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Eric J Bartelsman, Jonathan Haskel
and Ralf Martin

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Eric J Bartelsman, Vrije Universiteit Amsterdam and Tinbergen Institute
Jonathan Haskel, Queen Mary University, CeRiBA, IZA and CEPR
Ralf Martin, Centre for Economic Performance, LSE and CEriBA

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Centre for Economic Policy Research
53–56 Gt Sutton St, London EC1V 0DG, UK
Tel: (44 20) 7183 8801, Fax: (44 20) 7183 8820
Email: cepr@cepr.org, Website: www.cepr.org

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ABSTRACT

Distance to Which Frontier? Evidence on Productivity Convergence from International Firm-level Data*

An extensive literature on the convergence of productivity between countries examines whether productivity is pulled towards the global frontier country, perhaps due to learning and knowledge spillovers. More recently, studies within countries use the wide dispersion of productivity across firms to explore convergence to the national frontier. Given this within-country dispersion however between country-dispersion is hard to interpret, for it is quite possible that the best firms in a laggard average country are above at least some firms in a leading average country. This paper therefore uses micro data sets across many countries to build better measures of global and national frontiers and firms' distance from them. Using UK data, we then find that (a) the national frontier exerts a stronger pull on domestic firms than does the global frontier and (b) 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 knowledge.

JEL Classification: J24, O47 and O57
Keywords: convergence, distance to frontier, productivity and spillovers

Eric J Bartelsman
ESI
Department of Economics
Vrije Universiteit Amsterdam
De Boelelaan 1105
NL-1081 HV Amsterdam
THE NETHERLANDS
Email: ebartelsman@econ.vu.nl

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Jonathan Haskel
Department of Economics
Queen Mary
University of London
Mile End Road
London
E1 4NS
Email: j.e.haskel@qmul.ac.uk

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Ralf Martin
London School of Economics
Houghton Street
London
WC2A 2AE
Email: R.Martin@lse.ac.uk

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1 Introduction

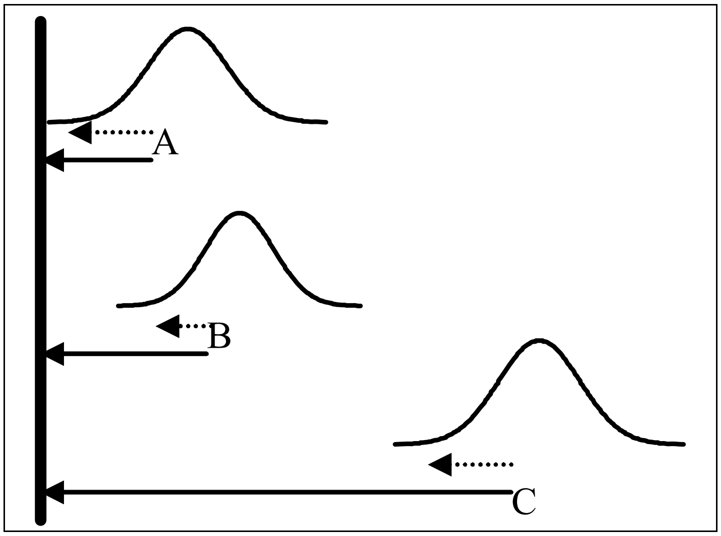
Productivity plays a key role not only in the prosperity of countries but also in the success of firms. Not surprisingly, there is an extensive literature on productivity levels and convergence between countries and an emerging literature on convergence between firms. The theoretical construct underlying 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 a 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 likely 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. However, assume 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

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[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 Griliches (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 $\alpha_2=\alpha_3$, so the overall growth of A only depends on the relative levels of $A_{\_i}$ and A_i.[3] 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 this setting α_3 measures the convergence speed. To avoid restricting it to be linear or homogenous across firms we interact it with variables of interest that differ across firms, such as absorptive capacity of the firm or the magnitude of the gap itself.

We take what we believe is 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

[3] This imposes constant returns to scale in the knowledge production function. This is consistent with the knowledge production function at the frontier as increasing returns would imply constantly increasing long term growth rates which is not what we see. However, there may be are non-constant returns for knowledge production behind the frontier. We experiment with non-constant returns below.

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 is

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

where A_G is the global knowledge stock. Thus our key interest in this paper is to better understand if α_{2N} and α_{2G} differ from each other.[4] 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.[5] 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., (2004) 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.

[4] This is in contrast to much of the convergence literature that explores the various biases to the lagged level term and its implications for convergence, see Quah (1996) or Sala-i-Martin (1996) for a review.

Third, it might be that α_{2N} and α_{2G} 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.[6] We shall account for this empirically in two broad ways.

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

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

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

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

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

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

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[5] 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.

[6] 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.

The second way 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 some of the measurement issues. Further, we set out descriptive statistics on the productivity dispersion in the sample countries, on the global frontier, and on the position of U.K. firms 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:

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

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.[7] 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

[7] 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.

'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.

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. Our main estimates are for labor productivity,, value added per worker, which our current data measures much better than TFP, but we do present some TFP estimates below.

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.

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

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 then converted into an internationally comparable national frontier, using ICOP PPPs, that is industry-of-origin PPPs from the Groningen Growth and Development Center, ICOP Database 1997 Benchmark (see e.g. O'Mahoney and van Ark 2003). So for labour productivity, the numerator of the firm-level productivity measure is calculated in local currencies in nominal terms. These are then converted into real local currency terms using deflators that vary by industry, but not by 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 country/industry-specific ICOP PPPs. Denoting the conversion rate for country N, industry *I*, into US$ by $PPP_{It}^{N\$}$ we have:

$$\ln A_{Nit} = \Pi^1_{Nit} - \ln(PPP_{It}^{N\$}) \tag{11}$$

Conversion of TFP raises some data problems that force us to carry out a TFP analysis with respect to the US only, see Appendix 1 for a more detailed discussion.

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

While the method above generates estimates of the global and national frontiers, we cannot estimate (5) using data for firms in all countries simultaneously, owing to confidentiality of the underlying firm-level data. Thus we study the industry and time-specific indicators of the global frontier merged into micro data only for UK firms.

Our UK business-level 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.

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

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 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, the quality of the underlying national data, or to the 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 (a) set the *average* of each industry-year observation of productivity, calculated from the firm-level data, 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)), and (b) allow the industry-year quartile-spreads to be generated from our quartile-industry-year data benchmarked to the STAN or 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 (see e.g. Timmer, Ypma and van Ark, 2007) for a discussion. 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: Frontier country-industries based on micro data

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

Industry average productivity

Figure 1 shows measures of average 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; the UK and Sweden are very close for example. 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, (the results of indicators benchmarked to GGDC are very similar and are available on request).

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

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.

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. For the purposes of this paper then, it is clear that average productivity levels are a poor proxy for the position of the best firms constituting the knowledge frontier.[11]

[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.

[11] In passing it is worth mentioning 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). The matter is more complicated than this, however, since economy-wide average productivity is a share -weighted average of log firm productivity. So low average productivity could be due to a long tail of low productivity firms, or a short tail but with those firms having a particularly high weight. Space precludes an extensive investigation of this but it is worth pointing out that the within-country ratios of 4th quartile to 1st quartile productivity are USA 4.86, and UK 3.97, suggesting that if anything it is the US who has the long-tail.

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

Figure 4 sets out a histograms 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. This is because in the data some of the U.K. firms lay above the average of the top quartile of firms from the highest top quartile country and so for ease of calculation the firm-specific distance-to-the-frontier (DTF) measure is truncated to zero:

$$\begin{aligned} DTF_{Git} &= A_{Gt} - \ln(\pi_{it}), if\ \ln(\pi_{it}) < A_{Gt} \\ DTF_{Git} &= 0, otherwise \end{aligned} \tag{12}$$

and we test the robustness of the econometric results to this truncation below.

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 mentioning. 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, 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:

$$\Delta \ln A_{it} = \alpha_1 + \alpha_{2N} DTF_{Ni,t-1} + \alpha_{2G} DTF_{Gi,t-1} + \gamma X_{it} + \varepsilon_{it}, \tag{13}$$

Where DTF stands for distance to frontier, as measured in (12), and 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. In estimation, α_1 is a constant, industry and time dummies. The α_2s measure the pull from the frontiers, while the γ s are the effects of firm and industry characteristics on firm-level productivity growth. Relative to (5), we assume for now that firm-level growth is homogeneous of degree zero in the level of global, national, and firm-specific knowledge, but relax this assumption in various robustness checks, below.

We experiment with a number of X variables. The first X variable in (13) 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.

We also allow the distance-to-the-frontier component of (13) to vary across specifications. First, we include only DTF_N, to provide a direct comparison to the firm-specific convergence literature. Next, DTF_G is used instead; and finally we include both frontiers. To further explore how the pull from the frontier varies across firms and by frontier, we allow the parameter to depend on the distance itself by using linear and squared terms for DTF. Alternatively, we allow the parameter 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, we set out a number of different robustness checks. For example, we estimate the pull for different groups of firms, e.g. those that are R&D intensive or for MNEs, separately. We also look at IV, long differences, re-writing the equation in terms of DTF_N and (A_G-A_N) given concerns that DTF and ΔlnA_{it} both have A_{it-1} in common, competition and other checks.

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. 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, as discussed above, and then examine robustness 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 decline stops 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 dummies signifying whether firms are above or below the national frontier. The results of this are shown in column 4. To understand the results, 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 marginal effect of DTF_G for firms below the national frontier is smaller, at 0.115 (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 assuming that the marginal impact itself is a function of DTF, which implies entering a linear and squared term in the regression. 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, so the "pull" of the global frontier is less than that of the national. Second, this average effect masks interesting heterogeneity which can be summarized as saying that the marginal effect of DTF_G declines as DTF_G increases. So, for firms close to or above the national frontier, the pull is higher from the global frontier; for firms further away, the pull from the global frontier is less.[12]

4.3 Robustness Checks

This section sets out a number of robustness checks.

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[12] It is worth noting again that these are associations and that when we use the word "pull" it is a shorthand description of the marginal effect at hand. That said, whilst it is possible that the gobal frontier typically the US is endogenously determined by low productivity UK firms, this seems unlikely and so the endogeneity bias here would be small.

a. 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 and year 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.

b. Results by firm characteristics

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.

c. Returns to scale in the knowledge production function

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. However, in terms of point estimates, the DTF_{G_top} and DTF_{G_bot} terms show a pattern consistent with the results found earlier; i.e. the distance to global frontier terms are quantitatively less than the DTF_N term and with the DTF_{G_top} is greater than the DTF_{G_bot} term.

d. Measurement error and the like

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 a firm's productivity is 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 are less subject to measurement error than 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. [13] Note that 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.

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[13] 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 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.

As with the overwhelming majority of other company level studies we have no data on company-specific prices. Thus our measure of productivity is revenue productivity $\ln\Psi_i - \ln P_I = \ln\prod_i + \ln P_i - \ln P_I$ (Griliches and Klette, 1996). This means that our regression is

$$\Delta\ln(\Psi_i / P_I) = \alpha_{2N}\ln\left(\frac{A_N}{(\Psi_i / P_I)}\right)_{t-1} + \alpha_{2G}\ln\left(\frac{A_G}{(\Psi_i / P_I)}\right)_{t-1} + \alpha_{2N}\ln\left(\frac{P_i}{P_I}\right)_{t-1} + \alpha_{2G}\ln\left(\frac{P_i}{P_I}\right)_{t-1} + \Delta\ln\left(\frac{P_i}{P_I}\right)_t \quad (14)$$

where the last two terms, being unobservable, are relegated to the regression error. Thus, there is bias to α if the physical productivity gap with the global and national frontiers are correlated with the levels and changes in price gaps between the global and national frontiers. What can we say about these biases?

First, in a multi-variate model, it is of course hard to sign the bias since the omitted variable biases depend upon both the covariance with the DTF_G and DTF_N terms but also the other included variables and the omitted terms themselves.

Second, the only paper we are aware of that has physical productivity and plant-specific price measures is Foster, Haltiwanger and Syverson (2004). They find a negative correlation between physical productivity and plant-specific prices (i.e. more productive establishments charge lower prices) and a positive correlation between revenue productivity and plant-specific prices. In case above, ignoring any correlations with $\Delta\ln(P_i/P_I)$ there is then a positive correlation between $\ln(\Psi/P_I)$ and $\ln(P_i/P_I)$ and hence the "pull" effect would be biased down. So we would tend to underestimate the "pull" to the frontier in this effect. Similarly, any correlation between $\ln(\Psi/P_I)$ and $\Delta\ln(P_i/P_I)$ would also generate bias, but the sign this correlation is difficult to establish.

Third, how does this bias relate to our key finding, namely of a different effect from the DTF_G and DTF_N both in magnitude and shape? Let us suppose that the true position is that $\alpha_{2G} = \alpha_{2N}$: we can ask, under what conditions would our finding of $\alpha_N > \alpha_G$ just be spurious? It would be the case if the downward bias to α_G was greater than that to $\alpha_{N.}$ This then depends on differences in the correlation between the $\ln[A_N/(\Psi/P_I)]$ and

$\ln[A_G/(\Psi/P_I)]$ terms and the $\ln(P_i/P_I)$ and $\Delta\ln(P_i/P_I)$ terms, or in practice whether the difference between A_N and A_G is correlated with $\ln(P_i/P_I)$ or $\Delta\ln(P_i/P_I)$. By construction, the price terms vary within industries over time, but A_N and A_G vary between industries over time. Since we include industry and time dummies, then the only correlation is if there is a (non-common) time-series correlation between the within-industry price variation and A_N and $A_{G.}$

Finally, one might worry that DTF and $\Delta\ln A_{it}$ both have A_{it-1} in common. One initial approach to this is to re-write (13) as $\Delta \ln A_i = \beta_{21} \ln\left(A_N / A_i\right)_{t-1} + \beta_{22}\left(A_G / A_N\right)_{t-1}$ where $\beta_{22}=\alpha_{2G}$ and $\beta_{21}=\alpha_{2G}+\alpha_{2N}$. Estimating in this way returns a absoloute t statistic of 3.80 on β_{22} suggesting that the A_N and A_G.effects differ and are not just an artifact of the DTF specification.

A second approach is by IV, where we instrumented the DTF_{t-1} terms with DTF_{t-2}. The results were sensitive to the inclusion of industry dummies. Without industry dummies, the coefficients (t statistics) on DTF_G and DTF_N were 0.035 (3.50) and 0.071 (5.46) replicating the pattern $\alpha_{2G}<\alpha_{2N}$ observed above. With industry dummies however, the results are 0.255 (2.10) and -0.223 (1.39). Thus the global effect is still significant, but recalling that the correlation between DTF_G and DTF_N is 0.89, it would seem that the instruments are might insufficiently good enough to estimate the DTF_N coefficient with much precision.

e. TFP

As mentioned above, it would be theoretically preferable to have measures of TFP. However, computing estimates of the global TFP frontier creates a number of measurement problems with the current dataset as discussed in more detail in Appendix 1. To nevertheless get a sense if our results carry over to TFP we proceeded as follows. Let us assume that the (top quartile) US firms represent also the global frontier. To convert capital into consistent units, we assumed that the aggregate user cost of capital is 0.05 and use this to normalize the units of capital across countries. Thus under constant returns the capital share of value added should then be equal to 0.05 times capital. This relation allows us to derive a scale factor denoted sf that adjusts the capital stock to common units (sf=(VA-wL)/0.05K). Finally, we deflate the US frontier with the ICOP PPPs.

Table 7 shows results using TFP in the regression setting introduced earlier. We start by mirroring our basic results from Table 4; that is, including year and STAN dummies and controls for R&D and MNE status. Columns 1 shows the inclusion of both DTF_N and DTF_G and shows the same result as above, namely, the marginal effect from DTF_G is much lower than that from DTF_N (entered separately the coefficients were 0.449 and 0.403 respectively). Column 2 divides the global distance into TOP and BOTTOM as before. Like before, the marginal effect of DTF when firms are nearer the global frontier exceeds that when firms are further away. Column 3 enters linear and squared terms. Again, the pattern is as we found with labour productivity, namely a concave (to the x axis) relation with DTF_G, but a convex relation for DTF_N. Thus the TFP growth of firms further and further from the global frontier is less and less related to the gap with global leaders in their industry.[14] In sum, our labour productivity results are robust to using these TFP measures.

f. Competition

Given the measurement problems, we cannot say whether our effects are knowledge spillovers or due to other factors. As a robustness test, we look here at whether our key correlations are affected by the inclusion of competition. Competition might control for non-spillover effects, such as prices, or it might of course be an incentive or avenue for firms to learn from others. We followed Aghion, Bloom, Blundell, Griffith and Howitt (2005) and generate a competition measure as (one minus) the (unweighted) average Lerner-index in the industry (see their equation 1). Table 7, column 4, includes this measure and its square following the Aghion et al (2005) prediction of an inverse U shape effect of competition. As the column shows, we have an inverted U shape effect, supporting their prediction. For the purposes of the current paper, our key finding is that the pattern of the DTF_G and DTF_N effects remain unchanged.

[14] The two major findings, namely a lower marginal effect of DTF_G relative to DTF_N in the linear case, and the convex and concave relation in the non-linear case are robust to: IV, omitting STAN dummies, inserting a lagged level term.

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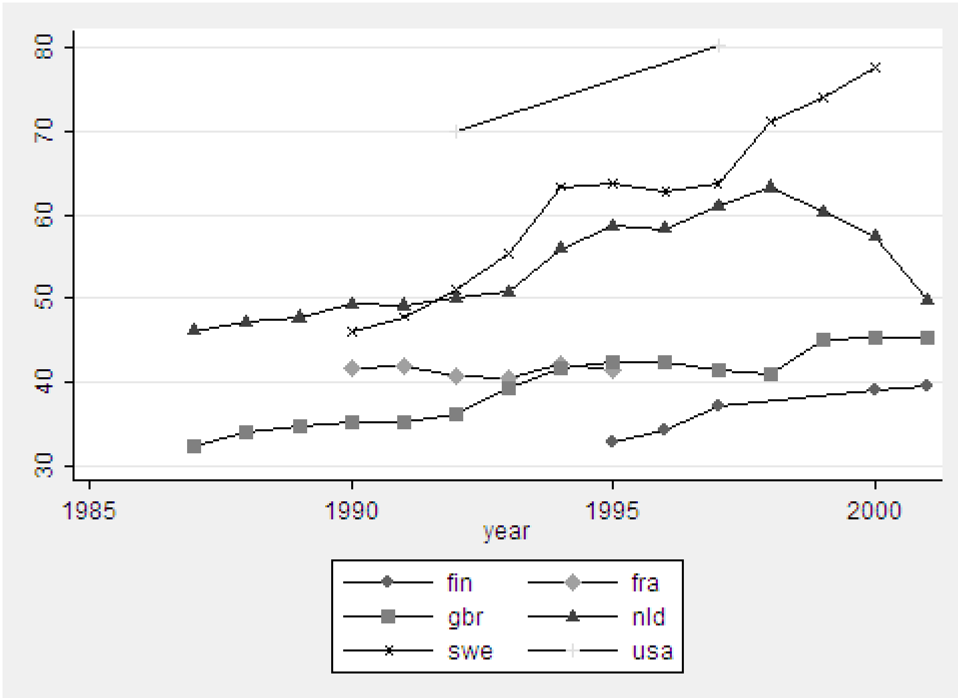
Figure 2 Value Added per Worker (1997 US$ 000s)



Notes to figure: countries are Finland (fin), Great Britain (gbr), Sweden (swe), France (fra), Netherlands (nld) and USA (usa)**.**

Source: authors' calculations from micro data.

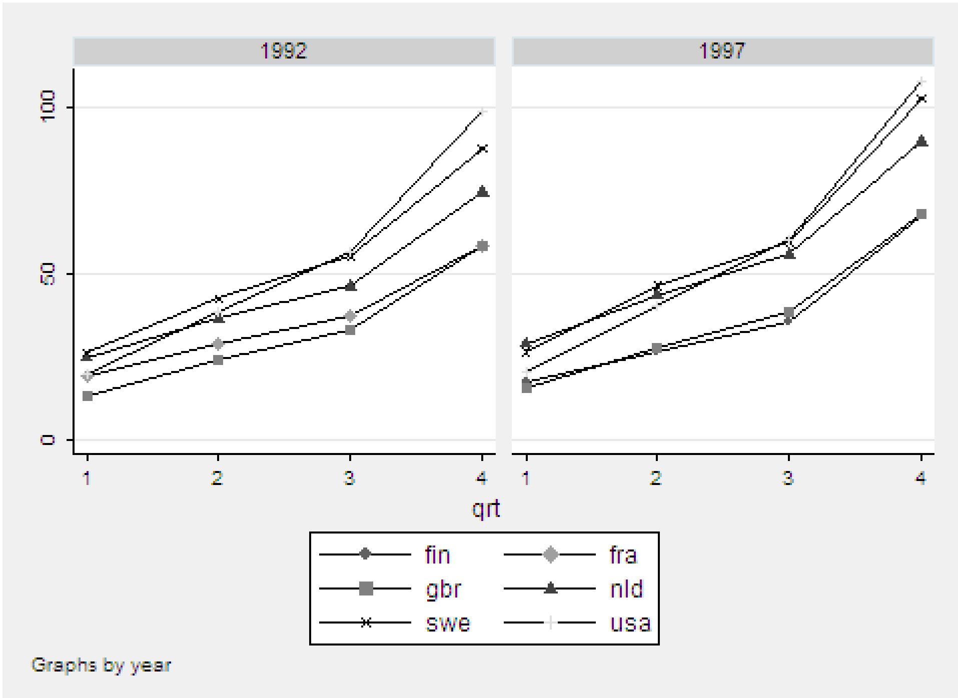
Table 1 Relative VA per Worker (USA=1): comparing micro and national accounts data

	BHS		GGDC	
country	1992	1997	1992	1997
USA	1.00	1.00	1.00	1.00
Sweden	0.73	0.79	0.72	0.82
Netherland	0.71	0.76	0.81	0.79
Great Brita	0.52	0.52	0.59	0.52
France	0.58		0.79	0.79
Finland		0.46	0.75	0.84

Note to table. Table shows value added per worker for all manufacturing, relative to the USA, with the BHS data calculated from the micro data and the GGDC calculated from their industry data. USA set to 1.

Source: authors' calculations from micro data and from GGDC data.

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



Notes to figure: countries are Finland (fin), Great Britain (gbr), Sweden (swe), France (fra), Netherlands (nld) and USA (usa).
Source: authors' calculations from micro data.

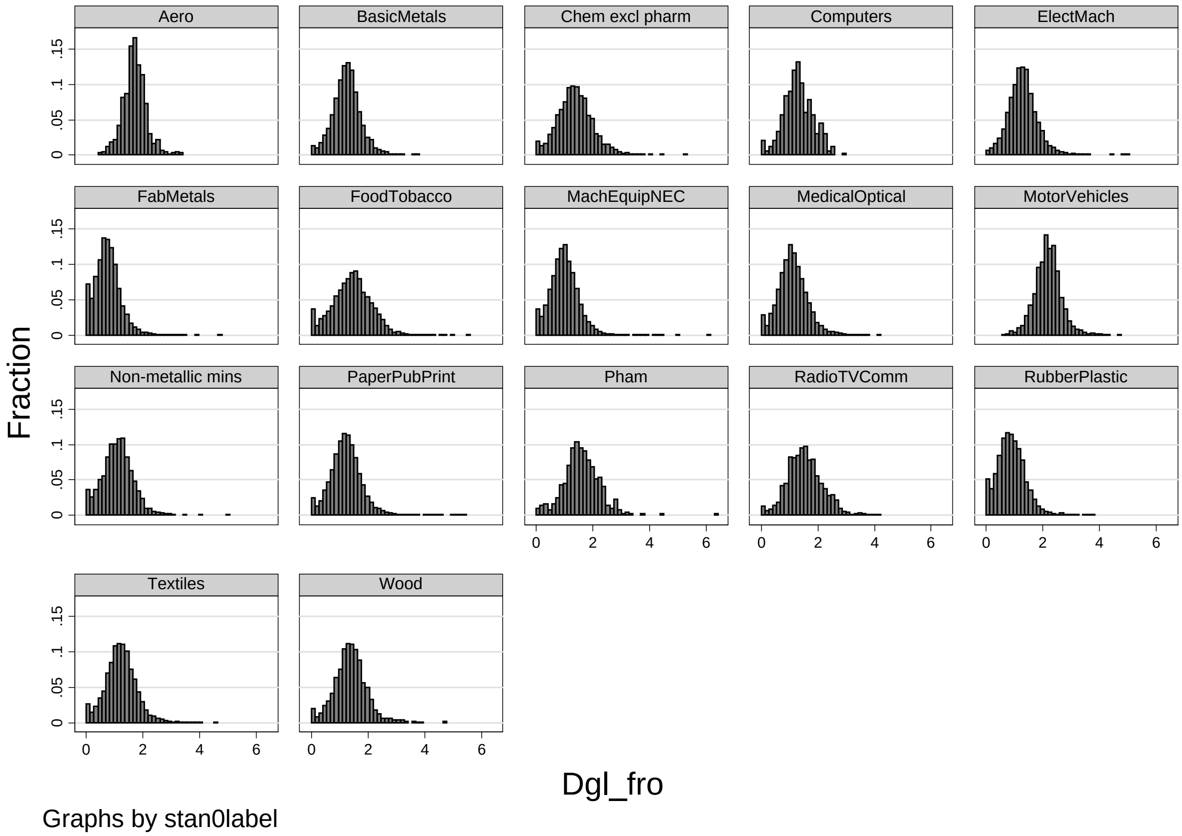
Table 2 Country Productivity Rankings; by Industry

	1992					1997				
Industry	1st	2nd	3rd	Π_2/Π_1	Π_3/Π_1	1st	2nd	3rd	Π_2/Π_1	Π_3/Π_1
FoodTobacco	USA	SWE	NLD	0.89	0.79	USA	NLD	SWE	0.97	0.92
Textile	USA	FRA	SWE	0.61	0.61	USA	NLD	SWE	0.77	0.69
Agriculture	USA	SWE	FRA	0.96	0.62	SWE	USA	FIN	0.73	0.51
Wood	USA	SWE	FRA	0.95	0.78	SWE	USA	FIN	0.65	0.64
PaperPublishing	USA	FRA	NLD	0.51	0.49	USA	NLD	FIN	0.60	0.57
Fuel	USA	SWE	NLD	0.91	0.84	USA	SWE	NLD	0.91	0.81
Pharma	SWE	NLD	USA	0.97	0.96	NLD	SWE	USA	0.93	0.89
Chemicals	NLD	SWE	USA	0.92	0.77	NLD	USA	FIN	0.73	0.68
Rubber	USA	NLD	SWE	0.78	0.73	SWE	USA	NLD	0.83	0.66
OtherMineral	SWE	USA	NLD	0.90	0.87	SWE	USA	NLD	0.99	0.97
BasicMetal	SWE	USA	NLD	0.99	0.90	USA	SWE	NLD	0.72	0.67
FabricatedMetals	USA	SWE	GBR	0.81	0.52	USA	SWE	NLD	0.83	0.52
MachineryNEC	USA	SWE	NLD	0.83	0.55	USA	SWE	GBR	0.51	0.41
OfficeMachinery	USA	SWE	NLD	0.70	0.62	SWE	USA	GBR	0.36	0.24
EletricalMachiner	USA	SWE	GBR	0.82	0.52	SWE	USA	GBR	0.92	0.50
RadioTVCommun	USA	FRA	NLD	0.36	0.31	USA	SWE	NLD	0.38	0.32
MedialOptical	USA	SWE	NLD	0.84	0.65	USA	SWE	NLD	0.63	0.61
MotorVehicles	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

Notes to table. Data shows productivity ranking by industry, with all manufacturing at the bottom. 1st, 2nd, 3rd, denote the frontier country for that industry. $\prod_2/\prod_1$ and $\prod_3/\prod_1$ denote, respectively, the ratio of the 2nd and 3rd quartiles averages in the UK to the frontier quartile average.

Source: authors' calculations from micro data.

Figure 4 Distance to Global Frontier - UK industries 1997



Notes to table. Data shows histogram of the distance to U.K. firms to the (industry specific) labour productivity global frontier for each STAN industry. UK firms above the global frontier are set with distance of zero. Distance is in log points.

Source: **authors' calculations from micro data**

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

Notes to table. Data shows value added and employment shares (columns 1 and 2) by industry for 1997 of top firms i.e. those above the global frontier for that industry. DTF_N and DTF_G are the employment-weighted average distance to the national and global frontiers respectively for that industry, with the number of observations in the final column.

Source: authors' calculations from micro data.

Table 4 Regression results – Baseline estimates of (13)

(dependent variable: Δln firm value added per employee)

	(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

Notes to table: all regressions include year and industry dummies. DTF terms are all lagged one period. Robust t statistics in parentheses

Table 5 Regression results: varying effects of distance (augmented estimates of (13))

(dependent variable: Δln firm value added per employee)

	(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 Robustness checks

(dependent variable: Δln firm value added per employee)

	(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.

Table 6 contd Futher Robustness checks, contd.

(dependent variable: Δln TFP in columns 1, 2 and 3, Δln firm value added per employee in column 4)

	(1)	(2)	(3)	(4)
	TFP	TFP	TFP	LP
	Baseline	DTF top vs bot	DTF linear & square	Compet
DTF_N	0.384	0.345	-0.101	0.2
	(9.60)	(11.5)	(2.52)	(-5.25)
$DTF_N{}^2$			0.178	
			(17.8)***	
DTF_G	0.061		0.292	0.125
	(2.03)		(7.30)***	(-3.7)
$DTF_G{}^2$			-0.036	
			(3.60)***	
DTF_G _top		0.246		
		(6.15)		
DTF_G _bot		0.119		
		(3.97)***		
COMPET				6.64
				(4.64)
COMPET SQd				-3.795
				(4.13)
Observations	25,983	25,983	25,983	8,620
R-squared	0.18	0.18	0.19	0.22

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. COMPET varies by industry and is the Aghion et al (2005) measure of one minus the unweighted industry Lerner index. Robust t statistics in brackets.

Appendix 1: Calculation of TFP in PPPs using available data

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,

$$TFP^{\$}_{Nit} = \frac{V^{real}_{it} / PPP^{N\$}_{t}}{(K^{real}_{it} / PPP^{N\$}_{K,t})^{\alpha_K} L^{\alpha_M}} = \frac{(PPP^{N\$}_{K,t})^{\alpha_K}}{PPP^{N\$}_{t}} TFP_{it} \tag{15}$$

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 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.