Productivity Convergence and International Openness

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Abstract

There is a strong partial correlation between openness and rates of productivity growth across UK manufacturing sectors. This paper investigates the relationship more formally, within a theoretical model of productivity catch-up. The model identifies three potential effects of international openness: openness may affect (a) domestic rates of innovation, (b) the quantity of technological know-how that may be transferred from the frontier to the less advanced economy, (c) the rate at which this technology transfer occurs. From the theoretical framework, we derive an econometric equation which is used to estimate the relationship between UK productivity growth, the UK-US productivity gap and the degree of international openness. We find that international openness primarily affects the rate of productivity convergence, and that this relationship is robust to the inclusion of information on R&D intensity, human capital, unionisation and capacity utilisation.

JEL CLASSIFICATION: O30, O47, O57

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1 Introduction

This paper analyses econometrically the relationship between international openness and productivity growth in UK manufacturing. A large theoretical literature suggests that international openness may be an important determinant of rates of economic growth. Most commonly, openness affects long-run rates of growth through its influence on the incentive to innovate and rates of total factor productivity growth (see, for example, Grossman and Helpman (1991) and Rivera-Batiz and Romer (1991)). But another strand of the theoretical literature (see for example Parente and Prescott (1994)) suggests that openness may be important in accelerating the rate of technology transfer or technology adoption.

At the same time, a considerable empirical literature purports to find a positive relationship between openness and growth across a wide cross-section of countries (see, for example, Ben-David (1993), Sachs and Warner (1995) and Proudman, Redding and Bianchi (1997)). At a more disaggregated level across UK manufacturing sectors, Cameron, Proudman and Redding (1997b) find evidence of a positive partial correlation between openness and rates of productivity growth.

This paper investigates more formally the relationship between international openness and rates of productivity growth in UK manufacturing. We begin by presenting a reduced-form theoretical model of productivity dynamics that follows Bernard and Jones (1996a). Productivity in a manufacturing sector may rise as a result of either 'innovation' or 'technology transfer' from the leading economy (which, throughout our analysis, we assume to be the United States). The model is extended to incorporate three potential effects of international openness: openness may either affect (a) domestic rates of innovation, (b) the quantity of technological know-how in the leading economy that may be transferred to its more backward counterpart, or (c) the rate at which this technology transfer occurs.

The model implies that one important potential determinant of rates of UK productivity growth is the size of the gap between UK and US levels of productivity. Hence, we examine relative levels of productivity in the United Kingdom and United States using a disaggregated data set containing information on 14 manufacturing sectors during the period 1970-92.[1] Another key implication of the theoretical model is that productivity levels in a less advanced economy relative to those in the frontier economy should exhibit 'conditional β-convergence' across manufacturing sectors. That is, controlling for the determinants of steady-state relative productivity, economies with low initial relative productivity levels should exhibit the fastest rates of growth of relative productivity. Visual evidence is presented of substantial variations in relative productivity across sectors; with those sectors enjoying the lowest initial levels of relative productivity appearing (even without controlling for the determinants of steady-state relative productivity) to exhibit the fastest rates of growth. This visual evidence is confirmed in a simple test for 'absolute β-convergence.'

The main bulk of the paper is concerned with estimating the econometric relationship between international openness and rates of productivity growth. We consider a variety of measures of international openness (the import-output ratio, export-output ratio, trade-weighted R&D stock and ratios of both inward and outward Foreign Direct Investment (FDI) flows to output), and test the hypothesis that openness affects the rate of productivity convergence against the alternative that it affects either the domestic rate of innovation or the quantity of technological know-how that may be transferred. Certain types of openness (in particular, the ratios of either exports or imports to output) are found to be especially important, others (particularly the flows of inward and outward FDI) less so.

Interestingly, we find that it is the rate of productivity convergence that is primarily affected by international openness (rather than either domestic rates of innovation or the quantity of technological know-how that may be transferred). By raising the rate at which knowledge is transferred from a leading economy, openness increases both rates of productivity growth in the transition to steady state and the steady-state level of relative productivity. We consider the robustness of this relationship to the intensity of R&D, the level of human capital (as

[1] In order to render the industrial classification in the United Kingdom comparable to that in the United States, it is necessary to aggregate some of the 19 manufacturing sectors examined in Cameron, Proudman and Redding (1997a). Further details concerning the dataset employed are contained in Appendix B.

measured by the ratio of those with high and medium qualifications to total staff) and the level of unionisation (as measured by the percentage of adult males covered by collective bargains).

The paper is structured as follows. Section 2 develops the theoretical framework. Section 3 examines the extent of productivity convergence between UK and US manufacturing sectors. Section 4 estimates the econometric relationship between openness and rates of UK productivity growth. We begin by estimating individual time-series equations for UK productivity growth for each manufacturing sector; first by OLS and second by Seemingly Unrelated Regressions (SUR). Pooling observations across industries, we then estimate the same relationship using panel data techniques. By pooling observations across industries, we dramatically increase the number of degrees of freedom, and it is here that we are able to consider the robustness of the relationship between openness and growth to the inclusion of other economic variables of interest. Section 5 analyses the implications of the parameter estimates for steady-state levels of relative productivity and quantifies the effect of international openness on rates of UK productivity growth. Section 6 summarises our conclusions.

2 Theoretical framework

As noted earlier, a large theoretical literature has developed on the effects of international openness (and, in particular, international trade in goods) on rates of economic growth (see for example Grossman and Helpman (1991) and Rivera-Batiz and Romer (1991)). This paper identifies three potential effects of openness upon rates of productivity growth in an economy behind the technological frontier. First, an increase in the degree of international openness may affect rates of domestic innovation in the less advanced economy (as, for example, in Grossman and Helpman (1991)). Second, an increase in openness may mean that a greater amount of the technological knowledge in the frontier economy may be transferred to its less advanced counterpart (for example, by reverse engineering imported goods, domestic manufacturers become aware of more of the technologies used in the advanced economy). Third, an increase in openness may change the rate at which knowledge may be transferred between the two economies (greater openness may reduce the costs of technology adoption $\Leftrightarrow$ see, for example, the models of technology adoption in Barro and Sala-i-Martin (1995, Chapter 8) and Parente and Prescott (1994)).

The basic theoretical framework is provided by Bernard and Jones (1996a), extended to incorporate the effects of international openness. Consider a world populated by two economies $i \in \{B, F\}$, each of which may produce any of a fixed number of manufacturing goods $j = 1, ..., n$. Each of these manufacturing goods is produced with labour and physical capital according to a neoclassical production technology **(1)**,

$$Y_{ij} = A_{ij}.F_j(L_{ij,}K_{ij}) \qquad \textbf{(1)}$$

where K and L denote physical capital and labour respectively; and where A is an index of technical efficiency, which we define as Total Factor Productivity (TFP). $F(.,.)$ is assumed to be homogenous of degree one and to exhibit diminishing marginal returns to the accumulation of each factor alone. A_{ij} may vary both across sectors j and between economies i.

At any point in time t and in any individual sector j, one of the two economies i will have a higher level of TFP than the other (except in the special case where TFP levels happen to be equal). The economy with higher TFP is termed the frontier economy F, and its counterpart is referred to as the economy behind the technological frontier B. In the present application, we are concerned with the United Kingdom and the United States. We find that UK TFP lies below US levels in all manufacturing sectors throughout the sample period (see next section), and begin with the assumption that this will continue to remain so in steady state (an assumption we subsequently show to be supported by our parameter estimates).

Following Bernard and Jones (1996a), TFP in sector j of each economy i may grow either as a result of sector-specific innovation or as a result of technology transfer from the frontier country,

$$\ln\left(\frac{A_{ij}(t)}{A_{ij}(t \Leftrightarrow 1)}\right) = \gamma_{ij} + \lambda_j . \ln\left(\frac{\omega_{ij}.A_{Fj}(t \Leftrightarrow 1)}{A_{i_j}(t \Leftrightarrow 1)}\right) \qquad \textbf{(2)}$$

$$\text{where} \qquad \gamma_{ij}, \lambda_j \geq 0, \; 0 < \omega_{Bj} \leq 1,$$

where γ_{ij} parameterises the rate of sector-specific innovation and ω_{ij} denotes the fraction of TFP in the frontier economy that may potentially be transferred to economy i.

If economy i is the frontier economy ($i = F$), it is already in possession of state-of-the-art technologies and there is no potential for technology transfer (more formally, $\omega_{Fj} = 1$ and $\ln(\omega_{ij}.A_{Fj}/A_{ij}) = 0$). If economy i is behind the technology frontier ($i = B$), then it may benefit from technology transfer, though not all of the leading economy's technology may be 'relevant' or transferable (we assume that at least some is transferable: more formally, $0 < \omega_{Bj} \leq 1$ and $\ln\left(\omega_{ij}.A_{Fj}/A_{i_j}\right) > 0$).[(2)] The parameter λ_j characterises the rate at which technology transfer occurs. Combining equation **(2)** for both the frontier and backward economies, one obtains a first-order difference equation for the evolution of relative TFP ($\tilde{A}_j \equiv A_{Bj}/A_{Fj}$),

$$\ln \tilde{A}_j(t) = (\gamma_{Bj} \Leftrightarrow \gamma_{Fj}) + \lambda_j . \ln \omega_{Bj} + (1 \Leftrightarrow \lambda_j). \ln \tilde{A}_j(t \Leftrightarrow 1) \qquad \mathbf{(3)}$$

from which we may solve for the steady-state level of relative TFP in each sector j,

$$\ln \tilde{A}_j^* = \ln \left(\frac{A_{Bj}^*}{A_{Fj}^*} \right) = \ln \omega_{Bj} + \frac{\gamma_{Bj} \Leftrightarrow \gamma_{Fj} .}{\lambda_j} \qquad \mathbf{(4)}$$

where for the initially backward economy to remain so in steady state, we require $\ln(A_B^*/A_F^*) < 0 \Leftrightarrow \gamma_{Fj} > \gamma_{Bj} + \lambda_j . \ln \omega_{Bj}$. In the long

(2) The presence of ω_{Bj} (not necessarily equal to one) generalises the specification in Bernard and Jones (1996a). If $\omega_{Bj} = 1$, then (as will be seen below) all the steady-state gap between UK and US TFP must be explained solely in terms of differences in the sector-specific rates of innovation γ_{ij} and the size of the parameter λ_j. Expressed another way, the model implies that, in the absence of continuing innovation in the two economies, UK TFP will in the long run equal US TFP. It is unclear to us that this is true (for example, as will be discussed further below, lower levels of human capital or impediments to the free flow of ideas may prevent the United Kingdom from attaining US TFP levels), and therefore we allow for ω_{Bj} not necessarily equal to one. But it is important to note that our empirical and theoretical results are not sensitive to this generalisation of the basic model.

run, the model implies that TFP in both economies grows at the same steady-state rate γ_{Fj} in sector j. The terms γ_{Bj}, ω_{Bj} and λ_j determine the steady-state level of relative TFP in the less advanced economy and the rate of TFP growth in the transition to steady state. From equations **(3)** and **(4)**, it is clear that the rate of growth of relative TFP may be expressed as a function of the gap between the actual and steady-state level of relative TFP,

$$\ln\left(\frac{\tilde{A}(t)}{\tilde{A}(t \Leftrightarrow 1)}\right) = \lambda_j \ln\left(\tilde{A}^* \Leftrightarrow \tilde{A}(t \Leftrightarrow 1)\right)$$

Thus a key implication of the model is that, after controlling for the determinants of steady-state productivity, sectors with low initial levels should experience the highest rates of growth of relative TFP. That is, the model implies that 'conditional β-convergence' should be observed across sectors.

Throughout the analysis so far, the terms γ_{ij}, ω_{ij} and λ_j in equation **(2)** have been treated simply as parameters. But there are a number of reasons for thinking that each may be a function of economic variables, and it is here that the analysis really departs from Bernard and Jones (1996a). In the econometric estimation that follows, we consider four economic variables that may affect either the rate of innovation γ, the fraction of technological knowledge that may be transferred ω, or the rate of technology transfer λ: international openness, R&D expenditure, human capital and unionisation.

Unless one is willing to impose identifying restrictions, it is not possible to distinguish an effect of openness on domestic rates of innovation γ from an effect on the fraction of transferable knowledge ω. Hence, in the econometric estimation we test whether openness affects (a) either the rate of innovation γ or the fraction of transferable knowledge ω, versus (b) the rate of technology transfer λ.[3] In order to capture possible lags in the adjustment process, we also incorporate lagged

[3] Two alternative identifying restrictions are that either there is a common world rate of innovation ($\gamma_{Bj} = \gamma_{Fj}$) or all of US TFP is potentially transferable to the United Kingdom ($\omega_{Bj} = 1$). Imposing the restriction $\omega_{Bj} = 1$ would not change any of the estimation results that follow, merely the interpretation of some coefficients.

values of the dependent variable into our econometric equation. Taken together, the specification in equation **(2)** becomes,

$$\ln\left(\frac{A_{Bj}(t)}{A_{Bj}(t-1)}\right) = \alpha_j + \xi_j(\underline{z}) + \beta_{1j}.\ln\left(\frac{A_{Bj}(t-1)}{A_{Bj}(t-2)}\right)$$

$$+\theta_j.\ln\left(\frac{A_{Fj}(t-1)}{A_{B_j}(t-1)}\right) \qquad \textbf{(5)}$$

$$+\mu_j(\underline{z}).\ln\left(\frac{A_{Fj}(t-1)}{A_{Bj}(t-1)}\right) + \varepsilon_j(t)$$

where $\underline{z}$ is the vector of explanatory variables (openness, R&D, human capital and unionisation), and the functions $\xi_j(\cdot)$ and $\mu_j(\cdot)$ are assumed to be log-linear in the explanatory variables. International openness enters equation **(5)** in two ways. First, it appears in log levels (through $\xi_j(\underline{z})$), corresponding to an effect of international openness on either the domestic rate of innovation γ_{Bj} or the fraction of transferrable knowledge ω_{Bj}. Second, it enters as an interaction term, which takes the form $\mu_j.[\ln(\text{Open}).\ln(A_{Fj}/A_{Bj})]$ and corresponds to an effect of openness upon the rate of technological transfer.

It is perhaps most plausible that international openness raises the rate at which technologies may be transferred to an economy behind the technological frontier. In this case, an increase in international openness in the United Kingdom will raise both the steady-state level of UK productivity relative to the United States and the UK rate of productivity growth in the transition to steady state.[4]

3 Productivity convergence

The theoretical model of the previous section implies that one important potential determinant of rates of UK TFP growth is the size of the gap between UK and US TFP levels. In this section, we briefly outline the methodology employed to measure rates of UK TFP growth and relative levels of TFP in the two economies, before examining movements in relative TFP levels during the sample period. We then

[4] The extent of international openness in the frontier economy (the United States) may also affect the long-run rate of growth of both economies γ_{Fj}, though we leave this issue to one side in the present paper.

analyse the evolution of relative productivity across sectors and time, and consider the issue of conditional β-convergence. The source for all of the data used in the paper is Cameron (1996), and we combine an ONS data set for the United Kingdom with Bureau of Labor Statistics data for the United States.(5)

In our empirical analysis, we follow the growth accounting literature (see, in particular, the seminal contribution of Solow (1957)) in assuming a constant returns to scale production function (equation **(1)** above) and perfect competition; under which assumptions TFP growth in discrete time may be approximated with the following Thörnqvist-Theil Divisia index,

$$\begin{aligned} \ln\left(\frac{A_{ij}(t)}{A_{ij}(t-1)}\right) &= \ln\left(\frac{Y_{ij}(t)}{Y_{ij}(t-1)}\right) - \bar{\alpha}_{ij}(t).\ln\left(\frac{L_{ij}(t)}{L_{ij}(t-1)}\right) \\ &\quad - (1 - \bar{\alpha}_{ij}(t)).\ln\left(\frac{K_{ij}(t)}{K_{ij}(t-1)}\right) \end{aligned} \quad \textbf{(6)}$$

for $i \in \{B, F\}$, where $\bar{\alpha}_{ij}(t) \equiv \{\alpha_{ij}(t) + \alpha_{ij}(t-1)\}/2$ is the average share of labour in total income in sector j in the periods t and $t-1$.(6)

Similar growth accounting techniques may be used to approximate relative levels of TFP in sector j at a given point in time (rather than productivity growth within a single economy over time). Here we follow Denny and Fuss (1983a,b) and Hall and Jones (1998) in employing an interspatial Divisia index. Under the assumptions of perfect competition and constant returns to scale, relative productivity levels may be approximated by,

$$\begin{aligned} \ln\left(\frac{A_{Bj}(t)}{A_{Fj}(t)}\right) &= \ln\left(\frac{Y_{Bj}(t)}{Y_{Fj}(t)}\right) - \tfrac{1}{2}(\alpha_{Bj}(t) + \alpha_{Fj}(t))\ln\left(\frac{L_{Bj}(t)}{L_{Fj}(t)}\right) \\ &\quad - \left(1 - \tfrac{1}{2}\left[\alpha_{Bj}(t-1) + \alpha_{Fj}(t-1)\right]\right)\ln\left(\frac{K_{Bj}(t)}{K_{Fj}(t)}\right) \end{aligned} \quad \textbf{(7)}$$

(5) Further details concerning the data set employed and an industry concordance are found in Appendices B and C. We have also replicated our analysis using the OECD's International Sectoral Data Base (ISDB). Source: OECD (1995a).

(6) See Cameron, Proudman and Redding (1997a) for further discussion concerning the measurement of productivity growth, and a detailed characterisation of rates of productivity growth at a disaggregated level within UK manufacturing.

where as before, $\alpha_{ij}(t)$ is the share of labour in total income in sector j of economy i at time t.

The United States is assumed to be the world leader in each of the manufacturing industries throughout the sample period. A key stage in implementing equation **(7)** to measure UK relative to US productivity is the conversion of constant price (here we use 1987 values) data on output and capital into common currency units using an appropriate exchange rate (labour in both countries is measured in terms of hours worked). Conceptually, the relevant exchange rate is the purchasing power parity (PPP) (the number of dollars required to buy the same quantity of goods as may be purchased with one pound sterling).

One approach would therefore be to use a single, economy-wide PPP to convert values of output and capital into a common currency (see, for example, Bernard and Jones (1996b) and Dollar and Wolff (1994)). But since the outputs of each industry are heterogeneous and UK/US relative prices may vary significantly across manufacturing industries, the whole-economy PPP may diverge substantially from the 'true' industry-specific PPP, giving rise to a potential bias in the measures of relative TFP levels across sectors. This paper therefore uses industry-specific PPPs for each of the 14 manufacturing industries, and, since relative factor prices may diverge significantly from relative output prices, a separate PPP for physical capital.[7]

For the capital PPP, we use the OECD's investment PPP from the International Sectoral Data Base (ISDB). In terms of the output PPP for each industry, two broad approaches are adopted in the existing literature. The first approach (employed in this paper) involves the use of unit value ratios (UVRs)[8] ⇔ the ratio of producers' sales values to the corresponding quantities ⇔ for individual products within each manufacturing industry. The UVRs for individual products are then aggregated using expenditure shares to yield an industry-specific PPP for each manufacturing sector.[9]

[7] Factors of production are assumed to be perfectly mobile across industries within an economy, and therefore a single PPP is used for capital input in all 14 manufacturing industries.

[8] Specifically, we use UVRs taken from van Ark (1992).

[9] For further details concerning the method, see Appendix A.

The second approach (following, in particular, Jorgenson and Kuroda (1990)) is based on the data on expenditure PPPs for 153 commodities contained in the United Nations International Comparisons Project (ICP) (see, for example Kravis, Kenessey, Heston and Summers (1975)). These commodities are allocated to 'appropriate' manufacturing industries, and the expenditure PPPs are aggregated using expenditure shares for each commodity. But since these are expenditure PPPs, in order to arrive at an industry-specific PPP that captures relative producer prices, allowance must be made for differences in indirect taxes and distribution margins between countries.

Each of the two approaches has its advantages and disadvantages. The main problems with the expenditure PPP-based methodology are the small number of commodities available for some industries, the absence of information on intermediate input prices, and the difficulty in controlling for differences in indirect taxes and distribution margins. It is largely for these reasons that we adopt a unit value based methodology (see van Ark (1996) for a fuller discussion of the advantages and disadvantages of each approach).

It remains true that different approaches yield different values for the industry-specific PPPs; and as a check on the robustness of our findings, we re-calculate relative TFP using four alternative sets of output PPPs: the whole-economy PPP (source: OECD), OECD expenditure-based estimates of industry-specific PPPs (derived from the UN ICP), our own estimates of expenditure-based PPPs (derived from an earlier edition of the UN ICP) and Pilat (1996)'s estimates of industry-specific PPPs (based upon a combination of UVR and expenditure-based approaches).

The main conclusions that emerge from this robustness analysis are as follows (see Appendix A for details). First, the whole-economy PPP (measured in £ per \$) is substantially lower than the industry-specific PPPs, and therefore its use in measurements of relative TFP considerably overestimates the level of UK TFP relative to the United States compared with any of the industry-specific exchange rates. Second, the main results of the paper relating to productivity convergence and the role of openness in the convergence process are not sensitive to the

PPP chosen.

Table A presents values for the output PPPs used in this study for each of the 14 manufacturing industries (these are taken from van Ark (1992) ⇔ see Appendix A for further details), along with the capital PPP (an OECD investment PPP) and, for comparison, estimates of the whole-economy PPP (based upon GDP deflators), and the market exchange rate (the source for both of the latter is the OECD's STAN database). Table A suggests that relative producer prices do vary significantly across manufacturing industries (from 0.48 £/\$ in Instruments to 1.04 £/\$ in Paper and Printing, compared with a whole-economy PPP of 0.56 £/\$) and, therefore, that the use of a whole-economy PPP would indeed be misleading. In all industries except two, the industry-specific PPP (measured in £ per \$) exceeds the whole-economy PPP, implying that manufactured goods are relatively more expensive in the United Kingdom than the United States, compared with the bundle of goods contained in GDP.[10]

[10] Using the 1987 PPPs and relative rates of inflation in the two economies, it is possible to construct time series for PPPs in each sector, following Jorgenson and Kuroda (1990).

Table A
Unit value ratios (UVR) by manufacturing industry
Source: Van Ark (1992).

Industry	**Code**	**1987 pounds/ dollar**
Total manufacturing		0.71
Food, beverages and tobacco	FBT	0.71
Textiles and apparel	TAT	0.68
Wood products and furniture	WPP	0.92
Paper and printing	PPP	1.04
Non-metallic minerals	NMM	0.65
Chemicals	CHEM	0.63
Rubber and plastic products	RPP	0.55
Primary metals	PM	0.67
Metal products	MP	0.67
Machinery	MACH	0.61
Electrical engineering	EENG	0.74
Transportation	TRAN	0.61
Instruments	PG	0.48*
Other manufacturing	OM	0.71†
Capital PPP		
All industries		0.73
Whole-economy PPP		0.56
Market exchange rate		0.61

* UVR not available, industry-specific expenditure PPP used, source: Pilat (1996).
† total manufacturing UVR used.

Having converted values of output and capital into a common currency (and measuring labour input by hours worked), equation **(7)** may be implemented to yield information on relative TFP levels in each of the 14 industries during the sample period. This information is summarised in Table B, where we present levels of relative TFP in 1970 and 1990, and average (logarithmic) rates of growth of relative TFP in the periods 1970-90, 1970-79 and 1980-89. From Table B, there are substantial variations in relative productivity levels across industries: in 1970, Paper and Printing displayed the lowest level of relative TFP (40.41%), less than half that in the industry with the highest level of relative TFP (82.02% in Machinery). Furthermore, there were substantial changes in the rankings of industries in terms of relative TFP over time: between 1970-90 relative TFP in transport rose from 46.73% to 73.35% (an annual average rate of growth of 2.25%), while relative TFP in Food and Drink fell from 72.10% to 57.25% of the US level (an annual average rate of growth of -1.15%).

Table B
Levels and rates of growth of relative Total Factor Productivity in UK and US manufacturing
All figures expressed as percentages, growth rates are logarithmic

Industry	$\widetilde{\mathbf{TFP}}_{70}$	$\widetilde{\mathbf{TFP}}_{90}$	$\overline{\triangle\mathbf{TFP}}_{70}^{90}$	$\overline{\triangle\mathbf{TFP}}_{70}^{79}$	$\overline{\triangle\mathbf{TFP}}_{80}^{89}$
FBT	72.10	57.25	-1.15	-1.04	-1.37
TAT	51.71	58.01	0.57	0.40	1.24
WPP	50.54	53.49	0.28	0.63	1.20
PPP	40.41	48.91	0.95	-0.56	2.15
NMM	76.54	76.29	-0.02	-0.81	1.26
CHEM	49.51	63.97	1.28	1.91	1.28
RPP	74.75	90.82	0.97	0.08	2.03
PM	51.46	71.77	1.66	-5.18	10.91
MP	41.72	61.07	1.91	1.89	2.77
MACH	82.02	76.88	-0.32	-0.43	0.73
EENG	60.57	57.42	-0.27	-1.10	0.28
TRAN	46.73	73.35	2.25	-0.22	4.69
PG	64.31	76.20	0.85	1.27	-0.96
OM	41.19	49.14	0.88	2.41	0.47
Total	52.28	61.18	0.79	0.18	1.27

Chart 1 plots the time profile of relative TFP in total manufacturing; Charts 2, 3 and 4 successively plot relative TFP in industries with the five highest, next five highest and four lowest levels of relative TFP in 1970. The visual evidence of these charts alone suggests that rates of growth of relative TFP are negatively correlated with initial levels, even without controlling for the determinants of steady-state relative productivity. In order to evaluate this hypothesis more formally, we undertake a test for what has been termed 'absolute β-convergence' in the cross-country growth literature (see for example Bernard and

Jones (1996b)). That is, we run the cross-section growth regression,

$$\frac{1}{T}\sum_{s=1}^{T}\ln\left(\frac{\tilde{A}_j(t+s)}{\tilde{A}_j(t+s\Leftrightarrow 1)}\right)=\alpha+\beta.\ln\tilde{A}_j(t)+u_j \qquad \mathbf{(8)}$$

for all $j \in \{1, ...14\}$, where a negative and statistically significant estimate for β constitutes evidence for absolute β-convergence. As shown in Table C, the estimated value of β is indeed negative and statistically significant (** indicates significance at the 5% level). This finding of β-convergence, even without controlling for the determinants of steady-state relative productivity, is consistent with the theoretical model of the previous section, if the variation in steady-state levels of relative productivity across sectors is not too large. Note that the finding of absolute β-convergence does not necessarily imply a declining cross-section dispersion of relative productivity: to suppose so would be to fall foul to Galton's Fallacy.[11] A full examination of convergence in relative productivity would require an analysis of distribution dynamics, of the kind undertaken elsewhere by Quah (1993b) and, in a productivity context, by Cameron, Proudman and Redding (1997a).

Table C
Testing for β-convergence
Standard errors in parentheses

Independent variable	α	β
$1/T\sum_{s=1}^{T}\triangle\tilde{A}_j(t+s)$	-0.0098	-0.0232**
	0.0049	0.0078

Diagnostics	
Mean dependent variable	0.0037
Standard deviation of dependent variable	0.0087
Standard error of regression	0.0069
R-squared	0.4253
Adjusted R-squared	0.3774
F-statistic (zero slopes)	8.8801

[11] Galton examined the heights of fathers and sons, and found that the sons of tall fathers tended to be shorter than their fathers, while the fathers of tall sons tended to be shorter than their sons. This finding does not, however, imply (as Galton appeared to think) that the cross-section dispersion of male heights is falling over time (see, in particular, the discussion in Quah (1993a)).

Space constraints preclude such an analysis here, and we examine the issue of productivity convergence more informally by looking directly at the evolution of relative productivity levels over time in Table B and Charts 1 to 4. The period as a whole was generally characterised by a convergence of UK TFP towards US levels: for manufacturing as a whole, relative TFP grew at an average annual rate of 0.79% between 1970-90, and only four of the 14 industries experienced declines in relative TFP. But for most of the industries (as shown in Table B and Charts 1 to 4), much of the convergence in relative productivity occurred in the 1980s. Relative TFP in total manufacturing exhibited little change between 1970-79, while between 1979-90, it rose from 53.15% to 61.18% of the US level.[(12)] There are four exceptions to this general pattern: Food, Beverages and Tobacco, Chemicals, Instruments and Other Manufacturing all had lower rates of growth of relative TFP in the 1980s than in the 1970s.

(12) The precise interpretation of the time path of relative TFP in each industry is complicated by cyclical factors. Measured TFP in any one country tends to be pro-cyclical, and the two countries examined here experienced somewhat different business cycles during the sample period. (Thus it is not clear that looking at peak-to-peak business cycles in the United Kingdom is the best response to this problem.) In our econometric analysis, we seek to control for the effect of cyclical factors on TFP growth by using information on changes in the degree of capacity utilisation.

Chart 1:The evolution of TFP in aggregate UK manufacturing relative to the United States

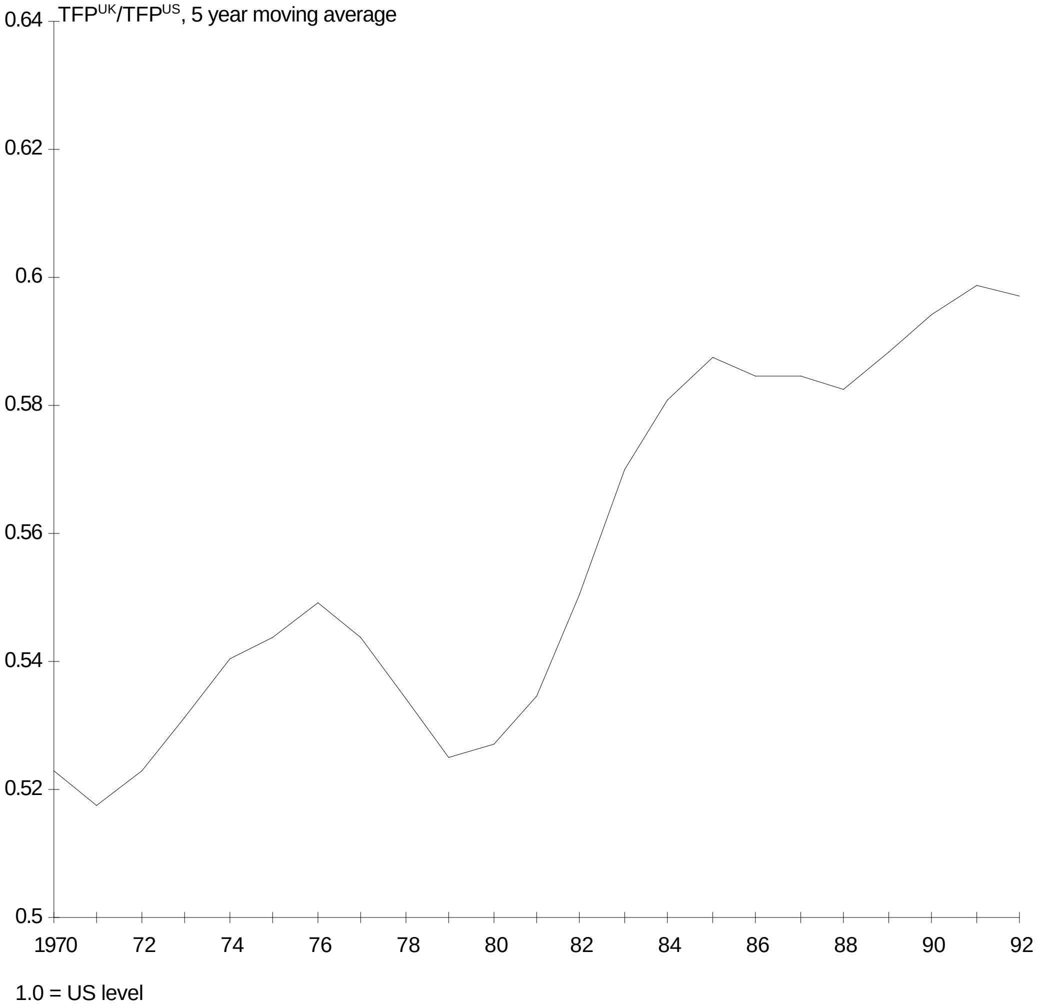
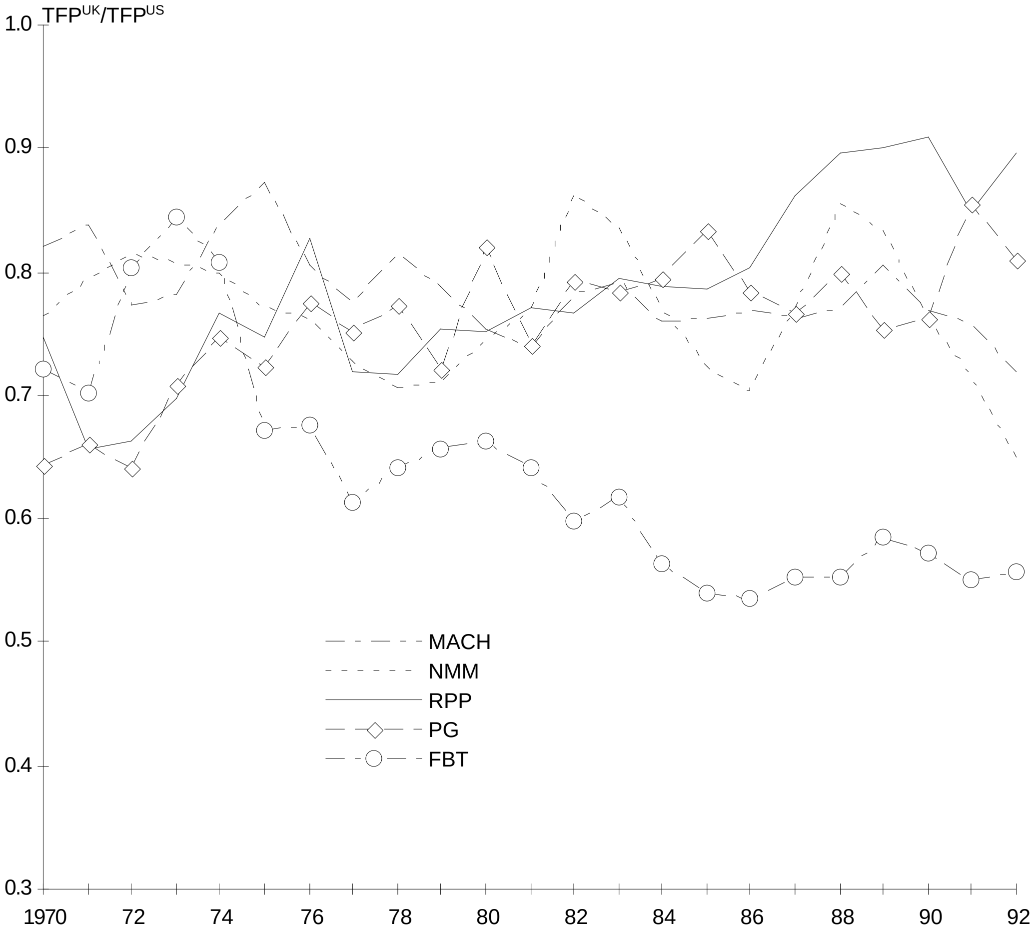
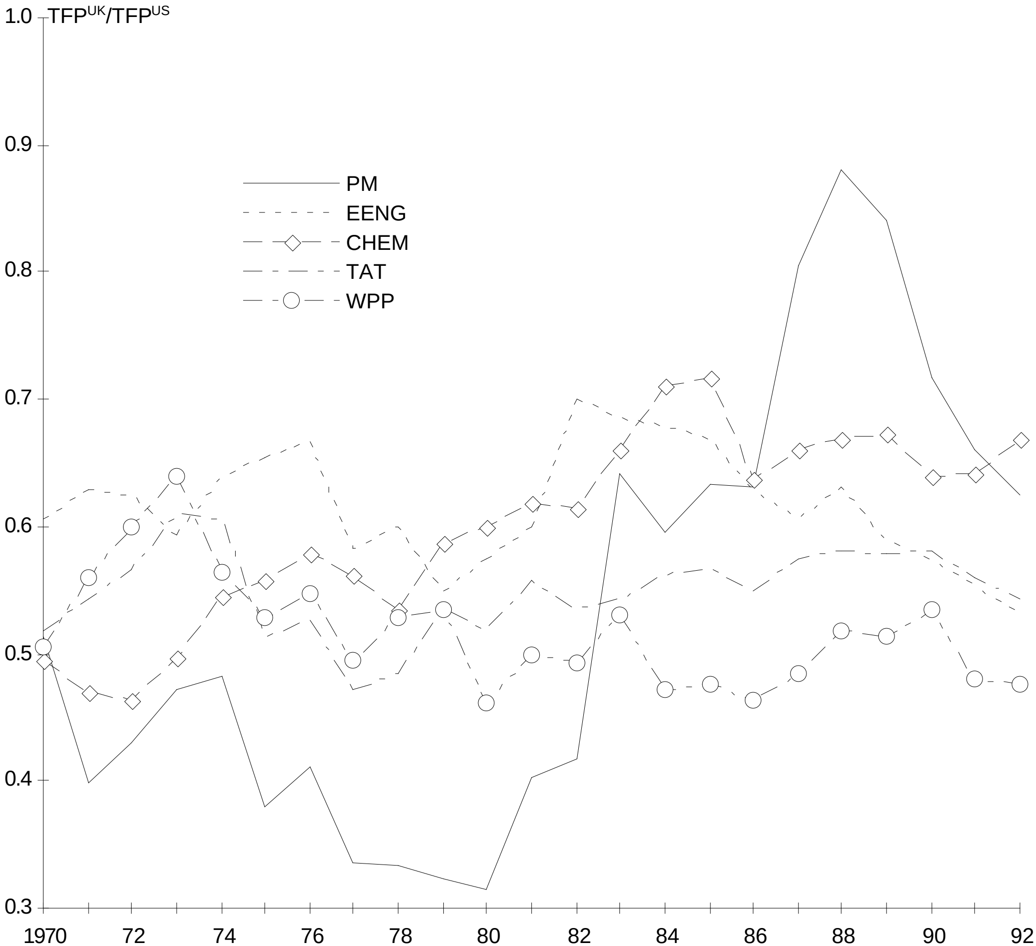


Chart 2: The evolution of relative TFP in the five UK manufacturing sectors with the HIGHEST initial level of TFP



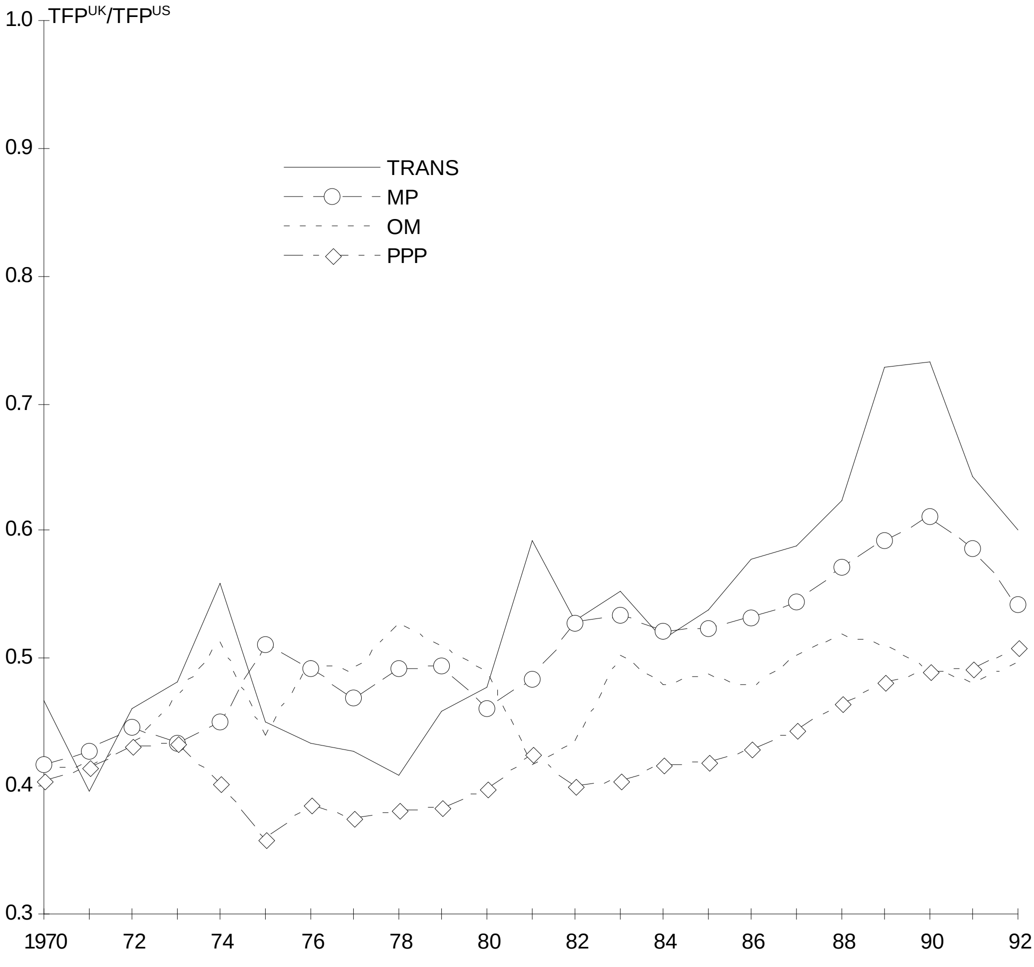
1.0 = US level

Chart 3: The evolution of relative TFP in the five UK manufacturing sectors with INTERMEDIATE initial levels of TFP



1.0 = US level

Chart 4:The evolution of relative TFP in the four UK manufacturing sectors with the LOWEST initial level of TFP



1.0 = US level

4 Econometric estimation

4.1 Introduction and econometric approach

Having examined movements in relative TFP in the sample period in the previous section, this section moves on to estimate econometrically the relationship between the rate of *growth* of TFP in the United Kingdom and relative *levels* of TFP in the United Kingdom and United States, paying particular attention to the potential role of international openness in facilitating technology transfer. The theoretical analysis of Section 2 provides the starting-point for the econometric estimation. The basic specification in equation **(5)** is augmented by an additional short-run dynamic term in US TFP growth, which permits a more flexible specification, but does not play an important role in the subsequent econometrics. Furthermore, since UK TFP may rise or fall in the short run with fluctuations in capacity utilisation, we also include the change in capacity utilisation as a dynamic term to control for this effect.(13) Thus the econometric equation estimated takes the form,

$$\begin{aligned} \triangle \ln\left(A_{Bj}(t)\right) = \alpha_j + \xi_j(\underline{z}) + \beta_{1j}.\triangle \ln\left(A_{Bj}(t \Leftrightarrow 1)\right) \\ +\beta_{2j}.\triangle \ln\left(A_{Fj}(t \Leftrightarrow 1)\right) + \beta_{3j}\triangle \mathrm{Cap}_j(t) \\ +\theta_j.\ln\left(\frac{A_{Fj}(t-1)}{A_{i_j}(t-1)}\right) \\ +\mu_j(\underline{z}).\ln\left(\frac{A_{Fj}(t-1)}{A_{i_j}(t-1)}\right) + \varepsilon_j(t) \end{aligned} \qquad \textbf{(9)}$$

where $\underline{z}$ is the vector of explanatory variables (openness, R&D, human capital and unionisation), and the functions $\xi_j(\cdot)$ and $\mu_j(\cdot)$ are assumed to be log-linear in the explanatory variables. Clearly, associated with this dynamic equation, there is an implied long-run solution for relative TFP akin to equation **(4)**. Any variable that is one of the vector of explanatory variables $\underline{z}$ and enters the equation in levels (rather than differences) will be part of the long-run solution. The presence of the lagged dependent variable in **(9)**, to capture partial adjustment to the

(13) The capacity utilisation variable is based upon CBI data on the percentage of firms operating below capacity. Hence one would expect 'Cap' to be high in recessions and low in booms. See Appendix C for further details concerning data definitions and sources.

long-run solution, may in principle introduce moving-average errors. In practice, we find this issue to be of little significance.

The dynamic equation **(9)** can be estimated separately for each industry, including all variables thought to influence γ_{Bj}, ω_{Bj} and λ_j, and using the time-series variation in these variables to identify the parameters of interest. But with only 21 time-series observations (after differencing and lagging) and a large number of potential determinants of these terms (besides the short-run dynamics), this would leave very few degrees of freedom. The main hypothesis of interest in the present paper is whether the rate of productivity convergence λ_j is a function of international openness. Hence for the remainder of the paper, we adopt a two-stage approach.

In the first stage, we estimate equation **(9)** separately for each of the 14 manufacturing industries, allowing international openness to affect the rate of productivity convergence (through $\mu(\cdot)$) but not domestic rates of innovation or the quantity of technological know-how that may be transferred (through $\xi(\cdot)$). We leave until the second stage of the analysis the question whether openness really does affect the rate of productivity convergence, rather than domestic rates of innovation/the quantity of technological know-how transferred. Similarly, at the first stage, we also abstract from the effect of other economic variables, such as R&D, human capital and unionisation; the effect of these variables is also considered in the second stage.

In the first stage, single-equation estimation, we allow the parameters of interest to vary across manufacturing sectors. A positive estimated value for θ_j implies that UK productivity growth rates are positively correlated with the relative level of US to UK TFP (which we term the 'productivity gap'); a positive estimated value of μ_j implies that the rate of productivity convergence is positively correlated with the extent of international openness over time. This first stage provides information on the relationship between openness and the rate of productivity convergence, controlling only for short-run dynamics and the productivity gap.

In the second stage, we test for the exact channel through which openness affects rates of productivity growth, and for the robustness of the relationship between openness and growth to the inclusion of other economic variables within a panel data framework. By pooling observations across industries, we dramatically increase the number of degrees of freedom, and are able to exploit the cross-industry variation in the independent variables to distinguish between the hypotheses of interest. We allow openness and each of the other economic variables to influence rates of productivity growth through both $\mu(\cdot)$ and $\xi(\cdot)$.

Before proceeding with the estimation, there remains the question of how to measure openness. Conceptually, the extent of international openness is concerned with the size of impediments to three main types of exchange between economies: flows of goods, factors of production and ideas. As such, openness has several different dimensions. But it is difficult to obtain direct information on the size of barriers to flows of goods, factors of production and ideas; and the information that is available (eg on tariff and non-tariff barriers) is often of poor quality and only available for limited time periods.(14) This paper follows a number of different authors in employing 'behavioural' measures of international openness, and we consider five alternative openness measures.

The ratios of exports and imports to output are used to capture the degree of impediments to flows of goods; the ratios of inward and outward FDI flows to output and the ratio of the stock of trade-weighted R&D to the stock of physical capital are used to quantify the exchange of ideas and flows of financial capital respectively. Trade-weighted R&D stocks are calculated in the manner described by Coe and Helpman (1995). For further discussion of the measurement of international openness, see Cameron, Proudman and Redding (1997b). Whenever openness measures are included in interaction terms, each measure is normalised by its mean across sectors and over time.(15)

(14) In the UK context, see the discussion in Cameron, Proudman and Redding (1997b).

(15) This is simply a convenient normalisation that makes the coefficient on the productivity gap term θ_j more easy to interpret. From equation (9), the total effect of the productivity gap for an unnormalised measure of openness is

$$[\theta_j + \mu_j . \ln(\text{Open})] . \ln\left(A_{Fj}/A_{Bj}\right) \tag{10}$$

The normalisation of each openness measure by its mean across sectors and over time (a number) means that, on average, the openness interaction term takes a

Behavioural measures of openness are clearly endogenous. But this is true, to a greater or lesser extent, of all openness measures, including direct measures of trade policy (as made clear in the recent literature dealing with the political economy of trade policy). No single econometric technique is likely to offer complete insulation against all possible problems of endogeneity and mis-specification. In this paper, we consider two alternative attempts to deal with this endogeneity problem and show that our results are robust to both. The first is simply to use lagged values of openness in our regressions. The second is to employ instrumental variables (IV) estimation.

4.2 Single-equation OLS estimation

Having briefly outlined the estimation methodology and discussed the measurement of international openness, we turn now to the single-equation estimation. Equation **(9)** is estimated using OLS on each of the 14 manufacturing industries. We begin with the import-output ratio measure of openness; the estimation results using this measure are presented in Table D. Positive estimated values for the productivity gap and interaction terms (θ_j and μ_j respectively) are denoted by a bold font, while asterisks indicate levels of significance (* denotes significance at the 10% level and ** significance at the 5% level). The productivity gap and import-output interaction terms were found to be positively signed in twelve and nine industries respectively, and both positively signed and statistically significant (at the 10% level) in seven and four industries respectively. There was no industry in which the productivity gap term was negatively signed and statistically significant, and only one industry (WPP) in which the import-output interaction term was negatively signed and statistically significant.

value of approximately zero. The sole effect of this normalisation is to re-scale the estimated value of θ_j: equation **(10)** may be re-written as,

$$\left[[\theta_j + \mu_j . \ln(\overline{\text{Open}})] + \mu_j . \ln(\frac{\text{Open}}{\overline{\text{Open}}}) \right] . \ln \left(\frac{A_{Fj}}{A_{Bj}} \right) \qquad \textbf{(11)}$$

Table D (Panel 1)
OLS estimation

$$\triangle \ln A_{Bj}(t) = \alpha_j + \beta_{1j}.\triangle \ln A_{Bj}(t \Leftrightarrow 1) + \beta_{2j}.\triangle \ln A_{Fj}(t \Leftrightarrow 1) + \beta_{3j}.\triangle(\mathrm{Cap}_j)$$

$$+\theta_j \,.\, \ln\left(\frac{A_{Fj}(t-1)}{A_{Bj}(t-1)}\right) + \mu_j \,.\, \left[\ln(\mathrm{Open}_j(t \Leftrightarrow 1)) \times \ln\left(\frac{A_{Fj}(t-1)}{A_{Bj}(t-1)}\right)\right] + \varepsilon_j(t)$$

	α_j	β_{1j}	β_{2j}	β_{3j}	θ_j	μ_j
FBT	-0.0830**	-0.1445	0.2573*	0.0869*	**0.0681**	-0.1397
	0.0307	0.1948	0.1470	0.0447	0.2555	0.3711
TAT	-0.1924**	-0.0302	0.0529	-0.0857*	**0.3470****	**0.0651***
	0.0964	0.1932	0.4292	0.0472	0.1676	0.0376
WPP	-0.2905**	-0.1094	0.3640	-0.0484	**0.4073****	-0.3038*
	0.1128	0.1985	0.4774	0.0548	0.1727	0.1662
PPP	0.0845	-0.2417	0.0242	-0.1234*	-0.1298	-0.0890
	0.1559	0.3600	0.6681	0.0725	0.2216	0.1539
NMM	-0.1336	0.7237**	-0.4019	-0.0764	**0.5985****	**0.0642**
	0.0515	0.2312	0.2719	0.0503	0.2681	0.1298
CHEM	0.0877	-0.5246*	0.4906	-0.1435*	-0.1435	-0.0453
	0.1490	0.3092	0.3424	0.0811	0.3567	0.1922
RPP	0.0137	-0.6262**	0.5591**	-0.0624	**0.3564**	**0.3523***
	0.0467	0.2757	0.2270	0.0454	0.3327	0.2079
PM	-0.0423	-0.1066	-0.4911	-0.2031**	**0.1659**	**0.2609**
	0.0882	0.2266	0.6584	0.0914	0.1496	0.2481
MP	-0.1694	0.1020	-0.8996**	-0.0569	**0.3584***	**0.0756***
	0.1152	0.2308	0.3314	0.0388	0.2129	0.0439
MACH	-0.0568**	0.1043	0.0126	-0.1310**	**0.2942****	**0.0173**
	0.0249	0.1165	0.1235	0.0218	0.1050	0.0511
EENG	-0.0334	-0.0294	0.1301	-0.0048	**0.0975**	-0.0259
	0.0982	0.3156	0.2612	0.0666	0.2056	0.0577
TRAN	-0.1168	0.1634	0.5254**	0.0151	**0.2096***	**0.0765**
	0.0795	0.2177	0.2463	0.0621	0.1259	0.0628
PG	-0.2218**	-0.1082	-0.2239	-0.0727*	**0.7278****	**0.3623****
	0.1013	0.2675	0.3242	0.0378	0.2780	0.1341
OM	-0.3593	0.0484	-0.1767	-0.1458	**0.4099**	**0.0924**
	0.2253	0.2870	0.2895	0.0918	0.2719	0.0881

Table D (Panel 2)
Diagnostics

Diagnostics			
FBT			
R^2	0.5690	LM: $\chi^2(2)$	0.3393
Adjusted R^2	0.4254	Mean dependent variable	-0.0026
Standard error of regression	0.0344	Standard deviation DV[(a)]	0.0454
TAT			
R^2	0.5693	LM: $\chi^2(2)$	0.0184
Adjusted R^2	0.4258	Mean dependent variable	0.0158
Standard error of regression	0.0354	Standard deviation DV	0.0467
WPP			
R^2	0.5729	LM: $\chi^2(2)$	0.9140
Adjusted R^2	0.4305	Mean dependent variable	-0.00005
Standard error of regression	0.0538	Standard deviation DV	0.0712
PPP			
R^2	0.2340	LM: $\chi^2(2)$	10.6476
Adjusted R^2	-0.0214	Mean dependent variable	0.0122
Standard error of regression	0.0565	Standard deviation DV	0.0559
NMM			
R^2	0.5046	LM: $\chi^2(2)$	0.0579
Adjusted R^2	0.3394	Mean dependent variable	-0.0127
Standard error of regression	0.0448	Standard deviation DV	0.0552
CHEM			
R^2	0.4229	LM: $\chi^2(2)$	0.8537
Adjusted R^2	0.2308	Mean dependent variable	0.0171
Standard error of regression	0.0633	Standard deviation DV	0.0722
RPP			
R^2	0.4219	LM: $\chi^2(2)$	0.2897
Adjusted R^2	0.2291	Mean dependent variable	0.0197
Standard error of regression	0.0524	Standard deviation DV	0.0597
PM			
R^2	0.3245	LM: $\chi^2(2)$	1.3948
Adjusted R^2	0.0993	Mean dependent variable	0.0273
Standard error of regression	0.1550	Standard deviation DV	0.1633

Table D (Panel 3)
Diagnostics (continued)

Diagnostics			
MP			
R^2	0.4415	LM: $\chi^2(2)$	4.0008
Adjusted R^2	0.2553	Mean dependent variable	0.0138
Standard error of regression	0.0370	Standard deviation DV[a]	0.0428
MACH			
R^2	0.8369	LM: $\chi^2(2)$	1.4077
Adjusted R^2	0.7825	Mean dependent variable	0.0163
Standard error of regression	0.0151	Standard deviation DV	0.0325
EENG			
R^2	0.0588	LM: $\chi^2(2)$	8.2596
Adjusted R^2	-0.2549	Mean dependent variable	0.0120
Standard error of regression	0.0512	Standard deviation DV	0.0457
TRAN			
R^2	0.3744	LM: $\chi^2(2)$	2.1991
Adjusted R^2	0.1659	Mean dependent variable	0.0175
Standard error of regression	0.0723	Standard deviation DV	0.0792
PG			
R^2	0.6900	LM: $\chi^2(2)$	0.6831
Adjusted R^2	0.5866	Mean dependent variable	0.3044
Standard error of regression	0.0411	Standard deviation DV	0.0640
Equation OM			
R^2	0.4022	LM: $\chi^2(2)$	0.3337
Adjusted R^2	0.2029	Mean dependent variable	0.0176
Standard error of regression	0.0691	Standard deviation DV	0.0774

[a] DV: dependent variable.

4.3 Single-equation SUR estimation

But OLS estimation, though consistent, is not efficient if the disturbances are correlated across manufacturing industries. This latter hypothesis is not implausible, in which case one may think of the 14 manufacturing sectors as a system. Making use of the information in the variance-covariance matrix of disturbances, one may re-estimate equation **(9)** for each industry as a system of seemingly unrelated regressions (SUR). More formally, stacking equation **(9)** for successive time periods in each industry, we obtain,

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_J \end{bmatrix} = \begin{bmatrix} X_1 & 0 & \cdots & 0 \\ 0 & X_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & X_J \end{bmatrix} . \begin{bmatrix} \phi_1 \\ \phi_2 \\ \vdots \\ \phi_J \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_J \end{bmatrix} \qquad \mathbf{(12)}$$

where y_j is a $(T \times 1)$ vector of the sample values of the dependent variable (here $\triangle \ln A_{Bj}(t)$), X_j is a $(T \times k)$ matrix of the sample values of the k explanatory variables, ϕ_j is a $(k \times 1)$ vector of the regression coefficients, and ε_j is a $(T \times 1)$ vector of the sample values of the disturbances. Stacking industries, equation **(12)** may be re-written as

$$y = X.\phi + \varepsilon \qquad \mathbf{(13)}$$

where, for example, y is now a $(JT \times 1)$ vector, X is a $(JT \times Jk)$ matrix and ϕ is a $(JK \times 1)$ vector. The ε_j are each assumed to be normally distributed with mean zero and variance-covariance matrix $E(\varepsilon_j \varepsilon_j') = \sigma_{jj}.\mathbf{I}_T$ for $j = 1, ...J$ (where $\mathbf{I}_T$ is an identity matrix of order $(T \times T)$). Suppose that the regression disturbances in different sectors are mutually correlated, so that $E(\varepsilon_j \varepsilon_m') = \sigma_{jm}.\mathbf{I}_T$ for $j, m = 1, 2, ..., M$, where $\sigma_{jm} \neq 0$ denotes the covariance of the disturbances of the j^{th} and m^{th} equations and is assumed to be constant over time. The variance-covariance matrix of the $(JT \times 1)$ vector ε is then,

$$\Omega = E(\varepsilon \varepsilon') = \begin{bmatrix} \sigma_{11}.\mathbf{I}_T & \sigma_{12}.\mathbf{I}_T & \cdots & \sigma_{1J}.\mathbf{I}_T \\ \sigma_{21}.\mathbf{I}_T & \sigma_{22}.\mathbf{I}_T & \cdots & \sigma_{2J}.\mathbf{I}_T \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{J1}.\mathbf{I}_T & \ldots & \cdots & \sigma_{JJ}.\mathbf{I}_T \end{bmatrix}$$

The SUR estimator is $\tilde{\phi} = (X'\Omega^{-1}X)^{-1}(X'\Omega^{-1}y)$; and clearly, SUR reduces to OLS in the special case where $\sigma_{jm} = 0$. Table E presents the results of SUR estimation for the 14 manufacturing industries. Twelve manufacturing sectors are now found to have positively signed estimated coefficients on both the productivity gap and openness interaction terms. Taken individually, the productivity gap and openness interaction terms are found to be positively signed and statistically significant (at the 10% level) in 13 and six industries respectively. SUR estimation should purely yield a gain in efficiency over OLS; as a check on the SUR results, we compared the estimated SUR coefficients with the OLS point estimates and standard errors. In each of the 14 industries, the SUR point estimate of the coefficient on the productivity gap and the openness interaction term lay within ± 1.96 standard errors of the OLS point estimate.

Table E (Panel 1)
Seemingly unrelated regression (SUR) estimates

$$\triangle \ln A_{Bj}(t) = \alpha_j + \beta_{1j}.\triangle \ln A_{Bj}(t \Leftrightarrow 1) + \beta_{2j}.\triangle \ln A_{Fj}(t \Leftrightarrow 1) + \beta_{3j}.\triangle(\mathrm{Cap}_j)$$

$$+\theta_j . \ln\left(\frac{A_{Fj}(t-1)}{A_{Bj}(t-1)}\right) . + \mu_j . \left[\ln(\mathrm{Open}_j(t \Leftrightarrow 1)) \times \ln\left(\frac{A_{Fj}(t-1)}{A_{Bj}(t-1)}\right)\right] + \varepsilon_j(t)$$

	α_j	β_{1j}	β_{2j}	β_{3j}	θ_j	μ_j
FBT	-0.0738**	-0.2662**	0.2846**	0.0615**	**0.1969****	**0.0777**
	0.0178	0.0691	0.0645	0.0157	0.0949	0.1336
TAT	-0.2405**	-0.0710	-0.1336	-0.0954**	**0.4341****	**0.0844****
	0.0375	0.0773	0.1646	0.0171	0.0644	0.0216
WPP	-0.2389**	-0.1973**	0.3007**	-0.0400**	**0.3341****	-0.2601**
	0.0464	0.0664	0.1217	0.0140	0.0705	0.0550
PPP	-0.0954	-0.1559	0.5107	-0.0636	**0.2014***	**0.1384**
	0.0820	0.2079	0.3447	0.0389	0.1156	0.0924
NMM	-0.1334**	0.5909**	-0.2979**	-0.0281*	**0.5428****	**0.0340**
	0.0207	0.0839	0.0913	0.0169	0.1173	0.0762
CHEM	-0.0445	-0.2635	0.1896	-0.1410**	**0.1638**	**0.0923**
	0.0707	0.1602	0.1743	0.0415	0.1644	0.0918
RPP	0.0013	-0.3415**	0.3580**	-0.0507**	**0.3979****	**0.3501****
	0.0199	0.1066	0.0853	0.0135	0.1181	0.0904
PM	-0.0525	-0.2187**	0.0128	-0.1012**	**0.2355****	**0.4470****
	0.0561	0.1052	0.2286	0.0375	0.0745	0.1233
MP	-0.2426**	-0.1379*	-0.7974**	-0.0238	**0.5035****	**0.1035****
	0.0365	0.0729	0.1182	0.0148	0.0681	0.0168
MACH	-0.0604**	0.1079**	-0.0328	-0.1159**	**0.3137****	**0.0146**
	0.0125	0.0503	0.0588	0.0112	0.0517	0.0322
EENG	-0.2101**	0.1247	-0.0090	0.0135	**0.4595****	-0.0559
	0.0399	0.1297	0.1086	0.0271	0.0796	0.0362
TRAN	-0.1412**	0.2849**	0.5158**	0.0176	**0.2455****	**0.0842****
	0.0349	0.0954	0.1046	0.0217	0.0501	0.0294
PG	-0.3606**	0.1402	-0.3698**	-0.0494**	**1.1314****	**0.5062****
	0.0440	0.1209	0.1411	0.0161	0.1246	0.0623
OM	-0.2490**	-0.0306	-0.1424	-0.0894**	**0.3140***	**0.0458**
	0.1102	0.1427	0.1306	0.0405	0.1409	0.0450

Table E (Panel 2)
Diagnostics

Diagnostics			
FBT			
R^2	0.5316	LM: $\chi^2(2)$	1.7146
Adjusted R^2	0.3755	Mean dependent variable	-0.0026
Standard error of regression	0.0359	Standard deviation DV[(a)]	0.0454
TAT			
R^2	0.5578	LM: $\chi^2(2)$	0.0175
Adjusted R^2	0.4104	Mean dependent variable	0.01581
Standard error of regression	0.0359	Standard deviation DV	0.0467
WPP			
R^2	0.5488	LM: $\chi^2(2)$	0.4395
Adjusted R^2	0.3984	Mean dependent variable	-0.00005
Standard error of regression	0.0553	Standard deviation DV	0.0712
PPP			
R^2	0.0761	LM: $\chi^2(2)$	1.0510
Adjusted R^2	-0.2319	Mean dependent variable	0.0122
Standard error of regression	0.0620	Standard deviation DV	0.0559
NMM			
R^2	0.4237	LM: $\chi^2(2)$	1.4235
Adjusted R^2	0.2316	Mean dependent variable	-0.0127
Standard error of regression	0.0484	Standard deviation DV	0.0552
CHEM			
R^2	0.3613	LM: $\chi^2(2)$	0.1543
Adjusted R^2	0.1485	Mean dependent variable	0.0171
Standard error of regression	0.0666	Standard deviation DV	0.0722
RPP			
R^2	0.3608	LM: $\chi^2(2)$	1.4290
Adjusted R^2	0.1477	Mean dependent variable	0.0197
Standard error of regression	2.1808	Standard deviation DV	0.0597
PM			
R^2	0.2217	LM: $\chi^2(2)$	0.7714
Adjusted R^2	-0.0378	Mean dependent variable	0.0273
Standard error of regression	0.1664	Standard deviation DV	0.1633

Table E (Panel 3)
Diagnostics (continued)

Diagnostics			
MP			
R^2	0.3019	LM: $\chi^2(2)$	4.4196
Adjusted R^2	0.0692	Mean dependent variable	0.0138
Standard error of regression	0.0413	Standard deviation DV[(a)]	0.0428
MACH			
R^2	0.8289	LM: $\chi^2(2)$	0.2267
Adjusted R^2	0.7679	Mean dependent variable	0.0163
Standard error of regression	0.0157	Standard deviation DV	0.0325
EENG			
R^2	-0.2647	LM: $\chi^2(2)$	2.1765
Adjusted R^2	-0.6863	Mean dependent variable	0.0120
Standard error of regression	0.0594	Standard deviation DV	0.0457
TRAN			
R^2	0.3590	LM: $\chi^2(2)$	0.5655
Adjusted R^2	0.1454	Mean dependent variable	0.0175
Standard error of regression	0.0732	Standard deviation DV	0.0792
PG			
R^2	0.6352	LM: $\chi^2(2)$	0.3000
Adjusted R^2	0.5136	Mean dependent variable	0.0304
Standard error of regression	0.0446	Standard deviation DV	0.0640
OM			
R^2	0.3319	LM: $\chi^2(2)$	0.3050
Adjusted R^2	0.1091	Mean dependent variable	0.0176
Standard error of regression	0.0730	Standard deviation DV	0.0774

[(a)] DV: dependent variable.

This analysis was repeated for each of the four other measures of international openness; for sake of brevity, we only report the OLS results. The results with the export-output ratio were very similar to those presented above: the coefficients on the productivity gap and openness interaction terms were positively signed in twelve and nine sectors respectively. With the ratio of trade-weighted R&D to physical capital, the estimated coefficients on the same two terms were positive in thirteen and nine sectors respectively. Measures of both inward and outward FDI are only available for ten of the manufacturing sectors. With the ratio of inward FDI flows to output, the productivity gap and openness interaction coefficients were positively signed in eight and two of these ten sectors respectively. For the ratio of outward FDI flows to output, the same two coefficients were positively signed in eight and four sectors respectively.

Taken together, the results suggest there is clear evidence that levels of relative productivity in the United Kingdom and United States (the productivity gap) are an important determinant of productivity growth rates in the United Kingdom. The picture for the openness interaction term is more mixed. For three out of the five measures of international openness (the ratios of imports to output, exports to output and trade-weighted R&D to physical capital), there is substantial evidence of a positive relationship between openness and the rate of productivity convergence, though this is more pronounced in some sectors than in others. The same relationship does not appear to exist for flows of FDI, and we return to consider this point further below.

4.4 Panel data estimation

The preceding analysis suggests a positive relationship between openness and productivity growth through the rate of productivity convergence. Single-equation estimation has allowed us to explore this relationship within a framework in which each coefficient is allowed to vary across industries. Nonetheless, the cost of allowing all coefficients to vary is the relatively small number of degrees of freedom we have in each time series equation. With such a small number of degrees of freedom, tests of whether the rate of productivity convergence is a function of openness, as opposed to some other economic variable, are likely to have little power. But without examining the relationship between growth and the other economic variables, we cannot be sure that the estimated relationship between openness and growth is not explained by omitted variables bias.

Panel data estimation techniques, on the other hand, increase dramatically the number of degrees of freedom, by exploiting the cross-section as well as the time-series variation in the independent variables, albeit at the cost of imposing constant coefficients across industries. Within this framework, we test for the exact channel through which openness affects rates of productivity growth and for the robustness of the relationship between openness and productivity growth to the inclusion of other economic variables. In the remainder of this section, we pool industries and estimate the parameters of interest using the Least Squares Dummy Variables (LSDV) estimator, in which only the constant α_j is allowed to vary across industries. More formally, stacking equation **(9)** across time periods and industries, we estimate,

$$y = X.\pi + Z.\zeta + \varepsilon \tag{14}$$

where y is a $(JT \times 1)$ vector, X is a $(JT \times (k \Leftrightarrow 1))$ vector of explanatory variables, π is a $((k \Leftrightarrow 1) \times 1)$ vector of parameters and ε is a $(JT \times 1)$ vector of disturbances. Z is a $(JT \times J)$ matrix of dummy variables Z_j, which take the value one if an observation belongs to industry j and zero otherwise, while ζ is a $(J \times 1)$ vector of sector-specific constants.

There are two points to note about this estimation technique. First, in the presence of a lagged dependent variable, it is well known that the LSDV estimator is biased for small T, owing to the correlation between the lagged dependent variable and the industry-specific fixed effect (see Nickell (1981)). But this bias is asymptotically vanishing in the number of time periods T. In the present application, the relatively large number of time-series observations (compared with most panel data studies) means that this bias is unlikely to be large.(16) Furthermore, in testing down to our preferred specification, the lagged dependent variable is not found to be significant, and is excluded. In

(16) Note that the parameter estimates produced by single-equation OLS estimated with a lagged dependent variable are, in general, biased for small values of T. In single-equation estimation with a lagged dependent variable, one is also effectively invoking the asymptotic properties of OLS in T (see for example Harvey (1990), pages 79-81).

order to evaluate the size of any potential bias from the initial inclusion of the lagged dependent variable, we estimate the parsimonious specification including and excluding this variable, and compare the estimated coefficients.

Second, single-equation OLS estimation did suggest a degree of variation in estimated coefficients across industries, and we begin by comparing the LSDV parameter estimate with the results of the single-equation estimation. Even if one can reject the hypothesis that a coefficient estimated by single-equation OLS equals the point estimate produced by LSDV, the variation in coefficients across industries may well reflect the omission of some of the other economic variables thought to be important in determining rates of productivity growth.

We begin with the same specification as estimated by single-equation OLS above and re-estimate the parameters of interest by LSDV, imposing the equality of all coefficients (except the constant) across industries. Table F presents the results of this estimation for three alternative measures of international openness (the ratios of imports to output, exports to output and trade-weighted R&D to physical capital). For the two trade flow based measures of international openness, the productivity gap and openness interaction coefficients are both positively signed and statistically significant at the 5% level. For the ratio of trade-weighted R&D to physical capital, the two coefficients are again positively signed, but only the productivity gap term is statistically significant at the 5% level.

The same regression was also run for the two FDI-based measures of international openness. The productivity gap term was again positively signed and statistically significant at the 5% level. But the openness interaction terms were now negatively signed, though statistically insignificant. This confirms the finding from single-equation estimation that there is a positive relationship between openness and the rate of productivity convergence for the trade flow and trade-weighted R&D stock measures of international openness (with the relationship by far the strongest in the case of trade flows), but not for the FDI-based measures of international openness.

Table F
LSDV single-equation specification
Sample: 1972-92. 294 observations

$\triangle$**uktfp**	**Imports**	**Exports**	**Trade-weighted R&D**
β_1 ($\triangle$uktfp(-1))	-0.1049*	-0.0991	-0.1098*
	0.0603	0.0604	0.0610
β_2 ($\triangle$ustfp(-1))	0.1537*	0.1449*	0.1563*
	0.0823	0.0826	0.0836
β_3 ($\triangle$Cap)	-0.0865**	-0.0854**	-0.0849**
	0.0164	0.0164	0.0166
θ (Gap(-1))	**0.1527****	**0.1627****	**0.1447****
	0.0363	0.0385	0.0483
μ (InterOpen(-1))	**0.0593****	**0.1052****	**0.0203**
	0.0208	0.0380	0.0171
Fixed effects α_j			
FBT-C	-0.0564	-0.0207	-0.0376
TAT-C	-0.0767	-0.0639	-0.0269
WPP-C	-0.0947	0.0198	-0.0464
PPP-C	-0.0908	-0.0083	-0.0561
NMM-C	-0.0287	-0.0250	-0.0346
CHEM-C	-0.0481	-0.0658	-0.0459
RPP-C	-0.0045	-0.0006	-0.0073
PM-C	-0.0681	-0.0603	-0.0325
MP-C	-0.0409	-0.0466	-0.0523
MACH-C	-0.0226	-0.0340	-0.0214
EENG-C	-0.0465	-0.0486	-0.0604
TRAN-C	-0.0727	-0.0966	-0.0889
PG-C	-0.0241	-0.0401	-0.0205
OM-C	-0.1441	-0.1942	-0.0857

Diagnostics	**Imports**	**Exports**	**Trade-weighted R&D**
R-squared	0.2082	0.2070	0.1890
Adjusted R-squared	0.1563	0.1551	0.1359
SE of regression[a]	0.0653	0.0654	0.0661
LM: $\chi^2(2)$	0.1668	0.1973	0.2833
Mean DV[b]	0.0138	0.0138	0.0138
Standard deviation DV[b]	0.0711	0.0711	0.0711
Sum squared residuals	1.1736	1.1753	1.2020
F-statistic	18.0737	17.9454	16.0228
Prob(F-statistic)	0.0000	0.0000	0.0000

(a) SE: standard error.
(b) DV: dependent variable.

The lack of a positive relationship for the FDI measures may reflect the definition of FDI used by the Office for National Statistics,(17) or the fact that the FDI data is often available at a more highly aggregated level than the productivity growth data.(18) Pain and Wakelin (1996) report evidence of a positive relationship between ONS FDI data and export performance in a majority of twelve OECD countries (though the relationship does not hold for all countries). Our finding is nonetheless interesting, and an exploration of the relationship between FDI and rates of productivity growth is one of the areas in which we would like to undertake further research. In the remainder of this paper, we concentrate upon the relationship between productivity growth and the trade flow based measures of international openness.

There are clearly differences between the productivity gap and openness interaction coefficients estimated for some sectors using single-equation OLS, and those estimated using LSDV. Nonetheless, for the import-output ratio, the mean productivity gap and openness interac-

(17) The ONS definition of FDI is investment that 'adds to, deducts from or acquires a lasting interest in an enterprise operating in an economy other than that of the investor, the investor's purpose being to have an effective voice (an 'effective voice' means that a single foreign (non-resident) investor controls 20% or more of the ordinary shares or voting power of an incorporated enterprise) in the management of the enterprise'. As such, it includes both 'green-field' investment and the purchase of an existing overseas company.

(18) See Appendix B for further details concerning the industrial classification used.

tion coefficients across sectors in Table D (0.2686 and 0.0545 respectively) correspond reasonably closely to the LSDV estimates in Table F (0.1527 and 0.0593 respectively). Considering each sector in turn, we find that the coefficients estimated by LSDV for the productivity gap and import-output interaction terms both lie within the 95% confidence intervals around the respective OLS point estimates in twelve out of the fourteen industries (the two exceptions are NMM and PG for the productivity gap term, and WPP and PG for the import-output interaction term).

Having re-estimated the same specification as in the single-equation analysis, we now move on to consider the robustness of the relationship between openness and the rate of productivity convergence to the inclusion of other explanatory variables, and to test the hypothesis that openness affects the rate of productivity convergence λ_j against the alternative hypothesis that it influences the rate of innovation γ_{Bj} or the degree of transferability of knowledge ω_{Bj}.

We consider three economic variables that may be important in determining either λ_j or γ_{Bj} and ω_{Bj}. First, there is a wealth of theoretical models and empirical studies that suggest that R&D expenditure is an important determinant of rates of economic growth.(19) Second, a number of authors have argued that the level of human capital may play an important role in determining an economy's ability to assimilate existing technologies or generate innovations.(20) Third, there are several reasons to think that trade unions may play an important role in determining firms' incentives to adopt technologies or invest in innovation.(21)

In the first two columns of Table G, we re-estimate equation **(9)**, including the log level of the ratio of R&D expenditure to output, human capital and unionisation (corresponding to an effect of these variables on γ_{Bj} or ω_{Bj}), together with the log level of each of these variables interacted with the productivity gap term (corresponding to an effect on λ_j). Furthermore, in the light of a literature (see in particular Stoneman and Francis (1994)) that has argued that changes in the ratio of

(19) See for example Aghion and Howitt (1992) and Griliches (1980) respectively.
(20) See in particular Benhabib and Spiegel (1994).
(21) See for example Bean and Crafts (1996).

input to output prices may lead to biases in the measurement of total factor productivity using single-deflated value added, we also include terms for the level and change in this variable.[22] One of the main motivations for the use of single-deflated value-added data is our concern about the accuracy of input price deflators at a disaggregated level within manufacturing.[23] But at the same time, we want to be sure that any estimated relationship between openness and rates of productivity is not simply the result of omitting information on movements in relative input to output prices. Hence, we include information on relative input to output prices in total manufacturing as a robustness test.

Columns **(i)** and **(ii)** of Table G estimate this general specification for the import-output and export-output measures of international openness respectively. In each case, the productivity gap and openness interaction coefficients are both positively signed and statistically significant at the 5% level, with the point estimates showing little change from those in Table F (in each case, the new point estimate lies within ± 1.96 SEs of the estimated coefficient in Table F). The level of R&D expenditure relative to output is positively signed and significant at the 5% level, suggesting a role for R&D expenditure in determining the medium-run rate of growth of UK total factor productivity and the long-run level of UK relative to US TFP.

None of the other interaction terms (besides openness) are significant at conventional critical values, though the human capital interaction term (InterEd) is positively signed, with a large coefficient and a t-statistic of more than one for both of the openness measures. The terms in the level of unionisation and human capital are incorrectly signed (relative to our theoretical priors), though each is far from being statistically significant.

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(22) The data on relative input prices are for total manufacturing (see the discussion below): further details concerning all the variables used are found in Appendix C. Changes in the ratio of input to output prices will affect measured TFP in both economies: the reported coefficient on this variable in the regression gives the net effect (if any) on relative TFP.

(23) See van Ark (1996) for a strong argument in favour of the use of single-deflated value-added data.

The ratio of input to output prices (though not the change in this ratio) is statistically significant (with a t-statistic of just over 2 in both columns **(i)** and **(ii)**), suggesting that the relative value of input and output prices affects measured TFP (using single-deflated value-added) during the sample period. The estimated coefficient on this variable is of a plausible magnitude; and openness remains significant when this variable is included, so that the estimated relationship between openness and productivity growth is robust to the inclusion of information on movements in relative input to output prices. As a further test on the robustness of our results to the inclusion/exclusion of this variable, the final column of Table G re-runs the general specification without the input-output price ratio for the export-output openness measure. As is clear from a comparison of columns **(ii)** and **(v)**, our results are not sensitive to the exclusion of this variable.(24)

(24) We show later that the inclusion of this variable does not substantially affect estimated steady-state levels of relative productivity.

Table G
LSDV general specification
Sample: 1972-92. 294 observations

$\triangle$**uktfp**	**(i)**	**(ii)**	**(iii)**	**(iv)**	**(v)**
Δln uktfp(-1)	-0.0834	-0.0777	-0.0830	-0.0798	-0.0718
	0.0608	0.0606	0.0610	0.0610	0.0605
Δln ustfp(-1)	0.0839	0.0619	0.0836	0.0637	0.0875
	0.0835	0.0833	0.0837	0.0836	0.0834
Δln Cap	-0.0855**	-0.0854**	-0.0857**	-0.0852**	-0.0903**
	0.0167	0.0166	0.0168	0.0166	0.0164
Gap(-1)	**0.1896****	**0.2015****	**0.1900****	**0.2021****	**0.2084****
	0.0433	0.0437	0.0436	0.0438	0.0440
Intermy(-1)	**0.0525****	-	**0.0477**	-	-
	0.0246		0.0550		
Interxy(-1)	-	**0.1125****	-	**0.1299****	**0.0977****
		0.0423		0.0656	0.0419
InterR&D(-1)	-0.0169	-0.0416	-0.0163	-0.0491	-0.0301
	0.0266	0.0283	0.0275	0.0357	0.0278
InterEd(-1)	0.1351	0.1059	0.1362	0.1087	0.1013
	0.1058	0.1057	0.1066	0.1061	0.1063
InterUn(-1)	-0.0222	-0.0502	-0.0282	-0.0386	-0.0494
	0.1128	0.1126	0.1289	0.1177	0.1136
ln M/Y(-1)	-	-	0.0040	-	-
			0.0411		
ln X/Y(-1)	-	-	-	-0.0136	-
				0.0392	
ln R&D/Y(-1)	0.0405**	0.0520**	0.0404**	0.0547**	0.0432**
	0.0195	0.0200	0.0196	0.0215	0.0198
ln Ed(-1)	-0.0448	-0.0171	-0.0458	-0.0202	0.0183
	0.0613	0.0610	0.0623	0.0618	0.0585
ln Un(-1)	0.0212	0.0330	0.0261	0.0210	0.0350
	0.0672	0.0673	0.0844	0.0757	0.0676
ln Pr(-1)	-0.1137**	-0.0994**	-0.1146**	-0.0983**	-
	0.0470	0.0460	0.0480	0.0461	
Δln Pr	-0.0066	0.0120	-0.0067	0.0099	-
	0.0645	0.0648	0.0646	0.0652	

Fixed effects	**(i)**	**(ii)**	**(iii)**	**(iv)**	**(v)**
FBT-C	0.1844	0.1106	0.1743	0.1532	-0.0700
TAT-C	0.1902	0.0823	0.1793	0.1287	-0.0898
WPP-C	0.1937	0.1822	0.1837	0.2212	-0.0147
PPP-C	0.1507	0.0986	0.1406	0.1410	-0.0953
NMM-C	0.2260	0.1286	0.2182	0.1719	-0.0461
CHEM-C	0.1220	-0.0143	0.1115	0.0367	-0.1857
RPP-C	0.2593	0.1598	0.2508	0.2039	-0.0178
PM-C	0.1588	0.0486	0.1477	0.0987	-0.1270
MP-C	0.2066	0.0805	0.1967	0.1252	-0.0999
MACH-C	0.1882	0.0555	0.1778	0.1089	-0.1204
EENG-C	0.1083	-0.0133	0.0979	0.0361	-0.1888
TRAN-C	0.0947	-0.0409	0.0829	0.0137	-0.2116
PG-C	0.1785	0.0373	0.1670	0.0930	-0.1368
OM-C	0.0595	-0.1320	0.0481	-0.0841	-0.2903
Diagnostics					
R-squared	0.2615	0.2682	0.2615	0.2686	0.2497
Adjusted R-squared	0.1895	0.1970	0.1865	0.1943	0.1828
SE of regression[(a)]	0.0640	0.0637	0.0641	0.0638	0.0643
LM: $\chi^2(2)$	0.3750	0.3267	0.3747	0.3169	0.2190
Mean DV[(b)]	0.0138	0.0138	0.0138	0.0138	0.0138
Standard deviation DV[(b)]	0.0711	0.0711	0.0711	0.0711	0.0711
Sum squared residuals	1.0946	1.0846	1.0946	1.084	1.1120
F-statistic	7.8766	8.1554	7.2444	7.5125	8.9520
Prob(F-statistic)	0.0000	0.0000	0.0000	0.0000	0.0000

(a) SE: standard error.

(b) DV: dependent variable.

In Columns **(iii)** and **(iv)** of Table G, we test the hypothesis that openness affects λ_j against the alternative that it influences either γ_{Bj} or ω_{Bj}. That is, the specifications in columns **(i)** and **(ii)** are augmented with a term for the log level of openness (as measured by the import-output and export-output ratios respectively). In both cases, the term in the log level of openness is dominated by the openness interaction term. The estimated coefficient on the log level of openness is small in absolute value, with a t-statistic an order of magnitude lower than the openness interaction term. With the import-output measure, the point estimate for the interaction term shows little change from column **(i)**, though the standard error more than doubles, so that the t-statistic drops below the 10% critical value. With the export-output measure, the estimated coefficient on the interaction term again shows little change, but now remains statistically significant at the 5% level.

Thus the positive relationship between openness and productivity growth rates uncovered in Table F is robust to the inclusion of information on the level of R&D expenditure, human capital, unionisation and relative input to output prices. Openness appears to affect the rate at which UK productivity converges to the US λ_j, rather than the sector-specific growth rate γ_{Bj} or the fraction of US TFP transferable to the United Kingdom. The econometric results are similar for either of the measures of international openness based on trade flows.

From the general specification in Table G, we now test down to a more parsimonious representation. Columns **(vi)** and **(vii)** in Table H present one such specification (though not our preferred equation), in which we retain the lagged dependent variable, even though it is not statistically significant at conventional critical values. The specification is the same for both the import and export-output measures of international openness. In column **(vi)** (with the import-output measure), the coefficients on the productivity gap, openness interaction and R&D intensity are all positively signed and statistically significant at the 5% level. The coefficient on the human capital interaction is positively signed and significant at the 10% critical value; while the coefficient relative input to output prices is negatively signed and significant at the 5% level. The results in column **(vii)** (with the export-output measure) are essentially the same, except that all variables (with the exception of the lagged dependent variable) are now significant at the

5% level.

The presence of the lagged dependent variable in columns **(vi)** and **(vii)** means, as discussed earlier, that the OLS estimates of the parameters of interest may be biased.[25] Nonetheless, the lagged dependent variable is not significant at conventional critical values, and our preferred specification (shown for the import and export-output measures of openness in columns **(viii)** and **(ix)** respectively) excludes this variable. A comparison of columns **(vi)** and **(viii)** (or **(vii)** and **(ix)**) provides an assessment of the likely size of the bias: as is clear from Table H, the point estimates for each measure of international openness are essentially unchanged.[26]

[25] See Nickell (1981), though the relatively large number of time periods means that this bias is unlikely to be large.

[26] When we come to calculate the steady-state level of relative productivity implied by the parameter estimates in Table H, we employ our preferred specification in columns **(viii)** and **(ix)**. But the small estimated coefficients on the lagged dependent variable in columns **(vi)** and **(vii)** mean that the analysis is not substantially changed if we use the parameter estimates from these instead.

Table H
LSDV parsimonious specification
Sample: 1972-92. 294 observations

Δ**uktfp**	**(vi)**	**(vii)**	**(viii)**	**(ix)**
Δuktfp(-1)	-0.0730	-0.0672	-	-
	0.0576	0.0575		
ΔCap	-0.0917**	-0.0910**	-0.0908**	-0.0904**
	0.0157	0.0156	0.0139	0.0139
Gap(-1)	**0.1939****	**0.2144****	**0.2025****	**0.2178****
	0.0376	0.0399	0.0357	0.0376
Intermy(-1)	**0.0426****	-	**0.0394****	-
	0.0221		0.0198	
Interxy(-1)	-	**0.0886****	-	**0.0780****
		0.0375		0.0347
InterEd(-1)	0.0750*	0.0882**	0.0788*	0.0899**
	0.0430	0.0402	0.0413	0.0389
ln R&D/Y	0.0320**	0.0323**	0.0352**	0.0350**
	0.0149	0.0149	0.0142	0.0142
ln Pr(-1)	-0.0955**	-0.0896**	-0.0942**	-0.0901**
	0.0374	0.0368	0.0356	0.0349
Fixed effects α_j				
FBT-C	0.0664	0.0956	0.0778	0.1024
TAT-C	0.0761	0.0838	0.0877	0.0935
WPP-C	0.0810	0.1720	0.0970	0.1774
PPP-C	0.0399	0.1031	0.0497	0.1051
NMM-C	0.1074	0.1127	0.1212	0.1236
CHEM-C	-0.0045	-0.0233	-0.0041	-0.0204
RPP-C	0.1337	0.1381	0.1423	0.1441
PM-C	0.0330	0.0364	0.0316	0.0347
MP-C	0.0818	0.0774	0.0902	0.0839
MACH-C	0.0637	0.0517	0.0721	0.0609
EENG-C	-0.0161	-0.0232	-0.0139	-0.0197
TRAN-C	-0.0327	-0.0578	-0.0334	-0.0560
PG-C	0.0504	0.0324	0.0536	0.0378
OM-C	-0.0517	-0.1074	-0.0443	-0.0908

Diagnostics	(vi)	(vii)	(viii)	(ix)
R-squared	0.2538	0.2588	0.2591	0.2619
Adjusted R-squared	0.1991	0.2045	0.2102	0.2132
SE of regression[a]	0.0636	0.0634	0.0631	0.0630
LM: $\chi^2(2)$	0.4138	0.3713	0.3942	0.3732
Mean DV[b]	0.0138	0.0138	0.0131	0.0131
Standard deviation DV	0.0711	0.0711	0.0710	0.0710
Sum squared residuals	1.1059	1.0958	1.1481	1.1437
F-statistic	15.4763	15.8867	20.1392	20.4346
Prob(F-statistic)	0.0000	0.0000	0.0000	0.0000

(a) SE: standard error.

(b) DV: dependent variable.

As discussed earlier, one further econometric concern is the potential endogeneity of the explanatory variables. In order to mitigate the scale of this potential problem, we have used lagged values of each of the economic variables of interest (international openness, R&D intensity, human capital and unionisation) as regressors throughout our econometric estimation. As an additional cross-check, columns **(viii)** and **(ix)** were re-estimated by two-stage least squares. For each of the explanatory variables, with the exception of capacity utilisation, the first and second lag of the variable were used as instruments. For the change in capacity utilisation, two lags of the change in the mortgage lending rate, the change in capacity utilisation in total manufacturing and the change in competitiveness were used as instruments (each of which should be exogenous with regard to an individual industry). The parameter estimates were essentially unchanged relative to those in Table H, though, as is to be expected, there was some loss in efficiency relative to OLS.

As a further check upon the robustness of our results, columns **(viii)** and **(ix)** were re-estimated, dropping one industry at a time from the sample. This provides a check that our parameter estimates are not largely being driven by a single outlying industry. In all 14 cases, and for both the import and export-output measures of openness, the new parameter estimates lay within the 95% confidence interval around the point estimates in columns **(viii)** and **(ix)**.

5 Steady states and quantification

The parameter estimates in columns **(viii)** and **(ix)** represent our preferred specification of the relationship between international openness and productivity growth. Columns **(viii)** and **(ix)** correspond to equation **(2)** in the theoretical analysis; associated with each of these equations, there is a long-run solution for the steady-state level of relative productivity that is directly analogous to **(4)**.

As equation **(4)** makes clear, the steady-state level of relative productivity in each sector depends, in part, upon the long-run rate of growth of US TFP as a result of sector-specific innovation γ_{Fj} (as technological leader, there is no opportunity for the United States to benefit from technological transfer). In principle, one could model the determinants of the long-run productivity growth rate in each manufacturing sector in the United States; but, in the present analysis, we take the US growth process as exogenous, and proxy the long-run rate of growth of US TFP in each sector by its sample mean.

Taking the import-output ratio as our measure of openness, the parameter estimates in column **(viii)** and our assumption about the long-run rate of growth of US TFP in each sector imply the following steady-state level of relative TFP ($\widetilde{TFP} \equiv TFP_j^{UK}/TFP_j^{US}$) in each sector,

$$\ln \widetilde{TFP}_j(t) = \frac{1}{\lambda_j(t)}.\left[\begin{array}{r} \alpha_j \Leftrightarrow \overline{\gamma}_j^{US} + \psi.\ln(\frac{\mathrm{R\&D}_j(t)}{\mathrm{Y}_j(t)}) \\ +\delta.\ln(\Pr(t)) \end{array}\right] \qquad \mathbf{(15)}$$

$$\text{where } \lambda_j(t) = \theta + \mu.\ln(\mathrm{Open}_j(t)) + \eta.\ln(\mathrm{Ed}_j(t))$$

Table I reports the estimated steady state levels of relative TFP in 1970 and 1990 (industries where actual relative TFP exceeds its estimated steady state value are denoted by †). Between these two years, the mean steady state level of log $\widetilde{TFP}$ across the 14 manufacturing sectors rose by 18.4%. Using equation **(15)**, we decompose the growth in log $\widetilde{TFP}$ between 1970-90 into the contributions of changes in openness, human capital, R&D intensity and relative input to output prices. Of the 18.4% increase in mean log relative TFP, we find that 9.3% was due to an increase in our measure of openness, 10.1% to a rise in human capital, 2.1% to the fall in the ratio of input to output prices and -3.1% to the decline in R&D intensity in the sample period.

Substituting the 1990 values of the log import-output ratio into the expression for the rate of productivity convergence λ_j, and holding levels of human capital constant at their 1970 values, we find that the increase in openness between 1970-90 was responsible for a rise in the mean rate of productivity convergence λ_j across manufacturing sectors from 0.15 to 0.19. This implies a reduction in the number of years taken to close half the gap between actual and steady-state levels of log $\widetilde{TFP}$ from 4.2 to 3.3 years.

Table I
Actual and estimated steady-state levels of UK relative to US TFP (%)[a]
† indicates an industry where actual exceeds steady-state TFP

	Relative TFP in 1970		Relative TFP in 1990	
Sector	Actual	Steady-state	Actual	Steady-state
FBT	72.10†	55.27	57.25	67.43
TAT	51.71	57.55	58.01	58.27
WPP	50.54	55.55	53.49	57.57
PPP	40.41	45.37	48.91	52.98
NMM	76.54†	71.72	76.29	82.57
CHEM	49.51	57.34	63.97	78.46
RPP	74.75	81.92	90.82	92.12
PM	51.46	53.81	71.77†	66.93
MP	41.72	51.69	61.07	70.52
MACH	82.02†	72.40	76.88	85.95
EENG	60.57†	51.66	57.42	70.10
TRAN	46.73†	46.26	73.35†	66.33
PG	64.31	81.37	76.20	78.39
OM	41.19	43.36	49.14	57.22

[a] Steady-state values are derived from the estimated long-run coefficients of equation (viii) in Table H.

Table J
Percentage point increase in TFP growth from a one per cent increase in the import-output ratio

$\mathbf{TFP^{UK}/TFP^{US}}$	**percentage point increase in TFP growth**
40%	0.036
50%	0.027
60%	0.020
70%	0.014

If we wish to use these parameter estimates to make inferences about the effect of future changes in the import-output or export-output measures of openness upon the rate of growth of TFP, one must assume that the estimated coefficients are invariant to changes in the marginal process determining the import-output or export-output ratio (whether or not those changes are policy related). Under this assumption, the estimates of Table H imply that a 1% increase in openness (as measured by the import-output ratio) raises the rate of productivity convergence λ_j by a factor of little under 4% (where, on average across time and industries, λ_j was a little above 0.2). The effect upon the rate of UK TFP growth of a 1% increase in openness will depend upon the size of the productivity gap, and Table J presents the percentage point increase in the rate of TFP growth in the first year after a 1% increase in openness (as measured by the import-output ratio) for different values of the productivity gap. For an industry with TFP at 50% of the US level (slightly below the mean level in 1970), our parameter estimates imply that a 1% increase in the import-output ratio will increase the rate of growth of UK TFP by 0.027 percentage points in the first year (where, on average during the sample period, the rate of TFP growth was 1.38%) and then by diminishing amounts thereafter.

6 Conclusions

This paper has examined the relationship between international openness and rates of Total Factor Productivity (TFP) growth in the UK manufacturing sector in the period 1970-92. The analysis began with a theoretical model of productivity dynamics that followed Bernard and Jones (1996a), and which identified two potential sources of productivity growth in each UK manufacturing sector: innovation or technology transfer from the leading economy (which, throughout our analysis, was assumed to be the United States).

Two implications of the model were, first, that the size of the productivity gap from the leading economy is an important determinant of UK rates of TFP growth; and second, that, controlling for the determinants of steady-state relative productivity, sectors with low initial levels of relative TFP should experience the highest rates of growth of relative TFP.

A large theoretical literature suggests that international openness is an important determinant of productivity growth rates, and the basic theoretical model was extended to incorporate three potential effects of international openness. Openness may affect: (a) domestic rates of innovation, (b) the quantity of technological know-how in the leading economy that may be transferred to its more backward counterpart or (c) the rate at which technological transfer occurs. Without imposing identifying restrictions, it is not possible to separately identify (a) and (b), and in our econometric analysis we test whether openness affects either domestic rates of innovation/the quantity of technological knowledge transferred or the rate of technological transfer.

Having presented a theoretical model that implies a link between rates of growth of UK TFP and the relative level of UK and US TFP, the next stage in the analysis involves the measurement of these two variables. We employ a data set based upon the Census of Production in each country and taken from Cameron (1996). An interspatial Divisia index is used to measure relative TFP in the United Kingdom and United States, and our results are shown to be robust to the use of alternative exchange rates to convert output and capital into common currency units (labour is measured using hours worked). The use of whole-economy Purchasing Power Parities (PPPs) is found to overstate substantially the relative level of TFP in the UK compared with a variety of industry-specific PPPs. We employ van Ark's (1992) industry-specific PPPs, based upon the unit value ratio (UVR) approach. Nonetheless, the main results of the paper relating to productivity convergence and the role of openness in the convergence process are found to be robust to the exchange rate chosen.

The sample period as a whole was characterised by a convergence in UK productivity towards US levels in the vast majority of industries, with much of the convergence occurring in the 1980s. In total manufacturing, UK TFP rose from approximately 52% of the US level in 1970 to about 61% in 1990. Across manufacturing sectors, average rates of TFP growth were negatively correlated with initial levels of relative TFP; so, even without controlling for the determinants of steady-state relative productivity, levels of relative TFP exhibited what is termed in the cross-country growth literature 'β-convergence'.

The theoretical model with which the paper began was used to derive an econometric equation linking rates of growth of UK TFP to the size of the productivity gap and the degree of international openness. Of the three channels identified above through which openness may affect TFP growth, it is perhaps most plausible that openness affects the rate of productivity convergence. Employing single-equation OLS and SUR estimation techniques, clear evidence was found that levels of relative TFP are an important determinant of rates of TFP growth in the United Kingdom. The picture for international openness was a little more mixed. But there was substantial evidence of a positive relationship between openness and the rate of productivity convergence for three of the five measures of international openness considered in this paper (the ratios of imports to output, exports to output and trade-weighted R&D to physical capital), with the relationship more pronounced in some sectors than in others and strongest for the trade-flow measures.

Single-equation estimation facilitates an exploration of the relationship between openness and growth within a framework in which the estimated coefficients are allowed to vary across sectors. But the relatively small number of degrees of freedom means that there is little power in (a) tests of whether openness affects the rate of productivity convergence, as opposed to domestic rates of innovation or the quantity of technological know-how transfered, and (b) tests of the robustness of the relationship between openness and growth to the inclusion of other economic variables. In contrast, panel data techniques offer the opportunity to increase dramatically the number of degrees of freedom, and to exploit the cross-section as well as the time-series variation in the independent variables.

Employing least squares dummy variables estimation, openness was found to affect the rate of productivity convergence, rather than either the domestic rate of innovation or the quantity of technological know-how in the leading economy that may be transferred. This relationship was shown to be robust to the inclusion of information on the intensity of R&D, the level of human capital and the level of unionisation. Instrumental variable (IV) estimation using lags of the explanatory variables as instruments yielded similar results, and the estimated parameters were shown to be robust to the exclusion of arbitrary industries.

Using the import-output ratio as our measure of openness, we estimate that the doubling of the log import to output ratio between 1970-90 was responsible for about half of the 18.4% increase in the estimated mean steady-state level of log-relative TFP. As a result of the increase in the import-output ratio in this period, the mean rate of productivity convergence λ_j across sectors rose from 0.15 to 0.19, implying a fall in the number of years taken to close half the gap between actual and steady-state relative TFP from 4.2 to 3.3 years. For an industry with TFP at 50% of the US level, a 1% increase in openness was estimated to raise the rate of growth of UK TFP by 0.027 percentage points in the first year (where on average during the sample period, the rate of TFP growth was 1.38%) and then by diminishing amounts thereafter.

Appendix A

Industry-specific PPPs

6.1 Unit value ratio-based (UVR-based) approach

Industry-specific PPPs are obtained from implementing the following five-stage procedure[27] :

1 In each of the two countries, unit values (price per unit) in a benchmark year (here, 1987) may be obtained for a large number of manufacturing products by dividing producers' sales values by the corresponding quantities (this information is typically available from a country's production census or survey data). For each product k in country $i \in \{B, F\}$, one obtains a unit value p_{ki}.
2 For as many of these products as possible, matches are made between the two countries, and a unit value ratio $UVR_k = p_{Fk}/p_{Bk}$ is obtained.
3 For each four-digit manufacturing industry l, an average unit value ratio was obtained by weighting matched unit values in each country by either the corresponding quantity weights of one of the two countries or the geometric average of these quantity weights (this paper uses UVRs based upon the geometric average of the quantity weights). That is,

$$UVR_l = \frac{\sum_k p_{Fk} . \tilde{q}_k}{\sum_k p_{Bk} . \tilde{q}_k}$$

where $\tilde{q}_k \in \{q_{Bk}, q_{Fk}, \bar{q}_k\}$. Note that p denotes unit value, q refers to the corresponding quantities, l indexes four-digit industries, k indexes products and $i \in \{B, F\}$ indexes countries.
4 In order to aggregate from four-digit industries l to two-digit industries j, the following procedure was implemented: (a) if more than 30% of sales in a four-digit industry were matched, value-added shares in the four-digit industry were used as weights to aggregate to the two-digit level,

$$UVR_j = \frac{\sum_l UVR_l . \widetilde{VA}_l}{\widetilde{VA}_j}$$

[27] The methodogy described here is taken from van Ark (1992). Readers are referred to this paper and van Ark (1996) for further details.

where $\widetilde{VA}_l \in \{VA_{Bl}, VA_{Fl}\}$ denotes value-added;
(b) if less than 30% of sales in a four-digit industry were matched, stage 3 was repeated for the two-digit industry, thereby directly yielding an average unit value ratio for the two-digit industry.
5 The two-digit UVRs were aggregated to the level of total manufacturing using value-added weights; for Other Manufacturing, the Total Manufacturing UVR was used.

Implementing this procedure, the UVRs in Table A1 were obtained by van Ark (1992). The industrial classification employed in this paper is slightly more aggregated than that in Table A1: value-added shares were used to aggregate to the 14 industry classification detailed above (see Table A in the main text). Table A also gives the value for the capital PPP used in the measurement of relative TFP.

Table A1
Unit Value Ratios (UVRs) by two-digit manufacturing industry[a]
Dollars per pound
Source: van Ark (1992)

	UK	US	Geometric mean
Industry	q_{Bk}	q_{Fk}	$\bar{q}_k$
Food products	1.34	1.17	**1.26**
Beverages	1.69	1.71	**1.70**
Tobacco products	2.11	2.10	**2.10**
Textiles	1.51	1.41	**1.46**
Wearing apparel	1.39	1.50	**1.44**
Footwear and leather	1.72	1.76	**1.74**
Timber and furniture	1.27	0.92	**1.09**
Paper and printing	1.02	0.89	**0.96**
Chemicals	1.66	1.49	**1.58**
Petroleum refining	1.56	1.54	**1.55**
Rubber and plastic	1.83	1.81	**1.82**
Minerals	1.53	1.54	**1.54**
Primary metals	1.51	1.48	**1.49**
Machinery and transport	1.64	1.63	**1.64**
Electrical engineering	1.36	1.34	**1.35**
Other manufacturing	1.49	1.34	**1.41**
Total manufacturing	1.49	1.34	**1.41**

[a] The first column uses UK quantity weights, while the second and third columns use US quantity weights and the geometric mean of the two countries' quantity weights respectively.

Robustness analysis

As a check for robustness, the analysis was repeated with four alternative sets of PPPs (I to IV respectively): the OECD whole-economy PPP, OECD estimates of expenditure-based PPPs derived from the UN ICP (adjusted for relative distribution margins), our own estimates of expenditure-based PPPs derived from the UN ICP (adjusted for relative distribution margins) and Pilat's (1997) estimates of industry-specific PPPs.[28] Table A2 compares the van Ark (1992) unit value based PPP for total manufacturing with each of these alternative PPPs.

Table A3 reports (a) measured levels of relative TFP in 1970 and 1990, (b) the average level of TFP between 1970-90, and (c) the cumulative growth in relative TFP between 1970-90 in Total Manufacturing for alternative PPPs. The main conclusions that emerge from this robustness analysis are as follows. First, the whole-economy PPP measured in £ per $ is substantially lower (substantially higher when measured in $ per £) than the industry-specific PPPs, and therefore its use in measurements of relative TFP considerably overestimates the level of UK relative to US TFP compared with any of the industry-specific exchange rates. Second, the main results of the paper relating to productivity convergence and the role of openness in the convergence process are not sensitive to the PPP chosen.

[28] The values for relative distribution margins are taken from Pilat (1997).

Table A2
Comparison of alternative PPPs
1987 dollars per pound

PPP	Total Manufacturing
van Ark (1992) UVR	**1.41**
OECD whole-economy **(I)**	1.78
OECD expenditure PPP	1.41
OECD expenditure PPP (adjusted) **(II)**	1.40
Authors' expenditure PPP	1.31
Authors' expenditure PPP (adjusted) **(III)**	1.29
Pilat (1997) mixed approach **(IV)**	1.44

Table A3
Relative TFP in Total Manufacturing, employing a variety of PPPs

PPP	TFP_{70}	TFP_{90}	$\overline{TFP}_{70}^{90}$	TFP_{90}-TFP_{70}
van Ark (1992) UVR	**0.52**	**0.61**	**0.56**	**15.73 %**
(I)	**0.66**	**0.77**	**0.71**	**15.73 %**
(II)	0.52	0.61	0.56	15.73 %
(III)	0.48	0.56	0.51	15.73 %
(IV)	0.54	0.63	0.58	15.73 %

Appendix B

Industry concordances

Table B1
Industrial classification for the ONS FDI data

Industry
Metal manufacturing
Chemicals
Mechanical instrument engineering
Electrical engineering
Transport equipment
Food, drink and tobacco
Paper, print and publishing
Other manufacturing
Rubber (outward FDI data not available)
Textiles, leather and clothing (outward FDI data not available)

Table B2
Industry concordance

Industry	US SIC	UK SIC (80)
Total Manufacturing	20 to 39(x29)	2 to 4
FBT	20,21	41,42
TAT	22,23,31	43,44,45
WPP	24,25	46
PPP	26,27	47
NMM	32	23/24
CHEM	28	25,26
RPP	30	48
PM	33	22
MP	34	31
MACH	35	32,33
EENG	36	34
TRAN	37	35,36
PG	38	37
OM	39	49

Appendix C

Data definitions and sources

Value-added: Value-added is gross value added at factor cost. Gross value-added was deflated by the producer prices (output) index, to yield a single-deflated value-added index, expressed in 1987 constant prices. The UK data were supplied by the Office for National Statistics (ONS) (see Cameron (1996) or Cameron, Proudman and Redding (1997a) for further details). The US data were supplied by the Bureau of Labor Statistics (see Bureau of Labor Statistics (1994)).
Labour input: Labour input is measured by annual hours worked. For the United Kingdom, these were calculated as follows: total employment is from the Census of Production. Normal and overtime hours worked per week (full-time males) are taken from the *New Earnings Survey* and from information supplied by the Employment Department. Weeks worked are taken from *Employment Gazette* (data for Total Manufacturing are assumed to apply to all industries). Annual hours worked are then simply employees times weeks worked times hours per week. The US data were supplied by the Bureau of Labor

Statistics (see Bureau of Labor Statistics (1994)).
Physical Capital: Physical capital is gross capital stock expressed in 1987 constant prices. Data for the United Kingdom were supplied by the ONS (see Cameron (1996)); data for the United States were supplied by the Bureau of Labor Statistics (see Bureau of Labor Statistics (1994)).
Export to Output ratio: The ratio of exports to gross output in the United Kingdom, taken from the OECD STAN database (see OECD (1995b)).
Import to Output ratio: The ratio of imports to gross output in the United Kingdom, taken from the OECD STAN database (see OECD (1995b)).
Ratio of trade-weighted R&D to physical capital: The UK data on physical capital were as above. Trade-weighted R&D stocks for the United Kingdom were calculated by implementing the Coe and Helpman (1995) methodology using the OECD ANBERD Database (see OECD (1996)).
Ratio of Inward Foreign Direct Investment flows to output: UK output is value-added at factor cost (as described above). The UK FDI data were supplied by the ONS (see Cameron, Proudman and Redding (1997b) for further details).
Ratio of Outward Foreign Direct Investment flows to output: Again, UK output is value added at factor cost (as described above). The UK FDI data were supplied by the ONS (see Cameron, Proudman and Redding (1997b) for further details).
R&D Intensity: Ratio of Business Enterprise Research and Development (BERD) expenditure to output. The UK data on BERD were taken from CSO (1995); UK output is again value added at factor cost (as described above).
Human capital: Proportion of workers holding high and medium-education qualifications in total workforce in the United Kingdom. These data were taken from the *General Household Survey*.
Unionisation: Proportion of adult male manual workers covered by some form of collective agreement times by the proportion of adult male manual workers in the total workforce in the United Kingdom. These data were kindly supplied by Brian Bell.
Capacity utilisation: The UK capacity utilisation variable follows Muellbauer (1991) and is based upon the percentage of firms operating below capacity in answer to the CBI Industrial Trends Survey question:

'Is your present level of output below capacity (ie are you working below a satisfactory full rate of operation) ?'
Relative input to output prices: UK input and output producer price indices for Total Manufacturing supplied by the ONS.

References

Aghion, P and Howitt, P (1992) 'A model of growth through creative destruction', *Econometrica*, March, pages 323-51.

van Ark, B (1992) 'Comparative productivity in British and American manufacturing', *National Institute Economic Review*, pages 63-74.

van Ark, B (1996) 'Productivity and competitiveness in manufacturing: a comparison of Europe, Japan and the United States', in (eds) Wagner, K and van Ark, B (1996) *International productivity differences: measurement and explanations*, North-Holland, Amsterdam, pages 23-52.

Barro, R and Sala-i-Martin, X (1995) *Economic Growth*, McGraw Hill, New York.

Bean, C and Crafts, N (1996) 'British economic growth since 1945: relative economic decline..and renaissance', in (eds) Crafts, C and Toniolo, G, *Economic Growth in Europe since 1945*, Cambridge University Press.

Ben-David, D (1993) 'Equalising exchange: trade liberalisation and income convergence', *Quarterly Journal of Economics*, pages 653-79.

Benhabib, J and Spiegel, M (1994) 'The role of human capital in economic development: evidence from aggregate cross-country data', *Journal of Monetary Economics*, vol 34, pages 143-73.

Bernard, A and Jones, C (1996a) 'Productivity across industries and countries: time series theory and evidence', *Review of Economics and Statistics*, vol 78, no 1, pages 135-46.

Bernard, A and Jones, C (1996b) 'Comparing apples to oranges: productivity convergence and measurement across industries and countries', *American Economic Review*, December, pages 1,216-38.

Bureau of Labour Statistics (1994) *Multifactor productivity and related data for 2-digit manufacturing industries on diskette*, Washington: Bureau of Labour Statistics.

Cameron, G (1996) 'Innovation and economic growth', *D. Phil. Thesis*, University of Oxford.

Cameron, G, Proudman, J and Redding, S (1997a) 'Deconstructing growth in UK manufacturing', *Bank of England Working Paper*, no 73.

Cameron, G, Proudman, J and Redding, S (1997b) 'Openness and its association with productivity growth in UK manufacturing industry', Bank of England, *mimeo.*

Coe, D and Helpman, E (1995) 'International R&D Spillovers', *European Economic Review*, vol 39, no 5, pages 859-87.

CSO (1995) *Business Expenditure on R&D in 1994*, Central Statistical Office, London.

Denny, M and Fuss, M (1983a) 'The use of discrete variables in superlative index number comparisons', *International Economic Review*, vol 24, no 2, pages 419-21.

Denny, M and Fuss, M (1983b) 'A general approach to intertemporal and interspatial productivity comparisons', *Journal of Econometrics*, vol 23, no 3, pages 315-30.

Dollar, D and Wolff, E (1994) 'Capital intensity and TFP convergence by industry in manufacturing, 1963-85', in (eds) Baumol, W, Nelson, R and Wolff, E, *Convergence of productivity: cross-national studies and historical evidence*, Oxford University Press, pages 197-224.

Griliches, Z (1980) 'Returns to R&D expenditures in the private sector', in (eds) Kendrick, K and Vaccara, B, *New Developments in Productivity Measurement*, Chicago University Press.

Grossman, G and Helpman, E (1991) *Innovation and growth in the global economy*, MIT Press.

Hall, R and Jones, C (1998) 'Fundamental determinants of output per worker across countries', *Quarterly Journal of Economics*, Forthcoming.

Harvey, A (1990) *The Econometric Analysis of Time Series*, Philip Allan, 2nd edition.

Jorgenson, D and Kuroda, M (1990) 'Productivity and international competitiveness in Japan and the United States', in (ed) Hulten, C, *Productivity growth in Japan and the United States*, National Bureau of Economic Research, Cambridge.

Kravis, I, Kenessey, A, Heston, A and Summers, R (1975) *A system of international comparisons of gross product and purchasing power*, Johns Hopkins University Press, Baltimore.

Muellbauer, J (1991) 'Productivity and competitiveness', *Oxford Review of Economic Policy*, vol 7, no 3, pages 99-117.

Nickell, S (1981) 'Biases in dynamic models with fixed effects', *Econometrica*, vol 49, no 6, pages 1,417-26.

OECD (1995a) *International Sectoral Data Base, 1960-1994*, OECD, Paris.

OECD (1995b) *The OECD STAN database: 1995 edition on diskettes*, OECD, Paris.

OECD (1996) *ANBERD 1973-1993 on diskette*, OECD, Paris.

Pain, N and Wakelin, K (1996) 'Foreign Direct Investment and Export Performance', *mimeo*, National Institute for Economic and Social Research, October.

Parente, S and Prescott, E (1994) 'Barriers to technology adoption and development', *Journal of Political Economy*, vol 102, no 2, pages 298-321.

Pilat, D (1996) 'Labour productivity levels in OECD countries: estimates for manufacturing and selected service sectors', *OECD Economics Department Working Papers*, no 169.

Quah, D (1993a) 'Galton's fallacy and the convergence hypothesis', *Scandanavian Journal of Economics*, vol 95, pages 427-43.

Quah, D (1993b) 'Empirical cross-section dynamics in economic growth', *European Economic Review*, vol 37, pages 426-34.

Proudman, J, Redding, S and Bianchi, M (1997) 'Is international openness associated with faster economic growth', *Bank of England Working Paper*, no 63.

Rivera-Batiz, L and Romer, P (1991) 'Economic integration and endogenous growth', *Quarterly Journal of Economics*, vol 106, no 2, pages 531-55.

Sachs, J and Warner, A (1995) 'Economic reform and the process of global integration', *Brookings Papers on Economic Activity*, no 1, pages 1-95.

Solow, R (1957) 'Technical change and the aggregate production function', *Review of Economics and Statistics*, vol 31, pages 312-20.

Stoneman, P and Francis, N (1994) 'Double deflation and the measurement of output and productivity in UK manufacturing, 1979-1989', *International Journal of the Economics of Business*, vol 1, no 3, pages 423-37.