	0.50
34	usa	fra	nld	0.36	0.31	usa	swe	nld	0.38	0.32
351	usa	swe	nld	0.84	0.65	usa	swe	nld	0.63	0.61
352a9	usa	swe	nld	0.61	0.47	usa	swe	nld	0.86	0.73
Manuf	usa	swe	nld	0.89	0.76	usa	swe	nld	0.95	0.83

Figure 4 Distance to Global Frontier - UK industries 1997

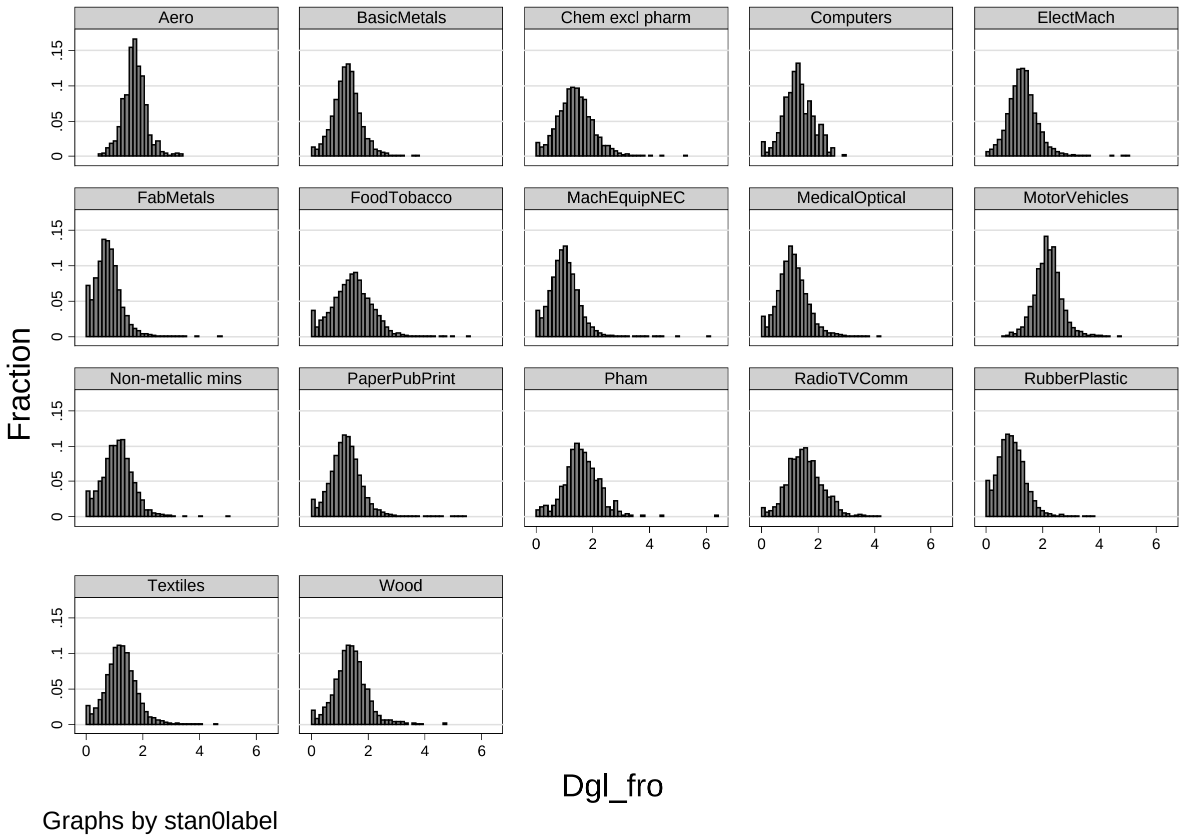

Table 3 UK Distance to Frontier indicators

stan	sharetop	emptop	DTF_N	DTF_G	nobs
FoodTobacco	0.06	0.11	1.13	1.44	1021
Textiles	0.09	0.07	0.80	1.30	1010
Wood	0.13	0.24	0.73	1.68	225
PaperPubPrint	0.09	0.19	0.75	1.39	1337
Pharm	0.09	0.28	0.95	1.52	92
Chem excl pharm	0.09	0.13	0.84	1.49	546
RubberPlastic	0.11	0.17	0.65	1.10	653
Non-metallic mins	0.12	0.12	0.80	1.25	456
BasicMetals	0.13	0.26	0.57	1.40	397
FabMetals	0.08	0.17	0.70	0.88	1066
MachEquipNEC	0.11	0.13	0.65	1.34	1002
ElectMach	0.09	0.11	0.72	1.53	383
RadioTVComm	0.05	0.12	0.94	2.30	220
MedicalOptical	0.14	0.23	0.67	1.25	443
MotorVehicles	0.08	0.42	0.69	2.29	312

Table 4 Regression results - Baseline

	(1)	(2)	(3)
	DTF_N only	DTF_G only	DTF_N & DTF_G
DTF_N	0.320		0.211
	(39.25)		(8.13)
DTF_G		0.287	0.101
		(39.66)	(4.68)
RD_sales	0.581	0.458	0.542
	(1.53)	(1.20)	(1.43)
MNE Dummy	0.072	0.072	0.073
	(15.87)	(15.76)	(16.02)
ΔA_{Git-1}	-0.061	0.103	-0.004
	(1.97)	(3.31)	(0.11)
Observations	27582	27582	27582
R-squared	0.18	0.18	0.18
Robust t statistics in parentheses			

Notes to table: all regressions include year and industry dummies. DTF terms are all lagged one period.

Table 5 Regression results: varying effects of distance

	(1)	(2)	(3)	(4)	(5)
	Baseline	DTF_N – by quartile	DTN & DTF_G – by quartile	DTF top vs bot	DTF linear & square
DTF_N	0.211			0.204	-0.094
	(8.13)			(7.92)	(2.63)
$DTF_N{}^2$					0.114
					(6.97)
DTF_G	0.101				0.209
	(4.68)				(7.70)
$DTF_G{}^2$					-0.003
					(0.25)
DTF_G _top				0.181	
				(6.62)	
DTF_G _bot				0.115	
				(5.30)	
DTF_N 1		0.490	0.222		
		(13.39)	(4.30)		
DTF_N 2		0.336	0.250		
		(22.62)	(6.27)		
DTF_N 3		0.279	0.186		
		(28.51)	(5.03)		
DTF_N 4		0.340	0.317		
		(37.30)	(6.70)		
DTF_G 1			0.155		
			(6.66)		
DTF_G 2			0.094		
			(3.87)		
DTF_G 3			0.097		
			(3.74)		
DTF_G 4			0.045		
			(1.34)		
RD_sales	0.542	0.624	0.607	0.549	0.553
	(1.43)	(1.65)	(1.61)	(1.45)	(1.47)
MNE dummy	0.073	0.072	0.072	0.073	0.069
	(16.02)	(15.96)	(16.01)	(16.00)	(15.33)
ΔA_{Git-}	-0.004	-0.065	-0.007	0.007	0.052
	(0.11)	(2.11)	(0.21)	(0.22)	(1.55)
Observations	27582	27582	27582	27582	27582
R-squared	0.18	0.18	0.18	0.18	0.19
Robust t statistics in parentheses					

Notes to table: all regressions include year and industry dummies. DTF terms are all lagged one period.

Table 6 Other robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	MNEs	Non-MNEs	RD_sales>0	RD_sales=0	add DlnKL	Add LP(t-1)	No truncation	Long diffs
DTF_G _top	0.154	0.209	0.122	0.188	0.169	0.056	0.270	0.291
	(4.05)	(5.32)	(1.22)	(6.64)	(6.21)	(1.55)	(7.50)	(4.00)
DTF_G _bot	0.090	0.129	0.065	0.121	0.119	-0.012	0.191	0.237
	(2.98)	(4.24)	(0.83)	(5.39)	(5.71)	(0.38)	(6.00)	(4.07)
DTF_N	0.245	0.186	0.257	0.198	0.169	0.180	0.104	0.213
	(6.77)	(5.27)	(2.76)	(7.41)	(7.26)	(6.55)	(3.32)	(3.26)
$Ln(\Pi_{,i,t-1})$						-0.148		
						(4.34)		
DlnKL					0.222			
					(12.57)			
Observations	9845	17737	1677	25905	24162	27582	27582	6707
R-squared	0.15	0.20	0.16	0.18	0.18	0.18	0.18	0.28

Notes to table: all regressions include year and industry dummies, MNE and R&D/Y terms and year-industry specific global labour growth (all not reported). DTF terms are all lagged one period. Robust t statistics in brackets. In the final column the year-industry specific global labour growth term is dropped since it is a long difference between 1997 and 1992 and the included indsutry dummies are collinear with this term.