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Technological convergence, R&D, trade and productivity growth

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Abstract

This paper analyses productivity growth in a panel of 14 United Kingdom manufacturing industries since 1970. Innovation and technology transfer provide two potential sources of productivity growth for a country behind the technological frontier. We examine the roles played by research and development (R&D), international trade, and human capital in stimulating each source of productivity growth. Technology transfer is statistically significant and quantitatively important. While R&D raises rates of innovation, international trade enhances the speed of technology transfer. Human capital primarily affects output through private rates of return (captured in our index of labour quality) rather than measured TFP.

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1. Introduction

‘It may be seriously argued that, historically, European receptivity to new technologies, and the capacity to assimilate them whatever their origin, has been as important as inventiveness itself.’¹

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¹ Rosenberg (1982, p. 245).

A number of authors have emphasised the transfer of technology from leader to follower countries as an important source of economic growth. Rosenberg (1982) notes that three of the great European technical developments – printing, gunpowder and the compass – are the result of technology transfer. Less prosaic examples include the development of the crucible steel industry in early 19th Century France based on British technology, the diffusion of mass production techniques for motor car manufacture from the US to Europe during the early 20th Century, and the development of the Japanese semi-conductor industry.²

This paper evaluates the role of technology transfer in explaining productivity growth at the industry-level in the United Kingdom since 1970. We present an empirical framework in which innovation and technology transfer provide two sources of productivity growth for an economy behind the technological frontier. The difference in levels of total factor productivity (TFP) between the United Kingdom and a frontier country (the United States) is used as a direct measure of the potential for technology transfer.³ This approach allows for knowledge spillovers from both formal research and development (R&D) and the informal activities not captured in R&D statistics that a wide range of empirical evidence suggests are important for productivity growth.⁴ ‘Technology transfer’ is used in the paper to refer to convergence in technical efficiency within individual industries over time. The analysis controls for both observable and unobservable characteristics that determine whether and at what speed technology transfer occurs. We consider the roles played by R&D, international trade, and human capital. We examine whether each variable has a direct effect on rates of TFP growth (innovation) and whether the variable’s effect on TFP growth depends on distance behind the technological frontier (technology transfer).

The use of panel data on industries over time enables us to examine the disaggregated forces underlying country-level growth performance, while at the same time controlling for unobserved heterogeneity in the sources of productivity growth. Existing work on R&D knowledge spillovers often assumes that technology transfer occurs through a specific mechanism such as international trade. An advantage of our approach is that we explicitly test whether technology transfer occurs through international trade against the alternatives that its pace is determined by domestic ‘absorptive capacity’ (in the form of human capital and R&D investments) and that it proceeds autonomously (independently of the economic variables considered).⁵ In steady-state, the level of productivity in non-frontier countries lies an equilibrium distance behind the frontier, such that productivity growth from innovation *and* technology transfer exactly equals productivity growth from innovation alone in the frontier. The analysis thus sheds

² See respectively Landes (1998, pp. 285–288), Womack et al. (1990, chapter 2), and Rosenberg (1994, chapter 7). Authors who have emphasised the role of technology transfer include Abramovitz (1986), Nelson and Phelps (1966), and Parente and Prescott (1994, 2000).

³ See Cameron (1996a) for an analysis of Japan and the United States and Griffith et al. (2000) for a study of 12 OECD countries.

⁴ See, for example, Enos (1958) and Bahk and Gort (1993) for evidence on learning by doing.

⁵ For further discussion of ‘absorptive capacity’ and the related concept of ‘tacit knowledge’ in a historical context, see David (1992) and Rosenberg (1982).

light on the existence and determinants of long-run differences in productivity across countries in individual industries.⁶

Our main results are as follows. First, we find an important role for technology transfer as a source of productivity growth in UK manufacturing. This result is robust across a wide range of econometric specifications and to the use of a number of different measures of TFP. Other things equal, the greater the gap in levels of technical efficiency between the United States and the United Kingdom in a manufacturing industry, the faster the rate of UK productivity growth. Second, there is a positive direct effect of R&D on productivity growth through rates of innovation. This finding is consistent with both the endogenous growth literature and the micro-econometric literature on R&D and productivity. The result is again robust across a wide range of specifications, to the use of different measures of R&D and TFP, and with different lag structures.

Third, we find that increased international trade raises rates of UK productivity growth through technology transfer but not innovation. Our measure of international trade is the ratio of a UK industry's imports from the whole world to gross output. A problem in the literature on trade and growth is the potential endogeneity of international trade. Another feature of our approach is the use of instruments that capture exogenous variation in the degree of international integration in individual industries over time. Estimating the model using instrumental variables strengthens the finding of trade-based technology transfer. The instruments are highly statistically significant in the first-stage regression, and we present evidence that the identifying assumptions underlying the instrumental variables estimation are satisfied.

Fourth, our preferred measure of TFP controls for variation across countries and industries in the skill composition of the workforce. Numbers of skilled and unskilled workers are weighted by their respective shares of the wage bill. In so far as any increased productivity of skilled workers is reflected in their wages (a private rate of return), it will already be captured in our measure of TFP. We present evidence that, once one controls for the direct effect of human capital on output through private rates of return, there is no evidence of an additional effect through externalities.

The paper relates to two main strands of existing literature. First, a body of empirical work has examined the relationship between R&D and productivity growth at the firm and industry-level. Classic references include Griliches (1980), Griliches and Lichtenberg (1984), and Mansfield (1980).⁷ The conventional approach regresses TFP growth on measures of R&D activity. Microeconomic foundations are supplied by the theoretical literature on endogenous innovation and growth,⁸ and a positive and statistically significant estimated coefficient provides evidence of R&D-based innovation.

⁶ Cross-country productivity differences have recently received renewed attention in both the theoretical literature and in empirical studies using aggregate data. See, for example, Acemoglu and Zilibotti (2000), Hall and Jones (1999), and Prescott (1998).

⁷ See Hall and Mairesse (1995) for a more recent example and Mohnen (1996) for a survey of this literature.

⁸ See, for example, Aghion and Howitt (1992, 1998), Grossman and Helpman (1991), and Romer (1990).

One branch of this first empirical literature has examined R&D knowledge spillovers across industries, countries, and regions.⁹ Foreign R&D knowledge is typically found to be an important source of productivity growth, although there remains much debate concerning the mechanisms through which this occurs. A number of studies assume that international trade flows are the conduit. However, this assumption has recently been questioned by Keller (1998). The use of the technology gap as a direct measure of the potential for technology transfer in our approach allows for knowledge spillovers from both formal R&D investments and informal sources of productivity growth. Rather than assuming a particular mechanism through which knowledge is transferred, we test the statistical significance of various economic mechanisms that have been proposed, while also allowing technology transfer to occur independently of international trade and the other economic variables considered.

Second, the use of a direct measure of distance from the technological frontier means that the analysis relates to both the literature on the measurement of TFP across countries, industries and time and to work on productivity convergence.¹⁰ By combining data from the Census of Production in the United Kingdom and United States with that from a number of other sources, we obtain a rich source of industry-level information, with which we are able to make a number of adjustments to standard TFP measures. For example, our analysis controls for variation across countries and industries in hours worked, the skill composition of the workforce, capacity utilization, and manufacturing prices as captured in industry-specific purchasing power parities (PPPs). In contrast to a number of existing papers which focus on a Cobb–Douglas production technology, we employ extremely general TFP measures consistent with any constant returns to scale production technology.

A large number of papers have examined convergence of income per capita and productivity at the country-level.¹¹ Typically, convergence is only observed after controlling for a variety of determinants of long-run income per capita/productivity levels ('conditional convergence'), and several country-level studies emphasize the idea that convergence is dependent on the promotion of 'absorptive capacity.' Thus, Benhabib and Spiegel (1994) argue for important effects from human capital, while Abramovitz (1986) stresses 'social capability'.

A companion literature has examined productivity convergence at the industry-level.¹² Our empirical framework is consistent with conditional productivity convergence, which emerges as an implication of a long-run cointegrating relationship between TFP levels

⁹ Griliches (1992) surveys the inter-industry spillovers literature. International studies include Bernstein and Mohnen (1998) Branstetter (2000), Coe and Helpman (1995), Coe et al. (1997), Eaton and Kortum (1996, 1999), Jaffe and Trajtenberg (1998), Keller (1998, 2000, 2002) among others. See Nadhiri (1993) and Keller (2001b) for surveys of this literature. Jaffe et al. (1993) present evidence of the geographical localization of knowledge spillovers within the United States.

¹⁰ See, for example, van Ark (1992, 1996), Bernard and Jones (1996a, 1996b), Caves et al. (1982a,b), Dollar and Wolff (1988, 1994), Jorgenson and Kuroda (1990), Harrigan (1997, 1999), and Pilat (1996).

¹¹ Examples include Barro and Sala-i-Martin (1992, 1995), Dowrick and Nguyen (1989), and Mankiw et al. (1992).

¹² See, for example, Bernard and Jones (1996a, 1996b), Dollar and Wolff (1988, 1994), Dowrick (1989), Hansson and Henrekson (1994), and Jorgenson and Kuroda (1990).

in the United Kingdom and United States. The econometric equation that we estimate is an equilibrium correction model (ECM) representation of this long-run cointegrating relationship. Our analysis also explicitly incorporates a role for R&D, human capital, and international trade in determining productivity growth. We test empirically whether each variable affects productivity growth through innovation and/or technology transfer.

The paper is structured as follows. Section 2 introduces the theoretical framework from which our main econometric equation is derived. The theoretical discussion provides structure for our empirical work and yields implications for the determinants of long-run relative productivity levels. Section 3 analyses the evolution of relative levels of TFP in the manufacturing sectors of the United Kingdom and United States since 1970. Section 4 estimates the econometric relationship between TFP growth, distance from the technological frontier, R&D, human capital, and international trade. Section 5 concludes.

2. Theoretical framework

Consider a world comprised of two countries $i \in \{B, F\}$, each of which may produce any of a fixed number of manufacturing goods, $j = 1, \dots, n$. Production in each sector takes place according to a standard neoclassical production technology

$$Y_{ijt} = A_{ijt} G_j(L_{ijt}, K_{ijt}), \quad (1)$$

where K and L denote physical capital and labour input respectively; A is an index of technical efficiency or total factor productivity (TFP). The function $G(\cdot, \cdot)$ is assumed to be homogeneous of degree one and to exhibit diminishing marginal returns to the accumulation of either K or L . We allow TFP (A) to vary across countries, industries, and time.

In general, at time t in sector j , one of the countries i will have a higher level of TFP than the other: we term this economy the ‘technological frontier’ F and index its less advanced counterpart by B . In the empirical analysis that follows, we take the United States to be the technological frontier. We show below that levels of TFP in the UK lie well below the US in all manufacturing industries throughout the sample period.¹³

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

$$\Delta \ln A_{ijt} = \gamma_{ij} + \lambda_{ij} \ln \left(\frac{A_{Fjt-1}}{A_{ijt-1}} \right), \quad \gamma_{ij}, \lambda_{ij} \geq 0, \quad (2)$$

where γ_{ij} corresponds to the rate of (sector-specific) innovation and λ_{ij} parameterises the rate of technological transfer. The further country i lies behind the technological

¹³ To the extent to which the US has been overtaken by third economies (e.g. Japan) in certain industries, our choice of the US as frontier will underestimate the extent of technology transfer. Studies of the US and Japan (e.g. Cameron, 1996a) suggest that Japan overtakes the US in only a minority of manufacturing sectors and not until relatively late in our sample period. The dominance of the US as technological leader receives support from the analysis of cross-country productivity levels in Pilat (1996) and a study of 12 OECD countries by Griffith et al. (2000).

frontier in sector j , the larger the second term on the right-hand side of Eq. (2) and the greater the potential for productivity growth through technological transfer.

For the frontier country, domestic innovation constitutes the sole source of productivity growth and the second term on the right-hand side of (2) is zero. Combining Eq. (2) for the non-frontier and frontier countries, one obtains a first-order difference equation for the evolution of relative TFP in sector j ,

$$\Delta \ln \left(\frac{A_{Bjt}}{A_{Fjt}} \right) = (\gamma_{Bj} - \gamma_{Fj}) - \lambda_{Bj} \ln \left(\frac{A_{Bjt-1}}{A_{Fjt-1}} \right). \quad (3)$$

As will be discussed further in the econometric section below, Eq. (2) can be thought of as an equilibrium correction model (ECM) of productivity growth, with adjustment towards a long-run or steady-state level of relative TFP. In steady-state, TFP in sector j of the non-frontier country will lie an equilibrium distance behind the frontier such that TFP growth through innovation *and* technology transfer exactly equals TFP growth through innovation alone in the frontier. Eq. (3) may be used to solve for this implied steady-state level of relative TFP ($\tilde{A}_j^* \equiv A_{Bj}^*/A_{Fj}^*$) where $\Delta \ln(A_{Bj}/A_{Fj}) = 0$,

$$\ln \tilde{A}_j^* \equiv \ln \left(\frac{A_{Bj}^*}{A_{Fj}^*} \right) = \frac{\gamma_{Bj} - \gamma_{Fj}}{\lambda_{Bj}}, \quad (4)$$

where, for the country which is initially less advanced to remain so in steady state, we require $\ln(A_{Bj}^*/A_{Fj}^*) < 0 \Leftrightarrow \gamma_{Fj} > \gamma_{Bj}$. Steady-state equilibrium relative TFP depends on rates of innovation in each country (γ_{Bj}, γ_{Fj}) and the speed at which technology transfer occurs (λ_{Bj}).

The exposition so far has treated the terms γ_{Fj} , γ_{Bj} , and λ_{Bj} as parameters. However, as noted in the introduction, there is an extensive theoretical and empirical literature which argues that R&D is an important determinant of innovation.¹⁴ A less developed strand of research suggests that R&D may also play a role in promoting technology transfer by raising ‘absorptive capacity’.¹⁵ Many studies in the theoretical endogenous growth literature and the empirical literature concerned with cross-country growth regressions have emphasised the roles of international trade and human capital in promoting innovation and/or technology transfer.¹⁶ We therefore extend the analysis to allow both innovation (γ_{ij}) and technology transfer (λ_{ij}) to be functions of R&D, international trade, and human capital,

$$\gamma_{ij} = \eta_{ij} + \delta Z_{ij}, \quad \lambda_{ij} = \theta + \mu Z_{ij}, \quad (5)$$

¹⁴ See, for example, Griliches (1980), Griliches and Lichtenberg (1984), and Aghion and Howitt (1992).

¹⁵ A key theoretical contribution is Cohen and Levinthal (1989). Empirical studies include Geroski et al. (1993), Jaffe (1986), and Griffith et al. (2000).

¹⁶ Analyses of human capital and growth include Benhabib and Spiegel (1994) and Krueger and Lindahl (2001). Studies that have stressed the role of international trade include Ben-David and Loewy (1998), Edwards (1998), Frankel and Romer (1999), and Lawrence and Weinstein (1999). A variety of mechanisms are proposed through which international trade may affect rates of productivity growth, including knowledge spillovers, increased competition, and the elimination of redundancy in research.

where Z_{ij} is a vector including R&D, human capital, and international trade. The earlier Eq. (2) for TFP growth in sector j of country i becomes

$$\Delta \ln A_{ijt} = \eta_{ij} + \delta Z_{ijt-1} + \theta \ln \left(\frac{A_{Fj}(t-1)}{A_{ij}(t-1)} \right) + \mu Z_{ijt-1} \ln \left(\frac{A_{Fjt-1}}{A_{ijt-1}} \right) + \varepsilon_{ijt}, \quad (6)$$

where the level term (δZ_{ijt-1}) captures a direct effect on rates of innovation and the interaction term ($\mu Z_{ijt-1} \ln(A_{Fjt-1}/A_{ijt-1})$) captures an effect on the speed of technology transfer.¹⁷ In this specification, potential heterogeneity in the rate of technology transfer across countries, industries, and time is related directly to differences in levels of R&D, human capital, and international trade. In the econometric analysis below, we explore more general forms of parameter heterogeneity and provide support for the more parsimonious specification above. We control for unobserved heterogeneity in the determinants of productivity growth that may be correlated with the explanatory variables by including a country-industry fixed effect (η_{ij}).

3. Relative levels of TFP

Our main data source is the Census of Production in the United Kingdom and United States, which provides information on real value-added and factor inputs. This is combined with data on numbers of non-production and production workers from the United Nations General Industrial Statistics Database (UNISD), the degree of capacity utilisation from the UK Confederation of British Industry (CBI) and US Bureau of Labour Statistics (BLS), and industry-specific purchasing power parity (PPP) exchange rates from van Ark (1992). This yields panel data on 14 manufacturing industries in the United Kingdom and United States during 1970–92.¹⁸

TFP growth in each country is evaluated using a superlative index number, consistent with the translog production technology, which provides an arbitrarily close local approximation to any underlying constant returns to scale production technology,¹⁹

$$\ln \left(\frac{A_{ijt}}{A_{ijt-1}} \right) = \ln \left(\frac{Y_{ijt}}{Y_{ijt-1}} \right) - \bar{\alpha}_{ijt} \ln \left(\frac{L_{ijt}}{L_{ijt-1}} \right) - (1 - \bar{\alpha}_{ijt}) \ln \left(\frac{K_{ijt}}{K_{ijt-1}} \right), \quad (7)$$

where Y_{ij} denotes real value-added in common currency units, L_{ij} is a measure of labour input, K_{ij} denotes real physical capital in common currency units, and $\bar{\alpha}_{ijt} = (\alpha_{ijt} + \alpha_{ijt-1})/2$ is the average share of labour in value-added in sector j of economy i in the periods t and $t - 1$.

¹⁷ When included as an interaction term, each element of Z_{ijt-1} is normalised by its mean across industries and time (a number, X): that is, $Z_{ijt-1}^* = Z_{ijt-1} - X$. This is a convenient normalisation, which means that the coefficient on the relative TFP term θ in Eq. (6) has the interpretation of the effect of technology transfer in industry-years with mean values of the explanatory variables Z_{ijt-1} . The sole effect of the normalisation is to rescale θ ; all other coefficients remain unchanged.

¹⁸ See the appendix for further details concerning the data. There is a major change in the UK's industrial classification in 1992, which means that it is not possible to extend the data for consistent manufacturing industries after 1992. The 14 industries that we consider are the most disaggregated sectors for which a consistent industry definition exists in the UK and US Census of Production.

¹⁹ See, in particular, Caves et al. (1982a,b).

An analogous superlative index number consistent with the translog production technology is used to measure relative levels of TFP in a sector j across countries i at a point in time t ,

$$\ln\left(\frac{A_{Bjt}}{A_{Fjt}}\right) = \ln\left(\frac{Y_{Bjt}}{Y_{Fjt}}\right) - \tilde{\alpha}_{jt} \ln\left(\frac{L_{Bjt}}{L_{Fjt}}\right) - (1 - \tilde{\alpha}_{jt}) \ln\left(\frac{K_{Bjt}}{K_{Fjt}}\right), \quad (8)$$

where $\tilde{\alpha}_{jt} = (\alpha_{Bjt} + \alpha_{Fjt})/2$ is the average share of labour in value-added in sector j in the two countries.

These superlative index number measures of TFP are already more general than those commonly derived from the Cobb–Douglas production function. In the literature on TFP measurement across countries and industries, a common starting point is a benchmark measure using a whole economy PPP to convert value-added and physical capital into common currency units, employment as the measure of labour input, and the real capital stock as the measure of capital input. We consider a number of extensions or corrections to this benchmark measure to control for errors of measurement in the share of labour in value-added, differences across countries in hours worked, country-industry variation in the skill composition of the workforce, differences across countries in relative output prices in manufacturing industries, and finally for cross-country variation in the utilisation of physical capital over the business cycle. We review each of these adjustments in turn.

The share of labour in value-added using industry-level data (α_{ijt}) is typically quite volatile over time. This suggests measurement error, and we follow [Harrigan \(1997\)](#) in using the properties of the translog production technology to smooth the observed labour shares. Given a translog production function and standard market clearing conditions, α_{ijt} can be expressed as the following function of the capital–labour ratio and a country-industry constant:²⁰

$$\alpha_{ijt} = \psi_{ij} + \phi_j \ln\left(\frac{K_{ijt}}{L_{ijt}}\right). \quad (9)$$

If actual labour shares differ from their true values as a result of an independently and identically distributed measurement error term, the parameters of Eq. (9) can be estimated separately for each industry j using the within groups estimator (where the fixed effect is for country i in industry j). The fitted values from this equation are then used as the labour cost shares in Eqs. (7) and (8).

The first measure of TFP growth and relative levels that we consider uses total annual hours worked as the measure of labour input, and controls for differences in hours worked in the United Kingdom and United States. The second and preferred measure uses UN data on the proportion of non-production and production workers to control for country-industry variation in the skill composition of the workforce. Labour input is measured using quality-adjusted total annual hours worked, which following [Harrigan \(1999\)](#) may be expressed as

$$L_{ijt} = (s_{ijt})^{\sigma_{ijt}} (u_{ijt})^{(1-\sigma_{ijt})} h_{ijt}, \quad (10)$$

²⁰ See [Caves et al. \(1982b\)](#) and [Harrigan \(1997\)](#).

where s_{ijt} denotes the number of non-production workers, u_{ijt} denotes the number of production workers, σ_{ijt} is the share of non-production workers in the wage bill, and h_{ijt} denotes average annual hours worked.

The use of an occupation-based measure of skills (non-production and production workers) follows a large number of influential papers in the trade and labour market literatures, including Berman et al. (1998), Feenstra and Hanson (1999), and Lawrence and Slaughter (1993). The main alternative is an education attainment-based measure of skills. The labour quality-adjustment that we make requires the wages of skilled and unskilled workers, which are not available by level of educational attainment for the 14 manufacturing industries in the United Kingdom and United States. However, there is evidence of a high time-series correlation between the share of non-production workers and the share of high-education workers in employment in each country during the sample period.²¹ Since the econometric estimation below uses the within groups (fixed effects) estimator, it is the time-series variation in the data that is used to identify the parameters of interest. As an additional check on the labour quality adjustment, we also report estimation results with our first TFP measure (using unadjusted hours worked).

In measuring rates of growth and relative levels of TFP using Eqs. (7) and (8), a key issue is how to convert real value-added and physical capital into common currency units (labour in both countries is measured in physical units of either hours worked or quality-adjusted hours worked). Conceptually, the appropriate rate of exchange is a purchasing power parity (PPP), and one common approach is to use a whole-economy PPP (see, for example, Bernard and Jones, 1996a,b; Dollar and Wolf, 1994). However, since the outputs of manufacturing industries are heterogeneous, UK/US relative prices may vary substantially across industries, giving rise to a potential bias in TFP measures using a whole economy PPP. In order to control for this, we follow van Ark (1992, 1996), and Pilat (1996) in using industry-specific output PPPs for both our TFP measures. Since relative factor prices may differ from relative output prices, we also employ a separate PPP for physical capital.

The industry-specific output PPPs are derived from unit value ratios (UVRs) for individual products in each manufacturing industry and are taken from van Ark (1992). For capital, we employ the investment goods PPP from the OECD's International Sectoral Data Base (ISDB). The output PPPs are used to convert constant price values (1987 prices) into a common currency (US dollars). Because all values are in 1987 prices, the PPPs take a single value in a particular country and industry for all years.²² Therefore, the PPP chosen has a substantial effect on *levels* of relative TFP and leads to different views concerning the size of the productivity gap between the United Kingdom and United States (a source of considerable recent policy debate – see for

²¹ See, for example, Machin and Van Reenen (1998). Based on individual-level data on educational attainment from the *Labour Force Survey* in the United Kingdom and the *Current Population Survey* in the United States, the time-series correlation during 1977–91 between the share of non-production workers in total manufacturing employment and the share of workers with a university degree or equivalent (the standard 'high education' measure used in the labour market literature) is 0.98 in the United Kingdom and 0.95 in the United States.

²² See Tables 6 and 7 in the appendix.

example McKinsey (1998)). However, it does not change the *time path* of relative TFP, and hence does not affect conclusions concerning whether productivity *convergence* has occurred.

In order to investigate the implications of using alternative PPPs, relative TFP was recalculated using a whole economy PPP and three alternative sets of industry-specific PPPs. The main findings that emerged from this analysis were as follows.²³ First, relative output prices do vary substantially across manufacturing industries in the United Kingdom and United States (see Table 7 in the appendix), so that as expected the use of a whole economy PPP yields misleading conclusions concerning relative levels of TFP. Second, the whole economy PPP (measured in £ per \$) is substantially lower than the vast majority of the industry-specific PPPs, so that its use in measurements of relative TFP overstates the level of TFP in the United Kingdom relative to that in the United States.

Third, the use of the within groups (fixed effects) estimator means that the paper's econometric results are not sensitive to the PPP chosen. The output PPP is a country-industry specific constant that multiplies one country's real value-added in the first-term on the right-hand side of the expression for relative TFP in Eq. (8). Taking logarithms, the output PPP becomes a country-industry specific intercept. Therefore, in specifications of the main econometric equation (6) without an interaction term ($\mu Z_{ijt-1} \ln(A_{Fjt-1}/A_{ijt-1})$), the country-industry fixed effect completely controls for any divergence between actual and true unobserved PPPs. The choice of output PPP thus has no effect whatsoever on the estimation results. In specifications with an interaction term, the country-industry fixed effect no longer completely controls for divergences between actual and true PPPs. However, we find empirically that it captures most of the effect so that the output PPP used has little impact on the estimation results.

Finally, we control for cross-country variation in the utilisation of physical capital over the business cycle (labour input is already measured using either hours worked or quality-adjusted hours worked). The change in UK capacity utilization is included as a control variable in the econometric equation for UK TFP growth. The capacity utilization variable is defined as one minus the proportion of all manufacturing firms answering yes to the question 'Is your present level of output below capacity (i.e. are you working below a satisfactory full rate of operation)?' in the Confederation of British Industry (CBI)'s Industrial Trends Survey.²⁴

Table 1 reports time-averaged TFP growth during 1971–92 in the UK and US using both unadjusted and quality-adjusted hours worked. In the UK, there are small negative rates of TFP growth in Food & Drink and Non-metallic Minerals using our preferred quality-adjusted measure. This is explained by the experience of these industries in the 1970s – a period characterised by substantial changes in capacity utilisation and

²³ A technical appendix available from the authors on request contains further details.

²⁴ See Muellbauer (1991) for further discussion of capacity utilisation and productivity measurement. We also experimented with directly adjusting the measure of capital input in Eqs. (7) and (8) using data on the degree of capacity utilisation in the United Kingdom and United States.

Table 1
Time-averaged rates of TFP growth in the UK and US (%), 1971–1992

Industry	UK hours	UK hours & skills	US hours	US hours & skills
Food & drink	-0.29	-0.17	1.46	1.43
Textiles & apparel	1.68	1.95	1.89	2.16
Wood products	0.16	0.38	0.60	0.77
Paper & printing	1.25	1.41	0.47	0.58
Non-metallic minerals	-1.19	-0.98	0.42	0.59
Chemicals	1.48	1.53	0.55	0.60
Rubber & plastic	1.34	1.42	1.06	1.19
Primary metals	0.92	1.14	0.30	0.58
Metal products	1.26	1.39	0.43	0.53
Machinery	1.45	1.61	2.63	2.70
Electrical engineering	1.99	2.07	3.19	3.27
Transportation	1.53	1.72	0.81	0.87
Instruments	3.03	3.09	3.07	2.94
Other manufacturing	1.63	1.76	1.11	1.25
Mean	1.16	1.31	1.28	1.39

Notes: TFP growth is measured using Eq. (7) during 1971–1992 and reported as a percentage. ‘hours’ denotes that total annual hours worked is the measure of labour input. ‘hours & skills’ denotes that total annual hours worked are adjusted for the variation in the skill composition of the workforce across countries and industries (Eq. (10)). For a full list of industry names and classification codes, as well as further details concerning the data used, see the appendix.

the costly adjustment of production processes to oil price rises.²⁵ There is a degree of correlation in industry rates of TFP growth across the two countries – on both measures, the same two industries have the highest rates of productivity growth in the UK and US (Electrical Engineering and Instruments). But there are also differences – with the UK Paper & Printing industry having more than twice the average rate of TFP growth of its US counterpart on our preferred measure.

Table 2 reports the level of UK TFP relative to the US (RTFP) at the beginning and end of the sample period. Similar information is displayed graphically in Fig. 1, which graphs our preferred quality-adjusted measure for the 14 manufacturing industries, grouped in terms of their initial levels of RTFP at the beginning of the sample period. Thus, Panel A graphs RTFP in the industries with the four highest initial levels of RTFP; Panel B repeats the exercise for the industries with the next four highest initial levels, and so on.

As is clear from Table 2, there is substantial variation in levels of relative productivity across manufacturing industries: in 1970, Paper and Printing displayed the lowest level of RTFP (39.5% on our preferred measure), less than half that in the industry with

²⁵ Griliches and Lichtenberg (1984) report negative rates of TFP growth for selected US industries during an earlier time period. If an adjustment for changes in capacity utilisation is made, average rates of TFP growth in Food & Drink and Non-metallic Minerals in the UK during 1971–1992 are positive. Even without the capacity utilisation adjustment, both industries experience positive average rates of TFP growth during 1981–1992.

Table 2
Levels of relative TFP (A_{UKj}/A_{USj}) in 1970 and 1992 (%)

Industry	RTFP ₇₀ hours	RTFP ₉₂ hours	RTFP ₇₀ hours & skills	RTFP ₉₂ hours & skills
Food & drink	71.48	55.76	68.44	55.33
Textiles & apparel	51.87	55.16	51.64	55.41
Wood products	52.09	47.65	51.83	48.14
Paper & printing	40.09	50.84	39.48	50.76
Non-metallic minerals	76.72	64.20	76.12	65.36
Chemicals	49.50	66.68	49.41	66.55
Rubber & plastic	74.59	89.82	74.16	88.91
Primary metals	49.20	62.22	49.67	62.54
Metal products	41.65	54.09	40.95	53.61
Machinery	82.04	72.96	79.51	72.40
Electrical engineering	59.82	53.37	58.90	52.72
Transportation	46.29	59.84	44.82	59.87
Instruments	62.75	78.75	62.14	81.17
Other manufacturing	41.27	49.93	39.82	48.18
Mean	57.10	65.27	56.21	65.20

Notes: RTFP denotes the level of UK TFP relative to the US, measured by taking exponents in Eq. (8) for 1970 and 1992; reported as a percentage. ‘hours’ denotes that total annual hours worked is the measure of labour input. ‘hours & skills’ denotes that total annual hours worked are adjusted for the variation in the skill composition of the workforce across countries and industries (Eq. (10)). For a full list of industry names and classification codes, as well as further details concerning the data used, see the appendix.

the highest level of RTFP (79.5% in Machinery). Furthermore, there were substantial changes in the rankings of industries in terms of relative TFP over time: between 1970 and 92, RTFP in transport rose from 44.8% to 59.9% on our preferred measure (an annual average rate of growth of 0.7%), while RTFP in Food and Drink fell from 68.4% to 55.3% of the US level (an annual average rate of growth of -0.6%).

From Table 2 and Fig. 1, the period as a whole was characterised by convergence of UK TFP towards US levels in 9 of the 14 manufacturing sectors. Taking all industries together, our preferred measure of relative TFP grew at an average annual rate of 0.3% during 1970–92.²⁶ Over the same period, aggregate income per capita in the UK rose from 65.9% to 70.9% of the US level (an annual average rate of increase of

²⁶ Under the assumption of a Cobb–Douglas production technology with the same shares of labour in value-added in the two countries, the evolution of relative TFP can be directly inferred from rates of TFP growth in each country. With more general production technologies, this is no longer true. When analysing TFP growth over time, the superlative index number in Eq. (7) averages labour’s share of value-added in a given country at two points in time t and $t - 1$. When analysing relative TFP, the superlative index number in Eq. (8) averages labour’s share of value-added across countries at a given point in time t . The Cobb–Douglas assumption is an extremely restrictive special case of the superlative index numbers employed here, which are consistent with any underlying constant returns to scale production technology. In the econometric estimation, we report a robustness test where we re-estimate the main econometric equation using a Cobb–Douglas measure of relative TFP.

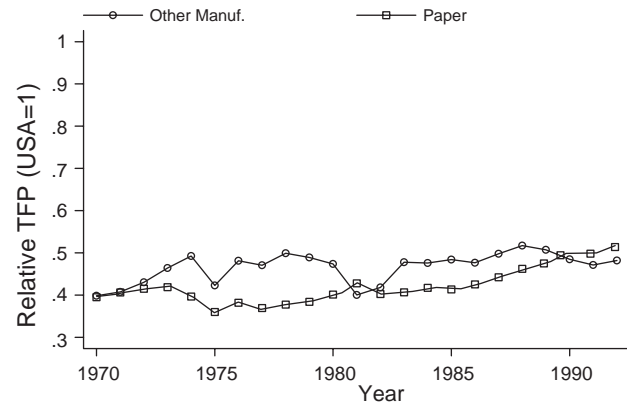
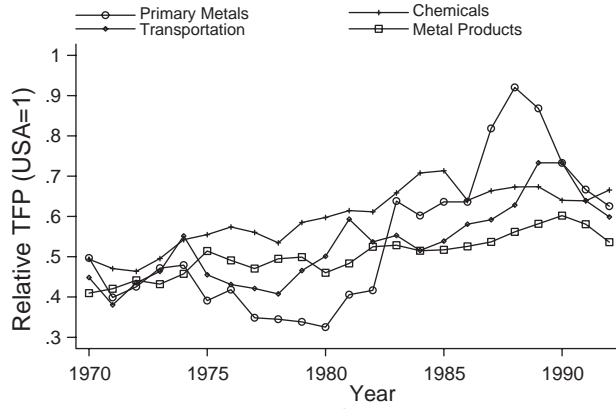
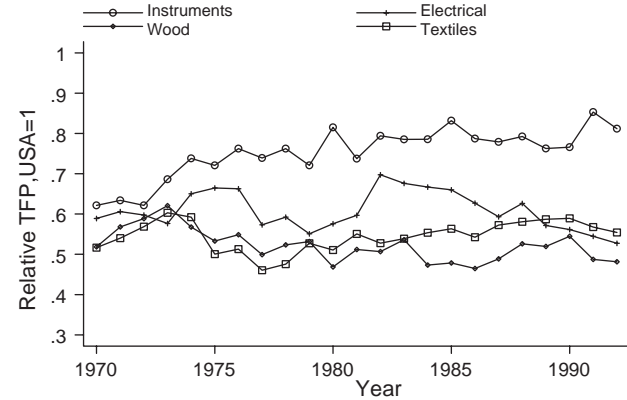
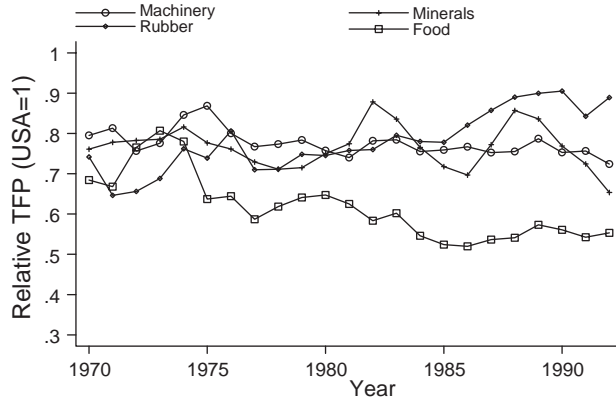


Fig. 1. Relative UK/US TFP, hours & skills.

0.2%).²⁷ There is also evidence of convergence in non-manufacturing sectors during this period. Bernard and Jones (1996a,b) find non-manufacturing convergence for a sample of 12 OECD countries including the UK and US during 1970–87, while the data used by Nickell et al. (2001) show that UK TFP in other production industries, business services, and other services converged towards the US during 1975–93.²⁸

The finding of productivity convergence in manufacturing industries is consistent with the results of Bernard and Jones (1996a,b), who find that the non-manufacturing industries above account for the majority of the whole economy convergence among OECD countries. Bernard and Jones are concerned with the OECD as a whole and focus on aggregate manufacturing and non-manufacturing sectors. Their analysis is therefore perfectly consistent with convergence in individual manufacturing industries between the United Kingdom and the United States. Furthermore, the measures of TFP used in this paper are more general than those employed by Bernard and Jones. Instead of assuming a Cobb–Douglas production technology, we make use of superlative index numbers, and we exploit both hours worked and quality-adjusted hours worked measures of labour input.

Note that the empirical finding of productivity convergence is not a necessary implication of the theoretical model presented in Section 2. In the model, productivity convergence either may or may not be observed, depending on the relationship between initial and steady-state levels of relative TFP (Eq. (4)) and depending on the evolution of steady-state relative TFP over time. Productivity convergence is *conditional* rather than *absolute*. That is, it depends on (is conditional on) the economic determinants of long-run productivity levels (on the variables which affect γ_{Bj} , γ_{Fj} , and λ_{Bj} in Eq. (4)). For example, a fall in rates of innovation in the United Kingdom (γ_{Bj}) relative to those in the frontier (γ_{Fj}) in a particular industry will lead to a fall in UK TFP relative to the frontier, so that productivity divergence is observed.

The concept of convergence used here is a *time-series* one, and is distinct from those of β and σ -convergence in the cross-country growth literature (see Barro and Sala-i-Martin, 1995). Instead, the analysis is more closely related to time-series tests of convergence, as considered for example by Bernard and Durlauf (1995, 1996). Thus, β -convergence is concerned with the relationship between a country's growth rate and its *own* initial level of income per capita or TFP, while the analysis here focuses on the relationship between a country's rate of TFP growth and its initial distance from the technological frontier (its initial level of TFP *relative to the frontier*). As will be shown below, Eq. (6) is an equilibrium correction model (ECM) representation of a long-run cointegrating relationship between UK and US TFP levels. A statistically significant coefficient on distance from the technological frontier provides evidence of dynamic adjustment towards this long-run or steady-state equilibrium relationship.

²⁷ The figures for aggregate income per capita are taken from the Penn World Tables, 5.6, which can be downloaded from <http://pwt.econ.upenn.edu/>.

²⁸ Other Production Industries are Mining and Quarrying (ISIC 20), Electricity, Gas, and Water (ISIC 40), and Construction (ISIC 50). Business Services corresponds to Financial Institutions (ISIC 81), Insurance (ISIC 82), and Real Estate and Business Services (ISIC 83).

Similarly, σ -convergence is concerned with the evolution of a measure of *cross-section* dispersion over time (usually the sample standard deviation of TFP or income per capita), while the analysis here focuses on the *time-series* relationship between TFP in a non-frontier and frontier country. Depending on the relationship between initial and steady-state levels of relative TFP, and depending on how steady-state relative TFP evolves over time, the theoretical model of Section 2 is consistent with a rising, constant, or declining dispersion of relative TFP across industries.²⁹

Despite the fact that productivity convergence is not a necessary outcome of the model, it is clear from the above that in the majority of manufacturing industries UK TFP converged towards US levels over time. In general for both TFP measures, most of the productivity convergence occurred in the 1980s, as is shown using the preferred measure in Fig. 1. On average across sectors, relative TFP using this measure grew at 0.15% during 1970–79 and 1.68% during 1980–89. There are six exceptions to the general pattern: food & drink, wood products, chemicals, metal products, instruments, and other manufacturing all had lower rates of growth of relative TFP during the 1980s than during the 1970s.

4. Econometric estimation

Our main econometric equation is derived from Eq. (6) of the theoretical model. This may be thought of as an equilibrium correction model (ECM) representation of a long-run cointegrating relationship between TFP in a non-frontier country and TFP in the frontier (see Hendry, 1995). Consider the following ADL(1,1) model of TFP in the non-frontier:

$$\ln A_{ijt} = \beta_0 + \beta_1 \ln A_{ijt-1} + \beta_2 \ln A_{Fjt} + \beta_3 \ln A_{Fjt-1} + \varepsilon_{ijt}. \quad (11)$$

Under the assumption of long-run homogeneity ($1 - \beta_1 = \beta_2 + \beta_3$), this can be expressed as

$$\Delta \ln A_{ijt} = \beta_0 + \beta_2 \Delta \ln A_{Fjt} + (1 - \beta_1) \ln \left(\frac{A_{Fjt-1}}{A_{ijt-1}} \right) + \varepsilon_{ijt}. \quad (12)$$

If we augment this specification to allow R&D, human capital, and international trade to affect the rate of innovation as well as the speed of technology transfer, this is Eq. (6) earlier, where the introduction of a term in contemporaneous frontier growth allows for a more flexible specification of the relationship between TFP in frontier and non-frontier countries.

²⁹ There is nevertheless a relationship between the time-series concept of convergence used here and those of β and σ -convergence. The theoretical model of Section 2 implies conditional β -convergence in *relative* TFP: controlling for the determinants of steady-state relative TFP levels, industries with low initial levels of relative TFP should have high rates of growth of relative TFP. Similarly, the theoretical model implies conditional σ -convergence in *relative* TFP: For example, if all industries have the same steady-state relative TFP and we begin from an initial equilibrium where levels of relative TFP vary across industries, the sample standard deviation of relative TFP will decline over time. These implications are not the main concern of the paper, but we find evidence of both β and σ -convergence in *relative* TFP during the sample period. For further critical discussion of the concepts of β and σ -convergence (see Quah, 1993).

There may be unobserved heterogeneity in the determinants of TFP growth and this unobserved heterogeneity may be correlated with the explanatory variables. We therefore employ the within groups (fixed effects) estimator, which allows for a country-industry fixed effect that is correlated with the explanatory variables. There may also be variations in the degree of utilisation of physical capital over the business cycle which affect measured TFP. Hence, we include the change in capacity utilisation as control variable in the TFP growth equation. From (6) and (12), our main econometric equation becomes

$$\begin{aligned} \Delta \ln A_{ijt} = & \eta_{ij} + \alpha \Delta \ln A_{Fjt} + \delta Z_{ijt-1} + \theta \ln \left(\frac{A_{Fjt-1}}{A_{ijt-1}} \right) + \mu Z_{ijt-1} \ln \left(\frac{A_{Fjt-1}}{A_{ijt-1}} \right) \\ & + \omega \Delta \ln CU_{ijt} + \varepsilon_{ijt}, \end{aligned} \quad (13)$$

where $\Delta \ln CU$ denotes the change in capacity utilisation.³⁰

Two of the key concerns of the paper are the role of technology transfer and R&D in driving rates of productivity growth. We begin by examining the relationship between TFP growth and these variables alone, before moving to the more general econometric specification in Eq. (13). Column (1) of Table 3 presents the results of regressing UK TFP growth on distance from the technological frontier ($\ln(TFP_{GAP})_{ijt-1} = \ln(A_{Fjt-1}/A_{ijt-1})$). Estimation is by within groups and uses our preferred quality-adjusted measure of relative TFP. Since the industries are of very different size, observations are weighted by industry shares of manufacturing value-added in 1970. The estimated coefficient on distance from the technological frontier is positive and highly statistically significant. Thus, consistent with the predictions of the theory, the further an industry lies behind the technological frontier, the higher its rate of TFP growth.

Column (2) of Table 3 introduces a role for R&D in determining both rates of innovation and technology transfer. We employ a standard measure of R&D activity – the ratio of Business Enterprise R&D Expenditure (BERD) to value-added – and this is included as both a level and an interaction term. The estimated coefficient on the R&D level (innovation) term is positive and statistically significant at the 10% level. As in the micro-econometric literature on R&D and productivity, this coefficient may be interpreted as a social rate of return to R&D-based innovation, and its magnitude (64%) is broadly consistent with existing empirical estimates.³¹ The estimated R&D interaction (technology transfer) coefficient is positive but not statistically significant at conventional critical values; the t -statistic is an order of magnitude smaller than that on the R&D level. Although there is a theoretical literature and some empirical evidence

³⁰ As is clear from (11), Eq. (13) may be re-written so that the level of UK TFP is expressed as a function of the level of US TFP, the lagged level of US TFP, and the lagged level of UK TFP. The presence of the lagged dependent variable implies that the within groups estimator is biased for small numbers of time periods T (see Nickell, 1981). However, the bias is asymptotically vanishing in T , and there are a large number of time-series observations in the present application. Cameron et al. (1998) obtain similar results with single equation time-series estimation.

³¹ For example, using US data, Sveikauskas (1981) estimates a social rate of return to R&D of 50%, while Griliches and Lichtenberg (1984) find a social rate of return of 41–62%. See Cameron (1996b) and Jones and Williams (1998) for surveys of the existing empirical literature.

Table 3
Roles of R&D and TFP gap in UK TFP growth

$\Delta \ln TFP_{UKjt}$	(1)	(2)	(3)	(4)	(5)	(6)
Obs	308	308	308	308	294	308
Years	1971–1992	1971–1992	1971–1992	1971–1992	1972–1992	1971–1992
$\ln TFP_{GAP}_{jt-1}$	0.0987** (0.0404)	0.1040** (0.0401)	0.1076** (0.0403)	0.1093** (0.0384)	0.0951** (0.0469)	—
$(R\&D/Y)_{UKjt-1}$	—	0.6422* (0.3537)	0.9014** (0.2674)	0.7072** (0.2469)	0.7179** (0.2660)	—
$(R\&D/Y)_{UKjt-1} \times \ln TFP_{GAP}_{jt-1}$	—	0.6660 (0.7259)	—	—	—	—
$\Delta \ln TFP_{USjt}$	—	—	—	0.2313** (0.0866)	0.2568** (0.0916)	0.2384** (0.0897)
$\Delta \ln CU_{UKjt}$	—	—	—	0.0681** (0.0153)	0.0698** (0.0164)	0.0598** (0.0184)
$\Delta \ln TFP_{USjt-1}$	—	—	—	—	—	0.2713** (0.1007)
$\Delta \ln TFP_{UKjt-1}$	—	—	—	—	—	-0.1565** (0.0687)
$\ln TFP_{GAP}_{jt-2}$	—	—	—	—	—	0.1040** (0.0421)
$(R\&D/Y)_{UKjt-2}$	—	—	—	—	—	0.5585** (0.2446)
Industry fixed effects	yes	yes	yes	yes	yes	yes
Hours and skills adjustment	yes	yes	yes	yes	yes	yes
Weighted	yes	yes	yes	yes	yes	yes
Instrumental variables	no	no	no	no	yes	no
<i>Diagnostics</i>						
R-squared	0.0572	0.0973	0.0933	0.2000	0.2190	0.2292
Root MSE	0.0652	0.0640	0.0641	0.0604	0.0600	0.0598
Serial correlation (p-value)	0.6269	0.3780	0.3846	0.4788	0.2455	0.7903
Sargan (p-value)	—	—	—	—	0.8510	—

Notes: Dependent variable is rate of UK TFP growth ($\Delta \ln TFP_{UK}$) for each industry-year observation. Independent variables are: log US TFP relative to the UK ($\ln TFP_{GAP}$); rate of US TFP growth ($\Delta \ln TFP_{US}$); ratio of Business Enterprise R&D Expenditure to value-added (R&D/Y); change in log capacity utilization ($\Delta \ln CU$). Total factor productivity (TFP) is adjusted for variation across countries and industries in hours worked and the skill composition of the workforce. All columns include an industry fixed effect. Huber–White heteroscedasticity robust standard errors in parentheses.

Observations are weighted by 1970 industry value-added shares. Serial Correlation is the Baltagi and Li panel data test for first-order autocorrelation in the residuals; null hypothesis is no autocorrelation. Endogenous variables in Column (5): $\ln TFP_{GAP}_{jt-1}$. Exogenous variables in Column (5): $(R\&D/Y)_{UKjt-1}$, $(R\&D/Y)_{UKjt-2}$, $\ln TFP_{GAP}_{jt-2}$, $\Delta \ln TFP_{USjt}$, and $\Delta \ln CU_{UKjt}$. Sargan is the Sargan test of the model's overidentifying restrictions.

**Denotes statistical significance at the 5% level;

*Denotes statistical significance at the 10% level.

that R&D may play a role in the imitation of others' discoveries, our results suggest that, for the UK, the dominant effect of R&D is on rates of innovation.

Column (3) excludes the statistically insignificant R&D interaction. The coefficient on the R&D level (innovation) term rises and becomes statistically significant at the 5% level. The estimate of R&D's social rate of return is now somewhat on the high side, but falls below as additional control variables are included. Column (4) of Table 3 demonstrates that the effects of autonomous technology transfer and R&D-based innovation are robust to introducing a term in contemporaneous frontier TFP growth (as suggested by the ADL(1,1) specification in Eqs. (12) and (13)) and a term in the change in capacity utilisation (to control for variation in the utilisation of physical capital over the business cycle). This is our baseline specification of the relationship between TFP growth, technology transfer, and R&D-based innovation. The estimated coefficient on contemporaneous frontier growth is positive and statistically significant at conventional critical values, as is required in Eq. (12) for a positive long-run cointegrating relationship between non-frontier and frontier TFP. The positive estimated coefficient on the change in capacity utilisation is also consistent with economic priors – as increases in the utilisation of physical capital over the business cycle lead to a rise in measured TFP. The coefficients on both distance from the technological frontier and the R&D level remain positive and highly statistically significant.

One potential econometric concern is measurement error. The fixed effect will control for time-invariant errors of measurement in individual countries and industries, while the use of data on capacity utilisation, hours worked, and the skill composition of the workforce directly controls for sources of measurement error suggested in the literature on TFP measurement. Nonetheless, shocks to the level of measured UK TFP at time $t-1$ will affect both UK TFP growth and initial distance from the technological frontier, giving rise to a potential endogeneity bias. To address this concern, Column (5) reports the results of instrumental variables estimation, using distance from the technological frontier and R&D at time $t-2$ as instruments.

For the instruments to be valid, we require that they are uncorrelated with the TFP growth residuals. We test this key assumption in two complementary ways. First, our instruments include lagged values of the explanatory variables. In order for them to be uncorrelated with the TFP growth residuals, the latter must be serially uncorrelated. Table 3 reports the results of a Baltagi–Li test for serial correlation in the residuals, and we are unable to reject the null hypothesis of no serial correlation at conventional levels of statistical significance. Second, since the model is overidentified, we explicitly test whether the instruments are correlated with the TFP growth residuals using a Sargan test of the model's overidentifying restrictions. As reported in Table 3, we are unable to reject the null hypothesis that the excluded exogenous variables are uncorrelated with the TFP growth residuals at conventional critical values.

The instruments are highly statistically significant in the first-stage regression: the null hypothesis that the coefficients on the excluded exogenous variables are equal to zero in the first-stage is easily rejected with a standard F -test (the p -value is 0.000). Therefore, each of these diagnostic tests provides support for the instrumental variables estimation. The IV estimate of the coefficient on distance from the technological frontier lies close to that estimated using within groups and is statistically significant at the 5%

level. This provides further evidence for the role of technology transfer in explaining UK productivity growth and suggests that the within groups results presented above are not being driven by measurement error.

The finding of technology transfer is not sensitive to the precise lag structure used. The equilibrium correction model (ECM) representation of a long-run cointegrating relationship between non-frontier and frontier TFP can be consistently estimated using lags of 1 year, 2 years, or longer. The disadvantage of using longer lags is the loss of time-series observations, and our preferred specification uses one-year lags based on the ADL(1,1) model. However, as a robustness test, Column (6) estimates an ADL(2,2) relationship between UK and US TFP, where two-year lags are used. A very similar pattern of results is observed, with all coefficients signed according to economic priors and statistically significant at the 5% level.

We also experimented with regressing TFP growth over longer periods of time (3 and 5 years) on initial distance from the technological frontier. The disadvantage of considering TFP growth over longer time periods is again the loss of time-series observations. However, when such an analysis is undertaken, we once more find evidence of a positive and statistically significant effect of both R&D and technology transfer on productivity growth. For example, in the specification in Column (4) using 3-year time periods, the estimated coefficients (*standard errors*) on R&D and initial distance from the technological frontier are 0.9226 (0.3698) and 0.3235 (0.0767), respectively.

As a further robustness test, the specification in Column (4) was re-estimated using an alternative measure of R&D activity: the ratio of the change in the R&D knowledge stock to output. This yields an extremely similar pattern of results: the estimated coefficients (*standard errors*) on the R&D variable and distance from the technological frontier were 0.6723 (0.2460) and 0.1131 (0.0391), respectively. The Column (4) specification was also re-estimated using our first measure of relative TFP (with unadjusted hours worked for labour input) and using a Cobb–Douglas measure of relative TFP (with quality-adjusted hours worked). Again, the results were extremely similar.

Table 4 examines the robustness of the R&D results to introducing a role for international trade and human capital in determining rates of TFP growth. Our measure of international trade is the ratio of a UK industry's imports from the whole world to gross output. We include both a level term (to capture an effect on innovation) and an interaction term between imports and distance from the technological frontier (to capture an effect on technology transfer).³² One problem in interpreting a relationship between international trade and productivity growth is that neoclassical trade theory (see, for example, Dixit and Norman, 1980) suggests that relative levels of productivity are a key determinant of international trade flows. Other things equal, positive shocks to UK productivity in a particular industry would be expected to lead to a *decrease* in UK imports from the rest of the world (as the opportunity cost of production in the UK decreases relative to the rest of the world), giving rise to a downwards estimated bias in the coefficients on the international trade terms.

³² The working paper version of this paper also reported similar results using bilateral UK imports from the US rather than UK imports from the whole world.

Table 4
Roles of R&D, Trade, Human Capital, and TFP gap in UK TFP growth

$\Delta \ln TFP_{UKjt}$	(1)	(2) ^(a)	(3) ^(a)	(4)	(5)
Obs	294	294	294	294	294
Years	1972–92	1972–92	1972–92	1972–92	1972–92
$\ln TFP_{GAP_{jt-1}}$	0.1663** (0.0573)	0.1381** (0.0533)	0.1196** (0.0420)	0.1187** (0.0409)	0.1413** (0.0541)
$\Delta \ln TFP_{USjt}$	0.2588** (0.0930)	0.2503** (0.0914)	0.2348** (0.0853)	0.2319** (0.0851)	0.2544** (0.0911)
$(R\&D/Y)_{UKjt-1}$	0.4983* (0.2591)	0.4956* (0.2585)	0.6376** (0.2615)	0.6279** (0.2573)	0.4994* (0.2617)
$(M/Y)_{UKjt-1}^{World}$	–0.1900 (0.1289)	—	—	—	—
$(M/Y)_{UKjt-1}^{World} \times \ln TFP_{GAP_{jt-1}}$	0.5662** (0.2698)	0.2119** (0.0936)	—	—	0.2537* (0.1520)
$\Delta \ln CU_{UKjt}$	0.0708** (0.0165)	0.0719** (0.0165)	0.0672** (0.0152)	0.0673** (0.0151)	0.0713** (0.0170)
H_{UKt-1}	—	—	–0.2325 (0.9457)	—	—
$H_{UKt-1} \times \ln TFP_{GAP_{jt-1}}$	—	—	1.0867 (1.8926)	0.7044 (0.8065)	–0.4895 (1.5933)
Industry fixed effects	yes	yes	yes	yes	yes
Hours and skill adjustment	yes	yes	yes	yes	yes
Weighted	yes	yes	yes	yes	yes
IV	yes	yes	no	no	yes
<i>Diagnostics</i>					
R-squared	0.2165	0.2273	0.2025	0.2024	0.2262
Root MSE	0.0603	0.0598	0.0605	0.0604	0.0600
Serial correlation (p-value)	0.9082	0.4856	0.4850	0.4694	0.6392
Sargan test	0.2816	0.8483	—	—	0.4957

Notes: Dependent variable is rate of UK TFP growth ($\Delta \ln TFP_{UK}$) for each industry-year observation. Independent variables are: log US TFP relative to the UK ($\ln TFP_{GAP}$); rate of US TFP growth ($\Delta \ln TFP_{US}$); ratio of Business Enterprise R&D Expenditure to value-added (R&D/Y); an industry's ratio of imports from the whole world to gross output ($(M/Y)_{UK}^{World}$); the change in log capacity utilization ($\Delta \ln CU$); the proportion of the over 25 population who have completed higher education (H). Total factor productivity (TFP) is adjusted for variation across countries and industries in hours worked and the skill composition of the workforce. All columns include an industry fixed effect. Huber–White heteroscedasticity robust standard errors in parentheses.

Observations are weighted by 1970 industry value-added shares. Serial Correlation is the Baltagi and Li panel data test for first-order autocorrelation in the residuals; null hypothesis is no autocorrelation. Endogenous variables in columns (1), (2), and (3) are (where included): $\ln TFP_{GAP_{jt-1}}$, $(M/Y)_{UKjt-1}^{World}$, $(M/Y)_{UKjt-1}^{World} \times \ln TFP_{GAP_{jt-1}}$, $H_{UKt-1} \times \ln TFP_{GAP_{jt-1}}$. Exogenous variables in columns (1) and (2) are: $(R\&D/Y)_{UKjt-1}$, $(R\&D/Y)_{UKjt-2}$, $\ln TFP_{GAP_{jt-2}}$, $\Delta \ln TFP_{USjt}$, $\Delta \ln CU_{UKjt}$, $(M/Y)_{OECDjt-1}^{World}$, and $(M/Y)_{OECDjt-1}^{World} \times \ln TFP_{GAP_{jt-2}}$, where $(M/Y)_{OECD}^{World}$ is an industry's ratio of imports from the whole world to gross output for the OECD as a whole. Exogenous variables in column (5) are all of the above, as well as H_{UKt-1} and $H_{UKt-1} \times \ln TFP_{GAP_{jt-2}}$. Sargan is the Sargan test of the model's overidentifying restrictions.

**Denotes statistical significance at the 5% level;

*Denotes statistical significance at the 10% level.

To capture increases in international trade that are exogenous with respect to UK productivity, we use the ratio of an industry's imports from the whole world to gross output for the OECD as a whole as an instrument. The secular rise in this ratio over time reflects the impact of successive rounds of GATT/WTO negotiations and the growing integration of the world economy. We use both the level of the OECD import share and the OECD import share interacted with distance from the technological frontier as instruments.³³ To control for potential measurement error in UK TFP at time $t - 1$, we also allow distance from the technological frontier at time $t - 1$ to be endogenous, including its own value at $t - 2$ and R&D/Y at $t - 2$ in the instrument set, and the OECD import share interaction included in the instrument set is defined using distance from the technological frontier at time $t - 2$.

Column (1) of Table 4 presents the instrumental variables estimation results. The estimated coefficient on the trade interaction is positive and statistically significant at the 5% level, while the trade level is negatively signed and statistically insignificant. This suggests that increases in international trade due to the growing integration of the world economy have had a positive effect on UK productivity growth through faster technology transfer but have not enhanced rates of innovation. There remains no evidence of serial correlation in the TFP growth residuals and, in a Sargan test of the model's overidentifying restrictions, we are unable to reject the null hypothesis that the excluded exogenous variables are uncorrelated with the TFP growth residuals. The instruments are again highly statistically significant in the first-stage regressions: in each case, the null hypothesis that the estimated coefficients on the excluded exogenous variables are equal to zero is easily rejected at conventional levels of statistical significance.

Column (2) excludes the statistically insignificant import level term. The import interaction remains statistically significant at the 5% level, and the estimated coefficients on the other explanatory variables are unchanged. Each of the diagnostic tests considered above continues to provide support for the IV estimates. The IV estimate of the coefficient on the import interaction in Column (2) is larger than that obtained using within groups, so that the direction of the bias using within groups is exactly as expected. Estimating the model using instrumental variables strengthens the finding of international trade-based technology transfer.

Columns (3) and (4) examine the role played by human capital. Our preferred measure of TFP weights numbers of non-production and production workers in a country-industry by their shares of the wage bill. Therefore, in so far as any increased productivity of non-production workers is reflected in their wages (a private rate of return), it will already be captured in the analysis. However, the theoretical literature on growth suggests the potential existence of both technological and pecuniary externalities to human capital.³⁴ These externalities may occur across sectors and we

³³ A complementary approach would be to exploit information on tariffs or price-based measures of international market integration. Unfortunately, time-series on these variables are not available for the 14 manufacturing industries considered here during 1970–92.

³⁴ Lucas (1988), Nelson and Phelps (1966), and Benhabib and Spiegel (1994) emphasize technological externalities, while Acemoglu (1996) and Redding (1996) present models with pecuniary externalities.

investigate their importance using country-level data on the proportion of the population that have completed higher education from Barro and Lee (1993, 2000). These data are widely used in the empirical growth literature and are available throughout our sample period.

Column (3) of Table 4 extends our baseline specification from Table 3 to include both a level (innovation) and interaction (technology transfer) term in the proportion of the population that have completed higher education. Neither term is statistically significant at conventional critical values, and we are unable to reject the null hypothesis that the two terms together are jointly insignificant. When the human capital level term is dropped in Column (4), the human capital interaction remains statistically insignificant. This suggests that, once one controls for the direct effect of human capital on output through private rates of return, there is no evidence of an additional effect through externalities. These results receive independent support from the micro-econometric estimates of production functions for the US in Griliches (1970) and for Israel in Griliches and Regev (1995). They are consistent with the empirical growth literature's finding of a positive effect of human capital on growth, but suggest that this effect corresponds to a private rate of return.

Column (5) allows the R&D level, the international trade interaction, and the human capital interaction to enter simultaneously as determinants of productivity growth. We again treat the import share and distance from the technological frontier at time $t - 1$ as being endogenous using an analogous instrument set. The estimated coefficients on the R&D level and international trade interaction remain of a similar magnitude to those in Column (2) and are statistically significant at conventional critical values. In contrast, the human capital interaction remains far from conventional levels of statistical significance. Each of the diagnostic tests considered above again provides support for the instrumental variables estimation.

In the light of the statistical insignificance of the human capital terms, our preferred specification for the determinants of UK productivity growth is that in Column (2). Taken together, the empirical results provide evidence of a robust role for autonomous technology transfer, R&D-based innovation, and international trade-based technology transfer in determining UK productivity growth. The estimated coefficients on distance from the technological frontier and the international trade interaction can be related to the speed of convergence towards the implied steady-state equilibrium level of relative TFP (Eq. (4) of the theoretical model). For example, the estimated coefficient of 0.14 on distance from the technological frontier in Column (2) of Table 4 implies that autonomous technology transfer closes half of the gap between actual and steady-state equilibrium relative TFP every 5 years.³⁵ This suggests relatively rapid conditional TFP convergence within disaggregated manufacturing industries, and

³⁵ This figure is obtained from the general solution to the first-order difference equation for relative TFP in (3).

that there do not exist large *un-arbitraged* differences in technical efficiency across countries.³⁶

At the same time, it is clear from Section 3 that there remain substantial differences in technical efficiency across countries. The analysis of this Section suggests that these are largely the result of systematic economic determinants captured in the model in steady-state equilibrium levels of relative TFP. From our preferred specification of Eq. (13), the empirical counterpart to Eq. (4) of the theoretical model is

$$\ln\left(\frac{A_{Bj}^*}{A_{Fj}^*}\right) = \frac{\gamma_{Bj} - \gamma_{Fj}}{\lambda_{Bj}} = \frac{\eta_{Bj} + \delta_1(R/Y)_{Bj} - (1 - \alpha)\overline{\Delta \ln A_{Fj}}}{\theta + \mu_2(M/Y)_{Bj}}, \quad (14)$$

where we model the long-run rate of TFP growth in the US (γ_{Fj}) by its time mean ($\overline{\Delta \ln A_{Fj}}$), and we use the fact that in steady-state equilibrium the change in capacity utilisation is equal to zero.

The systematic economic forces determining steady-state relative TFP include fixed characteristics of countries and industries (such as geographical location and institutions, captured in the fixed effect, η_{Bj}), as well as economic variables such as R&D (whose effects operate through the rate of innovation, $\delta_1(R/Y)_{Bj}$) and international trade (which impacts through the rate of technology transfer, $\mu_2(M/Y)$). These findings are consistent with the country-level theoretical work and calibration results of Parente and Prescott (1994, 2000), who emphasize the role of ‘barriers to technology adoption’ in preventing the implementation of technologies that are in principle available to all. Our results provide micro-econometric evidence in support of these ideas using industry-level data.

Finally, we consider a number of additional robustness tests. First, we noted earlier that, in specifications without an interaction term, the presence of the country-industry fixed effect controls for any divergences between actual and true unobserved output PPPs, so that the PPP used has no effect upon the estimation results. In specifications with an interaction term, the country-industry fixed effect no longer completely controls for divergences between actual and true PPPs. Therefore, as a further check upon our estimation results, we re-estimated the specification in Column (2) of Table 4 using

³⁶It is hard to directly relate the estimated coefficient of 0.14 to the 2% rate of convergence found in the cross-country growth literature. We are concerned with convergence in technical efficiency rather than income per capita (capital accumulation takes time and will be affected by consumption smoothing), and the analysis is undertaken at the industry-level (where one would expect convergence to be more rapid) rather than at the aggregate level. More importantly, we are concerned with the relationship between TFP growth and initial distance from the technological frontier (initial *relative* TFP) instead of the relationship between TFP growth and a country’s *own* initial level of TFP. Panel data estimation techniques are also used that exploit the time-series rather than the cross-section variation in the data. In the cross-country growth literature, those studies using panel data techniques typically find a more rapid rate of convergence than those based on cross-section regressions (for example, Caselli et al. (1996)) report an estimated convergence rate of 10%).

an alternative set of industry-specific output PPPs from Pilat (1996).³⁷ The estimation results were extremely similar; for example, the estimated coefficients (*standard errors*) on distance from the technological frontier, R&D, and the international trade interaction were respectively, 0.1369 (0.0552), 0.4323 (0.2428), and 0.1965 (0.0937). In practice, the use of the within groups estimator means that, even in specifications with interaction terms, the econometric results are not sensitive to the exact value of the output PPP used.

Second, another potential determinant of rates of productivity growth is the extent of unionisation. We investigated the role of unionisation using data on the proportion of workers covered by some form of collective agreement – a widely used measure in the labour market literature (see, for example, Bell and Pitt, 1998).³⁸ The level of unionisation and unionisation interacted with distance from the technological frontier were introduced as additional explanatory variables in our preferred specification in Column (2) of Table 4. In neither case was the unionisation variable statistically significant at conventional critical values, and the estimated coefficients on the other explanatory variables remained essentially unchanged.³⁹

Third, our preferred specification in Column (2) of Table 4 places a particular structure on the way in which the coefficient on distance from the technological frontier varies across industries and over time – namely, it varies with the extent of international trade. We now examine the robustness of the results to allowing more general forms of parameter heterogeneity following Pesaran and Smith (1995). In principle, the estimated parameters may vary across industries and/or over time. We therefore divide the sample period into two sub-periods (1970–80 and 1981–92), and estimate separate coefficients for each industry-sub-period (with 14 industries, this yields 28 estimated coefficients for each variable).

Table 5 reports the results of this robustness test. We begin with our baseline specification without the international trade interaction (Column (4) of Table 3). The international trade interaction is excluded, because it already constitutes a way of allowing the coefficient on distance from the technological frontier to vary across industry-sub-periods. Here, we wish to allow coefficients to vary freely across industry-sub-periods as dictated by the data alone. The baseline specification imposes common coefficients on distance from the technological frontier, R&D, frontier TFP growth, and capacity utilisation, and is reproduced in Column (1) of Table 5 below.

³⁷ The van Ark (1992) output PPPs used in the main body of the paper are derived from unit value ratios (the ratio of producer sales values to the corresponding quantities) for individual products. The main alternative approach uses the expenditure PPPs for individual products contained in the United Nations International Comparisons Project (ICP) (see, for example, Jorgenson and Kuroda (1990)). The Pilat (1996) output PPPs are derived from a combination of unit value ratios and expenditure PPPs. A technical appendix available from the authors on request discusses the construction of industry-specific output PPPs in further detail and re-evaluates relative TFP using four alternative sets of PPPs.

³⁸ See the appendix for further details concerning the data used.

³⁹ For example, when the unionisation interaction was included, its estimated coefficient (*standard error*) was 0.0016 (0.0016), while the estimated coefficients (*standard errors*) on distance from the technological frontier and the R&D level were 0.1469 (0.0526) and 0.4572 (0.2650), respectively.

Table 5
Heterogeneity of coefficients

Variable	(1)	(2)	(3)	(4)
	Pooled coefficient	Heterogeneous coefficient (mean)		
		Overall	High trade	Low trade
$\ln TFP_{GAPj(t-1)}$	0.1093	0.0420	0.1338	0.0029
$(R\&D/Y)_{UKj(t-1)}$	0.7072	0.8618	—	—
$\Delta \ln TFP_{USj(t-1)}$	0.2313	0.0894	—	—
$\Delta \ln CU_{UKj(t-1)}$	0.0681	0.0928	—	—

Notes: Dependent variable is rate of UK TFP growth ($\Delta \ln TFP_{UK}$) for each industry-year observation. Independent variables are: log US TFP relative to the UK ($\ln TFP_{GAP}$); rate of US TFP growth ($\Delta \ln TFP_{US}$); ratio of Business Enterprise R&D Expenditure to value-added (R&D/Y); change in log capacity utilization ($\Delta \ln CU$). Total factor productivity (TFP) is adjusted for variation across countries and industries in hours worked and the skill composition of the workforce. All columns include an industry fixed effect. Estimation weights observations by 1970 industry value-added shares. The time period is divided into two sub-periods (1970–80 and 1981–92), which, with 14 industries, yields 28 industry-sub-periods. Column (1) reports parameter estimates imposing common coefficients across all industry-sub-periods (the specification from Column (4) of Table 3). Columns (2)–(4) report parameter estimates from the same specification but allowing each coefficient in turn to vary across the 28 industry-sub-periods. Column (2) is the mean estimated coefficient across all 28 industry-sub-periods. Column (3) is the mean estimated coefficient across those industry-sub-periods with above average levels of the import share in the UK. Column (4) is the mean estimated coefficient for those industry-sub-periods with below average levels of the import share in the UK.

Column (2) allows each coefficient in turn to vary across industry-sub-periods, and the table reports the mean value of the coefficient across the 28 parameter estimates. For the R&D and capacity utilisation variables, the mean value of the heterogeneous coefficients lies close to the pooled coefficient estimated using within groups. This suggests that parameter heterogeneity is not a source of substantial bias in the estimated value of these coefficients.

For distance from the technological frontier, there is a noticeable difference between the mean value of the heterogeneous coefficients and the pooled coefficient estimated using within groups. This is precisely what is predicted by our preferred specification from Column (2) of Table 4, which implies that the coefficient on distance from the technological frontier will vary systematically across industry-sub-periods with the extent of international trade. Columns (3) and (4) of Table 5 test this hypothesis by dividing industry-sub-periods into those with above and below average levels of the UK's import share. Exactly as predicted, we find that industry-sub-periods with above average import shares have substantially higher mean values of the heterogeneous coefficients (0.1338 in Column (3)) than industry-sub-periods with below average import shares (0.0029 in Column (4)). This provides direct support for our more parsimonious preferred specification in Column (2) of Table 4. There is also some evidence in Table 5 of heterogeneity in the estimated coefficient on frontier TFP growth, although this has little effect on the estimated values of the other coefficients.

In a final robustness test, we investigate the sensitivity of the results to the inclusion of individual industries in the sample. Our preferred specification in Column (2) of Table 4 was re-estimated, sequentially excluding industries from the sample. In all 14 sets of estimation results, the estimated value of each coefficient lay within the 95% confidence interval around those reported for the full sample in Table 4 above.

5. Conclusions

This paper examines the determinants of productivity growth at the industry-level in the United Kingdom since 1970. We began by outlining innovation and technology transfer as two sources of productivity growth for a country behind the technological frontier. The difference in levels of total factor productivity (TFP) between the United Kingdom and a frontier country (the United States) is used as a direct measure of the potential for technology transfer, and we employ extremely general measures of TFP that control for a variety of sources of potential measurement error suggested in the literature on TFP measurement. Our framework allows for knowledge spillovers from both formal research and development (R&D) and the informal activities not captured in R&D statistics, while also controlling for observable and unobservable characteristics of countries and industries that affect the potential for technology transfer.

We find a positive and statistically significant effect of distance from the technological frontier on rates of productivity growth. Other things equal, the further an industry lies behind the technological frontier, the higher its rate of TFP growth. This finding is robust across a wide range of econometric specifications, to instrumenting distance from the technological frontier, to the use of alternative TFP measures, and to the inclusion of a series of control variables.

A key advantage of our approach is that we are able to explicitly test whether a number of variables proposed as determinants of productivity growth (such as R&D, international trade, and human capital) affect productivity growth directly (through rates of innovation) or indirectly through distance from the technological frontier (technology transfer). Unlike much of the literature, which assumes that technology transfer occurs through a particular mechanism such as international trade, we test econometrically whether international trade plays a role against the alternatives that its pace is determined by domestic ‘absorptive capacity’ (in the form of human capital and R&D investments) and that it proceeds autonomously (independently of the economic variables considered).

We find that R&D affects rates of UK productivity growth through innovation, while international trade facilitates the transfer of technology. These results are again robust across a wide range of econometric specifications and to instrumenting international trade in the UK with a measure based on OECD trade that captures exogenous variation in the degree of international integration in individual industries over time. Our preferred measure of TFP weights numbers of production and non-production workers in a country-industry by their shares of the wage bill. Once one controls for any increased productivity of non-production workers reflected in their wages (a private

rate of return), we find no evidence of an additional effect of human capital on productivity growth (no evidence of externalities). This is consistent with the empirical growth literature's finding of a positive effect of human capital on growth, but suggests that this effect corresponds to a private rate of return.

Taken together, our results emphasize the importance of technology transfer for countries behind the technological frontier. We find relatively rapid convergence of countries towards steady-state levels of relative TFP within individual industries, suggesting that observed cross-country productivity differences largely reflect systematic determinants, including fixed characteristics of countries and industries (such as location and institutions captured in the fixed effect), investments in R&D, and openness to international trade.

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Appendix. Data

Value-added: 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. UK data were supplied by the Office for National Statistics (ONS). US data were supplied by the Bureau of Labour Statistics (BLS).

Labour input: measured by either total annual hours worked or quality-adjusted total annual hours worked. For the United Kingdom, total annual hours worked were calculated as follows: total employment is from the Census of Production; UK 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; UK weeks worked are taken from *Employment Gazette* (data for Total Manufacturing

are assumed to apply to all industries). UK total annual hours worked are then employment times weeks worked times hours per week. For the United States, data on total annual hours worked were obtained from the BLS. For both countries, data on the proportion of production and non-production workers in employment and the wage bill by industry were obtained from the United Nations General Industrial Statistics Database (UNISD). To calculate quality-adjusted total annual hours worked, numbers of non-production and production workers were weighted by their shares in the total wage bill as specified in Eq. (10) in the main text. The UN stopped collecting disaggregated data on proportions of production/non-production workers after responsibility for the UNISD was moved from New York to Vienna. Data are therefore missing for the US in 1992 for the UK in 1991 and 1992. These missing values were replaced with predicted values using Stata's linear interpolation and extrapolation function. The econometric results are robust to dropping the last two years of observations.

Physical capital: gross capital stock expressed in 1987 constant prices. Data for the United Kingdom were supplied by the ONS; data for the United States were supplied by the BLS.

Imports as a share of gross output: ratio of UK imports from the whole world to gross output and the ratio of OECD imports from whole world to OECD Gross Output were obtained from the OECD Bilateral Trade and STAN databases.

R&D: ratio of Business Enterprise Research and Development (BERD) expenditure to value-added in the United Kingdom. The data on UK BERD were supplied by the ONS; value-added is value-added at factor cost as described above. Flows of constant price BERD were converted into R&D capital stocks using a 10% per annum depreciation rate. Following common practice in the literature on R&D and productivity growth (see for example Griliches, 1980; Coe and Helpman, 1995; Hall and Mairesse, 1995), the initial value for the R&D capital stock ($G(0)$) is specified as $G(0) = R\&D(0)/\omega + \varphi$, where ω is the proportional rate of growth of BERD and φ is the rate of depreciation.

Human capital: percentage of the over 25 population who have completed higher education from Barro and Lee (1993, 2000). The data are available at five-yearly intervals during 1950–2000. Following Feenstra et al. (1997) and Harrigan (1997), we interpolate between five-yearly observations using Stata's linear interpolation function.

Unionisation: proportion of adult male manual workers covered by some form of collective agreement multiplied by the proportion of adult male manual workers in the workforce in the United Kingdom. See Bell and Pitt (1998) for further discussion of these data.

Capacity utilisation: the UK variable is one minus the proportion of all manufacturing firms operating below capacity in an industry in answer to the Confederation of British Industry's *Industrial Trends Survey* question: 'Is your present level of output below capacity (i.e. are you working below a satisfactory full rate of operation)?' In a robustness test, we also use information on capacity utilisation in the United States based on a utilisation rate from the Bureau of Labor Statistics (BLS).

Table 6
Industry concordance

Industry	US SIC	UK SIC80
Food & drink	20, 21	41, 42
Textiles & apparel	22, 23, 31	43, 44, 45
Wood products	24, 25	46
Paper & printing	26, 27	47
Non-metallic minerals	32	23, 24
Chemicals	28	25, 26
Rubber & plastic	30	48
Primary metals	33	22
Metal products	34	31
Machinery	35	32, 33
Electrical engineering	36	34
Transportation	37	35, 36
Instruments	38	37
Other manufacturing	39	49

Table 7
Output PPPs by manufacturing industry

Industry	1987 £/\$
Food & drink	0.71
Textiles & apparel	0.68
Wood products	0.92
Paper & printing	1.04
Non-metallic minerals	0.65
Chemicals	0.63
Rubber & plastic	0.55
Primary metals	0.67
Metal products	0.67
Machinery	0.61
Electrical engineering	0.74
Transportation	0.61
Instruments	0.48 ^a
Other manufacturing	0.71 ^b
Capital PPP	0.73 ^c
Whole economy PPP	0.56 ^c
Market exch. rate	0.61 ^c

Source: van Ark (1992).

^aUVR not available, industry-specific expenditure PPP used from Pilat (1996).

^bTotal Manufacturing UVR used.

^cSource: OECD.

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