MAPPING THE TWO FACES OF R&D: PRODUCTIVITY GROWTH IN A PANEL OF OECD INDUSTRIES

Rachel Griffith, Stephen Redding, and John Van Reenen*

Abstract—Many writers have claimed that research and development (R&D) has two faces. In addition to the conventional role of stimulating innovation, R&D enhances technology transfer (absorptive capacity). We explore this idea empirically using a panel of industries across twelve OECD countries. We find R&D to be statistically and economically important in both technological catch-up and innovation. Human capital also plays an major role in productivity growth, but we only find a small effect of trade. In failing to take account of R&D-based absorptive capacity, existing U.S.-based studies may underestimate the return to R&D.

I. Introduction

This paper provides empirical evidence that there are two roles, or *faces*, of research and development (R&D) activity. The first of these is in stimulating innovation, and has received most attention in the existing empirical literature. The second is in facilitating the imitation of others' discoveries. Some knowledge is *tacit,* difficult to codify in manuals and textbooks, and hard to acquire without direct investigation. By actively engaging in R&D in a particular intellectual or technological field, one acquires such tacit knowledge and can more easily understand and assimilate the discoveries of others. An example, cited by Arrow (1969), is the jet engine: when plans were supplied by the British to the Americans during the Second World War, it took ten months for them to be redrawn to conform to American usage. The importance of tacit knowledge, or *absorptive capacity,* has been a central theme in the literatures on the history and microeconomics of technology. A large number of theoretical models have been proposed in which R&D has both an innovative and an imitative role.[1] However, there has been almost no rigorous econometric work assessing the statistical significance and quantitative importance of the second face of R&D, especially between countries.[2] This paper provides such an analysis, using a panel of industries across twelve OECD countries since 1970. We find strong evidence that R&D has a second face: country industries lagging behind the productivity frontier catch up particularly fast if they invest heavily in R&D.

We present an empirical framework in which innovation and technology transfer provide two potential sources of productivity growth for countries behind the technological frontier. A country's distance from the technological frontier is used as a direct measure of the potential for technology transfer, where the frontier is defined for each industry as the country with the highest level of total factor productivity (TFP). We examine whether R&D has a direct effect upon a country's rate of TFP growth (innovation), and whether R&D's effect on TFP growth depends upon a country's distance from the frontier (technology transfer). The further a country lies behind the technological frontier, the greater the potential for R&D to increase TFP growth through technology transfer from more advanced countries.[3] We argue that the return to R&D has generally been underestimated, insofar as most studies have focused on the United States, which is typically the technological leader in our data.

The paper relates to two other existing literatures—on the impact of R&D spillovers, and on the convergence debate. First, we build on the existing empirical literature examining the role of R&D in explaining rates of productivity growth, particularly through knowledge spillovers.[4] This paper extends the conventional specification to allow for a *second face* of R&D activity where we employ a direct measure of distance from the technological frontier based on relative TFP levels. Secondly, the paper relates to the literature on the convergence of TFP. Within the neoclassical Solow-Swan model, income convergence is explained by capital accumulation, but an older literature, dating back to Gerschenkron (1952), emphasizes the importance of technology transfer and the role of "absorptive capacity",[5] and recent years have seen a resurgence of interest in cross-country differences in aggregate productivity.[6]

Our results are easy to summarize. We find evidence of R&D effects on both rates of innovation and technology transfer across a wide range of specifications. These results are robust to a number of adjustments to the measurement of TFP (for example, controlling for cross-country differences

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* Institute for Fiscal Studies and University College London; Centre for Economic Performance and London School of Economics; and Centre for Economic Performance and London School of Economics, respectively.

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[1] See Cohen and Levinthal (1989), Aghion and Howitt (1997), or Howitt (2000).

[2] There is some firm-level evidence of absorptive capacity. Jaffe (1986) has results suggesting that high-R&D U.S. firms benefit most, in terms of productivity, from his spillover pool. Geroski, Machin, and Van Reenen (1993) found that U.K. firms with a history of innovation were those most likely to benefit from the innovations of other firms. However, there has been no systematic analysis of implications for industry productivity growth and social rates of return to R&D across countries.

[3] See Cameron (1996) for an analysis along these lines of Japan and the United States, and Cameron, Proudman, and Redding (1998) for an analysis of the United Kingdom and the United States.

[4] Important contributions to this literature include Griliches (1980, 1992), Coe and Helpman (1995), and Eaton and Kortum (1999).

[5] See also Abramovitz (1986) and Benhabib and Spiegel (1994).

[6] See, in particular, Acemoglu and Zillibotti (2001) or Parente and Prescot (1994).

in hours, skills levels, and markups of price over marginal cost) and to controlling for a number of econometric issues. Human capital has an important effect on rates of both innovation and technology transfer, whereas international trade has little robust effect on productivity.

The structure of the paper is as follows. Section II introduces the theoretical framework. Section III discusses the econometric specification. Section IV introduces the data and undertakes some data description. Section V presents the econometric results, quantifies their importance, and examines robustness. Section VI offers some concluding comments.

II. Theoretical Framework

This section outlines the theoretical framework underlying our modeling strategy.[7] Denote countries by $i = 1, \ldots, N$, and manufacturing industries by $j = 1, \ldots, J$. Value added (Y) in each sector at time t is produced with labor (L) and physical capital (K) according to a standard neoclassical production technology,

$$Y_{ijt} = A_{ijt}\mathscr{F}_{jt}(L_{ijt}, K_{ijt}), \tag{1}$$

where A is an index of technical efficiency, or *total factor productivity* (TFP), and where $\mathscr{F}_{jt}(\cdot\,,\cdot)$ is assumed to be homogeneous of degree 1 and to exhibit diminishing marginal returns to the accumulation of each factor alone; and we allow it to vary across sectors and time. We allow TFP to vary across countries, sectors, and time; and we call the economy with the highest level of TFP in sector j at time t the *frontier* ($i = F$) and call that TFP A_{Fjt}.

The starting point for our analysis is the empirical literature on R&D and productivity growth at the firm and industry levels.[8] TFP in equation (1) is assumed to be a function of the R&D knowledge stock (G). Taking logarithms and differencing with respect to time, the rate of TFP growth depends on the rate of growth of the R&D knowledge stock,[9]

$$\Delta \ln A_{ijt} = \eta \Delta \ln G_{ijt} + \gamma X_{i\,j\,t-1} + u_{ijt}, \tag{2}$$

where $\eta \equiv (dY/dG)(G/Y)$ is the elasticity of output with respect to the R&D knowledge stock, u is a stochastic error, and X is a vector of control variables, which includes human capital and international trade in the empirical application to follow. For small rates of depreciation of R&D knowledge, equation (2) may be expressed as follows.[10]

$$\Delta \ln A_{ijt} = \rho\left(\frac{R}{Y}\right)_{i\,j\,t-1} + \gamma X_{i\,j\,t-1} + u_{ijt}, \tag{3}$$

where $\rho \equiv dY/dG$ is the rate of return to R&D.

The theoretical rationale for this equation is provided by models of endogenous innovation and growth.[11] We augment the conventional specification in equation (3) in two ways. First, following the convergence literature, we introduce technology transfer as a source of productivity growth for countries behind the technological frontier. Second, there is a theoretical literature that suggests that R&D activity plays an important role in technology transfer. Griffith et al. (2000) present a general equilibrium model of endogenous growth through increasing productivity, following Aghion and Howitt (1992, 1997), that incorporates both of these considerations. The conventional quality ladder model is augmented to allow the size of innovations (and hence R&D's rate of return) to be a function of the distance behind the technological frontier. An equation for TFP growth of the following form is derived:

$$\begin{aligned}\Delta \ln A_{ijt} = {} & \rho_1\left(\frac{R}{Y}\right)_{i\,j\,t-1} + \underbrace{\delta_1 \ln\left(\frac{A_F}{A_i}\right)_{j\,t-1}}_{\text{technology transfer}} \\ & + \underbrace{\delta_2\left(\frac{R}{Y}\right)_{i\,j\,t-1} * \ln\left(\frac{A_F}{A_i}\right)_{j\,t-1}}_{\text{absorptive capacity}} \\ & + \gamma X_{i\,j\,t-1} + u_{ijt}.\end{aligned} \tag{4}$$

The second term on the right-hand side captures technology transfer. For nonfrontier countries, distance from the technological frontier [$\ln (A_F/A_i)_{j\,t-1}$] is positive, and a role for technology transfer in productivity growth implies a positive estimated coefficient δ_1. The third term on the right-hand side is an interaction term that captures the second face of R&D. The larger is $\ln (A_F/A_i)_{j\,t-1}$ in absolute magnitude, the further a country lies behind the frontier, and the greater the potential for R&D-based technology transfer. The existence of a second face of R&D thus implies a positive estimated coefficient δ_2. In this augmented specification, the speed of technology transfer is $\delta \equiv \delta_1 + \delta_2\,(R/Y)_{i\,j\,t-1}$, whereas the rate of return to R&D (from both innovation and technology transfer) is $\rho \equiv \rho_1 + \delta_2 \ln (A_F/A_i)_{j\,t-1}$.[12]

The expression for TFP growth in the frontier remains exactly the same as in the conventional specification [when $A_i = A_F$, equation (4) reduces to (3) where $\rho = \rho_1$]. Combining equation (4) for frontier and nonfrontier countries, we can obtain a first-order difference equation for the evolution of a nonfrontier country's distance to the techno-

[7] For a complete derivation, see Griffith, Redding, and Van Reenen (2000).

[8] See, in particular, Griliches (1980) and Griliches and Lichtenberg (1984).

[9] The substantive assumption here is separability between R&D and other factors of production. The alternative approach embracing nonseparability is followed by authors such as Bernstein and Nadiri (1989) and Nadiri and Kim (1997).

[10] In continuous time, $\dot{G}_{ijt} = R_{ijt} - \varphi G_{ijt}$, where φ is the rate of depreciation of R&D knowledge. If one explicitly assumes an R&D depreciation rate, equation (2) can be estimated directly. We adopted this approach as a robustness test, but note the great uncertainty surrounding the appropriate rate of depreciation for knowledge.

[11] See, for example, Romer (1990) and Aghion and Howitt (1992).

[12] See also Cameron (1996) and Cameron et al. (1998).

logical frontier. In steady-state equilibrium, TFP in a sector j in all countries i will grow at the same constant rate, equal to that of TFP growth in the frontier. The model allows for countries to endogenously switch between being nonfrontier and frontier countries. In steady-state equilibrium, the frontier country will be whichever of the countries has the highest rate of TFP growth from innovation alone in sector j [as a result of R&D activity (R/Y) and the value of the control variables (X) in equation (4)]. Each nonfrontier country will lie an equilibrium distance behind the frontier such that TFP growth from innovation and technology transfer exactly equals TFP growth from innovation alone in the frontier.

III. Econometric Specification

Equation (4) provides the starting point for our econometric estimation. There will clearly be unobserved country-industry characteristics, which affect rates of TFP growth and are not captured by our model. Moreover, it is likely that these unobserved country-industry characteristics will be correlated with the explanatory variables in equation (4). For example, features of the production technology in particular sectors of a country may result in a high rate of TFP growth in precisely the industries characterized by high R&D intensities. We control for unobserved heterogeneity that is correlated with the explanatory variables by allowing the error term (u_{ijt}) to include a country-industry specific fixed effect (ψ_{Fj}). There may also be common macroeconomic shocks that affect rates of TFP growth in all countries, and we therefore allow the error term (u_{ijt}) to include a full set of time dummies (T_t):

$$u_{ijt} = \psi_{ij} + T_t + \varepsilon_{ijt},$$

where ε_{ijt} is a serially uncorrelated error. Substituting for u_{ijt} in equation (4), we obtain our final econometric specification of TFP growth in sector j of a nonfrontier country,

$$\begin{aligned}\Delta \ln A_{ijt} = {} & \delta_1 \ln\left(\frac{A_F}{A_i}\right)_{j\,t-1} + \delta_2\left[\left(\frac{R_i}{Y_i}\right)\ln\left(\frac{A_F}{A_i}\right)\right]_{j\,t-1} \\ & + \rho_1\left(\frac{R}{Y}\right)_{i\,j\,t-1} \\ & + \gamma X_{i\,j\,t-1} + \Psi_{ij} + T_t + \varepsilon_{ijt}.\end{aligned} \tag{5}$$

TFP growth in sector j in the frontier is modeled as in the conventional specification,

$$\Delta \ln A_{Fjt} = \rho_1\left(\frac{R}{Y}\right)_{F\,j\,t-1} + \gamma X_{F\,j\,t-1} + \psi_{Fj} + T_t + \varepsilon_{Fjt}. \tag{6}$$

The equation for the frontier economy is stacked together with the equations for the nonfrontier economies with the cross-equation restrictions on the R&D intensity variable imposed. We are careful to examine the robustness of the results to dropping the frontier observations in case the cross-equation restrictions are invalid.[13] Our baseline results estimate equations (5) and (6) using the within-group estimator.

There are several issues involved with this econometric strategy relating to endogeneity, measurement error, the definition of the frontier and the relationship of our approach to the "convergence" literature. First, there may be a concern that the effect of R&D on TFP is overestimated in equations based on (3) because firms will invest heavily in R&D during periods when TFP is growing more quickly. This concern should not be overstated, as the ratio of R&D to value added (unlike TFP) is not generally procyclical.[14] Nevertheless, although we uncover a strong correlation between R&D intensity and productivity growth, we need to be cautious in interpreting the coefficient on R&D as causal. The important assumption that we need is

$$E((R/Y)_{i\,j\,t-1}\varepsilon_{ijt}) = 0. \tag{7}$$

This condition requires lagged R&D to be predetermined in the TFP equation, but allows current shocks to TFP (ε_{ijt}) to feed back to both current and future R&D,[15] that is, we allow $E\,((R/Y)_{i\,j\,t+s}\,\varepsilon_{ijt}) \neq 0$, $s \geq 0$. In samples that have a long time series component (like ours), the bias on the R&D coefficient is likely to be small (Nickell, 1981).

Despite its ubiquity, the assumption (7) might still be violated; for example, firms might be able to correctly predict future shocks 1 period ahead and immediately adjust their R&D in the light of these. If this were the case, we would expect the residuals in the TFP equation to be serially correlated, which would violate equation (7). In addition to testing for serial correlation, we also examine the scale of the potential problem by allowing $E\,((R/Y)_{i\,j\,t-1}\varepsilon_{ijt}) \neq 0$, but assume the weaker restriction $E((R/Y)_{i\,j\,t-s}\varepsilon_{ijt}) = 0$, $s \geq 2$. Under this assumption, the use of R&D lagged two periods eliminates any endogeneity bias. We also examine specifications of this form and find that the results are qualitatively unchanged. Finally, even if one were convinced that there was an upward bias on the R&D coefficient ρ_1, it is not obvious why there should be an upward bias on the interaction term between the TFP gap and R&D, δ_2, which is our main variable of interest. Unfortunately, there are hardly any papers that have found good external instrumental variables for R&D to deal with this endogeneity issue.

A second econometric concern is that measurement error could lead to bias in the estimated coefficients. We investigate the importance of this bias with an instrumental

[13] Griffith et al. (2000) discuss this in more detail.

[14] In addition, there is no significant change in the R&D coefficient when we correct for cyclical biases in the measurement of TFP.

[15] The requirement that lagged R&D be predetermined in the TFP equation is weaker than the assumption often made in the production function literature, which frequently conditions on the lagged level of investment. R&D is a much more persistent series than fixed investment (see, for example, Lach and Schankerman, 1989) and therefore it is less likely than fixed investment to respond quickly to shocks.

variables estimator. A complementary approach uses data on some of the variables suggested as sources of measurement error in the TFP literature.

Third, the model implies that it is not the *identity* of the frontier country that is important [equation (5)], but the measure of *distance from the technological frontier* that captures the potential for technology transfer. Our analysis does not preclude technological transfer from countries with levels of productivity higher than one's own but lower than the frontier. All we require is that distance from the technological frontier be correlated with the potential for technology transfer. We establish the robustness of our results to the use of alternative measures of the spillover potential, using for example the average of the countries with the two highest TFP levels in defining the location of the frontier, rather than simply the country with the highest relative TFP. We also demonstrate that our TFPGAP measure is capturing technological proximity to the leading edge by showing that we obtain different results if we use own TFP distance to the median TFP (instead of to the maximum TFP) in the industry.

Fourth, our analysis is related to the convergence literature. Consider a first-order au-toregressive distributed lag [ADL(1,1)] model where own TFP is cointegrated with frontier TFP: $\ln A_{ijt} = \alpha_1 \ln A_{i\ j\ t-1} + \alpha_2 \ln A_{Fjt} + \alpha_3 \ln A_{F\ j\ t-1} + u_{ijt}$. Under the as sumption of long-run homogeneity $[(\alpha_2 + \alpha_3)/(1 - \alpha_1) = 1]$, this has the following equilibrium correction model (ECM) representation with many attractive statistical properties.[16]

$$\Delta \ln A_{ijt} = \alpha_2 \Delta \ln A_{Fjt} + (1 - \alpha_1) \ln \left(\frac{A_F}{A_i}\right)_{j\ t-1} + u_{ijt}. \quad (8)$$

Ignoring R&D and the control variables, this is equation (4) with $\alpha_2 = 0$ and $1 - \alpha_1 = \delta_1$. In equation (4), the specification in equation (8) is augmented with a term for the R&D intensity, the coefficient on relative TFP $(1-\alpha_1)$ is allowed to be a function of R&D intensity, and we include a vector of control variables. As a robustness test, we also consider an additional specification to equation (4) where $\alpha_2 \neq 0$ for nonfrontier countries, which allows for a more flexible relationship between frontier and nonfrontier TFP.

Our estimates exploit the time series relationship between TFP in frontier and nonfrontier countries.[17] Nonetheless, the analysis also has implications for standard measures of β-convergence and σ-convergence.[18] For example, depending on the correlation between the initial and steady-state distributions of relative TFP, the cross-country within-industry sample standard deviation of relative TFP may either rise, decline, or remain constant over time. Although our sample period is characterized by σ-convergence in the majority of industries, this is a feature of the data and not a necessary implication of the model.

[16] See Hendry (1996).

[17] The analysis is, therefore, most closely related to the time series convergence literature: see Bernard and Durlauf (1995, 1996).

[18] In this context, β-convergence refers to the cross-section correlation between rates of growth and initial levels of relative TFP; σ-convergence refers to the evolution of the sample standard deviation of relative TFP over time. For further discussion in the context of the cross-country growth literature, see Barro and Sala-i-Martin (1995).

IV. Data Description: Data Sources and Sample Size

The data used in the empirical application come from a number of sources. The main one is the OECD International Sectoral Data Base (ISDB), which provides information at the two-digit industry level on value added, labor, and capital stocks. We have combined this with data on R&D expenditure from the OECD ANBERD data set and information from several other sources. For information on occupational skills we use the UNIDO database; for education we use aggregate data from Barro and Lee (1994) and industry data from Machin and Van Reenen (1998). Trade data are derived from the OECD Bilateral Trade Database.

Our sample consists of twelve countries over the period 1974–1990. For some of the countries, information is available for nine two-digit industries (ISIC 31–39); for others, ISIC 38 is additionally broken down into five three-digit industries. Where the more disaggregated information is available for the three-digit industries, we use it. At the same time, careful attention is paid to the robustness of the results to alternative samples of countries and industries. See the appendix for details.

We calculate the growth rate of TFP (ΔTFP_{ijt}, the empirical counterpart to $\Delta \ln A_{ijt}$ in section II) and the TFP distance between country *i* and the frontier [$TFPGAP_{ijt}$, the empirical counterpart to $\ln (A_F/A_i)_{jt}$ above]. In each case, we use the superlative-index-number approach of Caves, Christensen, and Diewert (1982a,b), which allows for a flexible specification of the production technology. Our baseline measures of TFP growth and relative levels of TFP use the raw data from the ISDB. However, in the literature much attention is paid to how TFP is measured and in particular how to correct for differences across countries in hours worked, skills levels, markups, capacity utilization, and other factors. To confirm the robustness of our results, we use a number of different measures that adjust for these factors. The way in which our baseline measure is calculated is described here. The way in which the adjusted measures are calculated is described in the appendix and in Griffith et al. (2000). Our preferred measure controls for differences in hours worked and variation in skills across countries and industries using information on wages and employment by occupation from the UNIDO database.

TFP growth is measured by a superlative index derived from the translog production function,[19]

[19] See Caves et al. (1982b).

$$\Delta TFP_{ijt} = \ln\left(\frac{Y_{ijt}}{Y_{ijt-1}}\right) - \frac{1}{2}(\alpha_{ijt} + \alpha_{i\,j\,t-1})\ln\left(\frac{L_{ijt}}{L_{i\,j\,t-1}}\right) - \left(1 - \frac{1}{2}(\alpha_{ijt} + \alpha_{i\,j\,t-1})\right)\ln\left(\frac{K_{ijt}}{K_{i\,j\,t-1}}\right), \quad (9)$$

where α_{ijt} is the share of labor in value added, Y_{ijt} is the real value added (converted to US dollars using an economy-wide PPP), L_{ijt} is the number of workers employed, and K_{ijt} is the real capital stock (converted to U.S. dollars using a capital PPP). One problem we face in measuring TFP is that the share of labor in value added, α_{ijt}, is quite volatile. This is suggestive of measurement error, and we therefore follow Harrigan (1997) in exploiting the properties of the translog production function to smooth the observed labor shares.[20]

We measure the gap between each country's TFP and the level in the frontier using an analogous superlative index number derived from the translog production function. We begin by evaluating the level of TFP in each country relative to a common reference point—the geometric mean of the TFPs of all other countries. This is done for each industry-year (for example, we measure TFP in the U.S. chemicals industry in 1980 relative to the geometric mean of the chemical industry TFPs in all other countries in 1980). This measure of TFP is given by

$$MTFP_{ijt} = \ln\left(\frac{Y_{ijt}}{\bar{Y}_{jt}}\right) - \tilde{\sigma}_{ijt}\ln\left(\frac{L_{ijt}}{\bar{L}_{jt}}\right) - (1 - \tilde{\sigma}_{ijt})\ln\left(\frac{K_{ijt}}{\bar{K}_{jt}}\right), \quad (10)$$

where a bar above a variable denotes a geometric mean; that is, $\bar{Y}_{jt}$, $\bar{L}_{jt}$, $\bar{K}_{jt}$ are the geometric means of output, labor, and capital in industry j at time t, respectively. The variable $\tilde{\sigma}_{ijt} = \frac{1}{2}(\alpha_{ijt} + \bar{\alpha}_{jt})$ is the average of the labor share in country i and the geometric mean labor share, where we again exploit the properties of the translog production function to smooth observed labor shares.

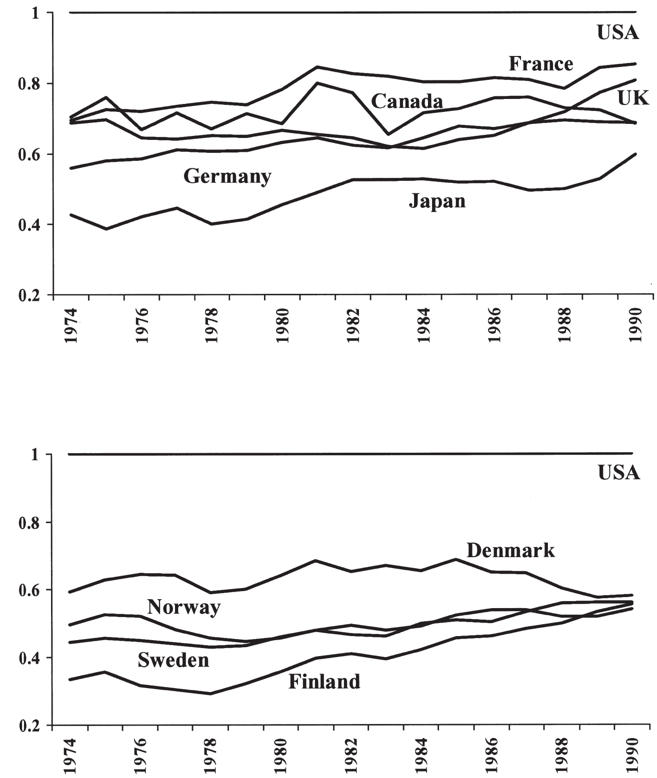
We define the frontier as the country with the highest value of TFP relative to the geometric mean in each industry j at time t (denoted $MTFP_{Fjt}$). Subtracting $MTFP_{ijt}$ from $MTFP_{Fjt}$, we obtain a superlative-index-number measure of a country's TFP distance from the frontier [denoted $TFPGAP_{ijt}$, the empirical counterpart to $\ln(A_F/A_i)_{jt}$ in section II],[21]

$$TFPGAP_{ijt} = MTFP_{Fjt} - MTFP_{ijt}. \quad (11)$$

To illustrate our method, figure 1 plots TFP levels in one industry—paper, printing and publishing (ISIC 34)—using our preferred measure. To make the figure easier to interpret visually, we graph the exponent of the negative of the TFPGAP. This corresponds to each country's TFP as a proportion of TFP in the frontier (relative TFP). The United States was the frontier country throughout our sample period except in the final year, when it is pushed into second place by the Netherlands (not shown in graph). In this industry most counties have narrowed the gap with the United States. Japan is notable for starting off as one of the countries furthest from the United States in 1973 and closing approximately half of the TFP gap by 1990. Other countries have not been so successful. Canada and Denmark have not improved their position relative to the United States, and Britain did not start catching up until the 1980s. The picture varies by industry, and table 1 shows which country has the highest (the frontier) and second highest level of relative TFP in 1971, 1981, and 1990.

In some industries, the identity of the frontier and the country with the next highest level of relative TFP remains constant over time (for example, ISIC 383, and 384); in other industries we see examples of loss of technological leadership as one economy leapfrogs another (for example,

FIGURE 1.—TFP, ADJUSTED FOR SKILLS AND HOURS, AS PROPORTION OF FRONTIER TFP: PAPER, PRINTING, AND PUBLISHING (ISIC 34)



[20] Under the assumption of a translog production function and standard market-clearing conditions, α_{ijt} can be expressed as a function of the capital-labor ratio and a country-industry constant, $\alpha_{ijt} = \xi_{ji} + \phi_j \ln(K_{ijt}/L_{ijt})$. If actual labor shares deviate from their true values by an i.i.d. measurement error term, then the parameters of this equation can be estimated by fixed-effects panel data estimation, where we allow the coefficient on the capital-labor ratio to vary across industries j. The fitted values from this equation are then used as the labor cost shares in our calculation of equation (9) and below.

[21] Note that equation (10) may be used to obtain a bilateral measure of relative TFP in any two countries a and b. Because we begin by measuring TFP compared to a common reference point (the geometric mean of all countries), these bilateral measures of relative TFP are transitive.

TABLE 1.—RELATIVE TFP AND THE IDENTITY OF THE FRONTIER

ISIC	TFP	1971	1981	1990	ISIC	TFP	1971	1981	1990
31	First	Jap	Jap	US	381	First	US	Ger	Ger
	Second	Can	US	Ita		Second	Ger	US	USA
	Mean exp(RTFP)	0.65	0.69	0.77		Mean exp(RTFP)	0.78	0.85	0.88
	SD exp(RTFP)	0.20	0.18	0.17		SD exp(RTFP)	0.32	0.17	0.10
32	First	Fra	Dnk	Nld	382	First	Ger	Ger	US
	Second	Swe	Fra	Fra		Second	US	Ita	Fra
	Mean exp(RTFP)	0.72	0.77	0.78		Mean exp(RTFP)	0.88	0.90	0.93
	SD exp(RTFP)	0.18	0.17	0.19		SD exp(RTFP)	0.10	0.07	0.05
33	First	US	US	US	383	First	US	US	US
	Second	Ger	Ger	Swe		Second	Fra	Fra	Fra
	Mean exp(RTFP)	0.79	0.85	0.81		Mean exp(RTFP)	0.75	0.88	0.94
	SD exp(RTFP)	0.17	0.15	0.12		SD exp(RTFP)	0.31	0.15	0.06
34	First	US	US	Nld	384	First	US	US	US
	Second	Fra	Fra	US		Second	Ger	Ger	Ger
	Mean exp(RTFP)	0.62	0.68	0.80		Mean exp(RTFP)	0.71	0.88	0.95
	SD exp(RTFP)	0.20	0.18	0.15		SD exp(RTFP)	0.19	0.15	0.04
35	First	Jap	Ger	Ger	385	First	US	Fra	Fra
	Second	Ger	Jap	Jap		Second	Ger	US	US
	Mean exp(RTFP)	0.55	0.70	0.79		Mean exp(RTFP)	0.67	0.82	0.87
	SD exp(RTFP)	0.23	0.20	0.19		SD exp(RTFP)	0.33	0.21	0.09
36	First	Can	Can	Nld	39	First	US	Dnk	US
	Second	Ger	Fra	Fra		Second	Dnk	US	Ger
	Mean exp(RTFP)	0.78	0.85	0.86		Mean exp(RTFP)	0.77	0.71	0.68
	SD exp(RTFP)	0.14	0.11	0.12		SD exp(RTFP)	0.24	0.24	0.22
37	First	US	Jap	Jap	30	First	US	US	Nld
	Second	UK	US	Ita		Second	Can	Nld	US
	Mean exp(RTFP)	0.55	0.66	0.72		Mean exp(RTFP)	0.68	0.79	0.81
	SD exp(RTFP)	0.23	0.23	0.14		SD exp(RTFP)	0.15	0.14	0.13
38	First	US	US	Nld					
	Second	Ger	Ger	US					
	Mean exp(RTFP)	0.54	0.71	0.76					
	SD exp(RTFP)	0.15	0.16	0.16					

31: food, beverages and tobacco; 32: textiles; 33: wood; 34: paper; 35: chemicals; 36: nonmetallic minerals; 37: basic metals; 38: fabricated metals; 381: metal products; 382: agricultural and industrial machinery; 383: electrical goods; 384: transport equipment; 385: instruments; 39: other manufacturing; 30: total manufacturing.

Note: "First" is the frontier; "Second" is the second highest TFP country; mean and SD of exp(RTFP) are the sample mean and standard deviation of the exponential of RTFP across countries. A value of the mean closer to unity corresponds to a higher average level of relative TFP. The measure of TFP used is adjusted for skills and hours worked; see appendix.

ISIC 35 and 381).[22] As discussed earlier, it is not the identity of the frontier country per se that is important in the econometric estimation, but the measure of distance from the technological frontier, which we use to capture the potential for technology transfer.

Table 1 therefore also reports the sample mean and standard deviation of relative TFP across countries for each industry in the years 1971, 1981, and 1990. Relative TFP is each country's TFP as a proportion of that in the frontier, and is equal to 1 for the frontier and less than 1 for nonfrontier countries. The further away from 1 (the smaller) that number), the greater a country *i*'s distance from the technological frontier. In all industries except one (ISIC 39, other manufacturing), average levels of relative TFP are higher in 1990 than 1971, and in all industries except two (ISIC 32, Textiles and ISIC 36, nonmetallic minerals), the standard deviation is lower in 1990 than in 1971. This suggests σ-convergence in levels of relative TFP within OECD manufacturing industries during the sample period.[23]

V. Results

A. Main Results

Column (1) of table 2 examines the role played by technology transfer in determining rates of TFP growth,

[22] For a discussion of technological leapfrogging in a historical context, see Brezis, Krugman, and Siddon (1993).

[23] This finding of σ-convergence within individual manufacturing industries is consistent with the results of Bernard and Jones (1996a,b). Our TFP measures are more general than those considered by Bernard and Jones: we control for cross-country differences in the skill composition of the workforce and measure TFP using a superlative index number (rather than assuming a Cobb-Douglas technology). The latter adjustment on its own is quantitatively important and strengthens findings of productivity convergence within individual manufacturing industries. Bernard and Jones are also concerned with aggregate manufacturing and nonmanufacturing, and their results are compatible with convergence within individual manufacturing industries.

TABLE 2.—IMPACT OF R&D AND HUMAN CAPITAL ON TFP GROWTH

ΔTFP_{ijt}		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$TFPGAP_{i\ j\ t-1}$	δ_1	0.080 (0.014)	0.085 (0.013)	0.067 (0.015)	0.066 (0.015)	0.059 (0.016)	0.013 (0.021)	0.019 (0.021)	0.002 (0.022)
$R/Y_{i\ j\ t-1}$	ρ_1	—	0.669 (0.165)	0.497 (0.188)	0.461 (0.185)	0.479 (0.177)	0.473 (0.172)	0.502 (0.174)	0.561 (0.186)
$(TFPGAP \times R/Y)_{i\ j\ t-1}$	δ_2	—	—	0.596 (0.333)	0.633 (0.328)	1.00 (0.346)	0.815 (0.350)	0.740 (0.351)	0.814 (0.385)
$H_{i\ t-1}$	ρ_2	—	—	—	—	—	0.229 (0.124)	0.258 (0.124)	0.267 (0.149)
$(TFPGAP \times H)_{i\ t-1}$	δ_3	—	—	—	—	—	0.464 (0.137)	0.426 (0.140)	0.559 (0.139)
$IMPS_{i\ j\ t-1}$	ρ_3	—	—	—	—	—	—	0.001 (0.011)	−0.064 (0.035)
$(TFPGAP \times IMPS)_{i\ j\ t-1}$	δ_4	—	—	—	—	—	—	0.073 (0.035)	0.060 (0.034)
Serial correlation (p-value)		0.328	0.309	0.311	0.390	0.453	0.388	0.896	0.553
Skills adjustment					Yes	Yes	Yes	Yes	Yes
Hours adjustment						Yes	Yes	Yes	Yes

Notes: Sample contains 1801 observations from 1974–1990; numbers in parentheses are robust standard errors; all regressions include full set of time dummies and full set of country-industry interactions (within-group estimators); observations are weighted using initial industry shares of total manufacturing employment; ΔTFP is growth in TFP; $RTFP$ is relative level of TFP; R/Y is R&D intensity; H is human capital; $IMPS$ is imports from the frontier (normalized on output); serial correlation is the p-value for the LM test for first-order serial correlation, distributed $N(0,1)$ under the null. In column (8), R/Y is lagged $t-2$; number of observations is 1695.

excluding both R&D terms. The relative TFP term enters positively and is significant at conventional levels, indicating that within each industry the countries that are further behind the frontier experience higher rates of productivity growth. Controlling for unobserved heterogeneity using the within-groups estimator increases the size of the estimated coefficient on relative TFP.[24]

As suggested in the discussion above, we are interested in exploring the two possible roles played by R&D. We enter the R&D intensity in levels, to capture an effect on innovation, as well as interacted with the relative productivity term, which will capture an effect on the rate of technological transfer. In column (2) of table 2, we introduce the lagged level of R&D intensity, which enters positively and is statistically significant at conventional levels. Column (3) considers both the level of R&D and the interaction between R&D and relative TFP. The interaction term is expected to have a positive coefficient: the further a nonfrontier country lies behind the frontier (the larger $TFPGAP_{i\ j\ t-1}$), the greater the potential for technologies to be transferred through R&D and the higher the rates of productivity growth. From column (3), the estimated coefficient on the interaction term is indeed positive and statistically significant at the 10% level. The linear term remains positive and significant.

In columns (4) and (5), we adjust our TFP measure to take account of cross-country differences in the skill composition of the workforce and in hours worked. Column (4) exploits information on the share of production and nonproduction workers in employment and the wage bill in individual industries to control for labor quality. In column (5), we also control for cross-country differences in hours worked. The upshot of these results is that R&D appears to have both a linear effect (R&D generates innovations) and an interactive effect with distance to frontier ($TFPGAP$) (R&D also spurs faster adoption of new technologies).

Although our baseline specification assumes that R&D is the critical factor in generating innovation and technology transfer, many authors have emphasized the roles of human capital and international trade in the growth process. The model presented earlier is therefore extended to incorporate these variables. Equation (5) becomes

$$\Delta \ln A_{ijt} = \delta_1 \ln\left(\frac{A_F}{A_i}\right)_{j\ t-1} + \left[\delta_2\left(\frac{R}{Y}\right)_{i\ j\ t-1} + \delta_3 H_{i\ t-1} + \delta_4 (IMPS)_{i\ j\ t-1}\right] \ln\left(\frac{A_F}{A_i}\right)_{j\ t-1} + \rho_1\left(\frac{R}{Y}\right)_{i\ j\ t-1} + \rho_2 H_{i\ t-1} + \rho_3 (IMPS)_{i\ j\ t-1} + u_{ijt}. \quad (12)$$

Our preferred measure of TFP weights the numbers of production and nonproduction workers in a country-industry by their respective shares of the wage bill. In so far as any increased productivity of nonproduction workers is reflected in their wages (a private rate of return), it will already be captured in our analysis. In this section, we are therefore concerned with estimating externalities to human capital accumulation. The existence of such externalities has been a frequent concern of the theoretical growth literature, including work on both *technological* externalities[25] and *pecuniary* externalities.[26] Because human capital's effect is thought to be an externality, we use country-level data on the percentage of the total population that has attained higher (tertiary) education from Barro and Lee (1994).[27] These data have the advantage of being available for all countries in our sample. We also investigate the use of

[24] If we reestimate the specification in column (1) of table 2 dropping the fixed effects, the estimated coefficients (*standard error*) on $TFPGAP$ is 0.020 (*0.005*). With OLS estimation there is evidence of serial correlation in the residuals (the p-value of the LM test statistic is *0.013*). Once we control for unobserved heterogeneity across country-industries, we find no evidence of serial correlation, as indicated by the LM test statistics reported at the bottom of table 2.

[25] See Lucas (1988) or Nelson and Phelps (1966).

[26] See Acemoglu (1996) and Redding (1996).

[27] Higher education is a more appropriate variable than secondary education for OECD countries.

industry-level educational attainment data from Machin and Van Reenen (1998), as discussed further below.

Column (6) of table 2 presents the results including R&D and human capital. The estimated coefficient on the level of human capital is positive and significant at the 10% level, and the interaction is positive and significant at the 5% level. This is consistent with positive externalities from higher educational attainment in the form of both a higher rate of innovation and more rapid technology transfer. The conclusions regarding the effects of R&D remain unchanged.

The role of the aggregate human capital variable is open to different interpretations.[28] For six countries we have industry-level educational variables, which we used instead of the aggregate variables. The human capital terms were correctly signed, but only the linear term was significant at the 10% level.[29] We also interacted the human capital variable with the R&D variable and find the coefficient is insignificant.[30]

The role of international trade is stressed in both the cross-country growth literature and work on international R&D knowledge spillovers. The theoretical literature suggests a variety of mechanisms by which trade may affect productivity growth (for example, spillovers of technology from the reverse engineering of imported goods, increased product market competition, and larger market size), and there are a number of ways to introduce international trade into the model. We take a simple and intuitive approach that, at the same time, is sufficiently general to allow trade to affect both innovation and technology transfer. The OECD bilateral trade database provides country-industry-level information on the source of imports from trading partners in the OECD. Using these data, we construct measures of import penetration for each industry in each country. Our preferred measure uses imports from the frontier, although we also experimented with using imports from the whole world, imports from other OECD countries excluding the frontier, and imports from non-OECD countries.[31] International trade flows are scaled by output, and we include both a level and an interaction term for import penetration.

In column (7) of table 2, we include information on R&D, human capital, and international trade. The magnitude and statistical significance of the coefficients on the R&D and human capital terms remain largely unchanged. The import level term is statistically insignificant. The import interaction term is positively signed and statistically significant at the 10% level. Thus, increased trade with the frontier tends to have a (weakly) positive effect on rates of productivity growth through the speed of technology transfer, but not through rates of innovation.[32]

As a check on our assumption of weak exogeneity of R&D, column (8) of table 2 dates R&D at $t-2$. We see that the level of R&D and its interaction with *TFPGAP* remain significant. Alternatively, treating $(R/Y)_{i\,j\,t-1}$ as endogenous and using the second lags of R&D intensity and its interaction with *TFPGAP* as instruments also gives very similar results.[33]

What about the quantitative importance of the estimated effects? Because the import interaction term is only weakly statistically significant, we concentrate on the results with R&D and human capital [column (6) in table 2], and we focus on the implications for total manufacturing. The estimated R&D effect [$\hat{\rho}_R \equiv \hat{\rho}_1 + \hat{\delta}_2 \ln (A_F/A_i)_{j\,t-1}$] consists of two components: one due to innovation ($\hat{\rho}_1$) and a second due to technology transfer or absorptive capacity [$\hat{\delta}_2 \ln (A_F/A_i)_{j\,t-1}$]. In table 3 we report the total return from R&D (column 1) and from human capital (column 3), as well as the percentage of the estimated R&D effect that is accounted for by technology transfer (column 2), with analogous figures also reported for human capital (column 4). The relative contribution from technology transfer varies with a country's distance to the technological frontier. We see that for the United States, which is typically the technological leader, R&D's contribution to productivity growth is largely due to innovation. In contrast, in Finland, where the average relative TFP is around 50% of the level in the frontier (TFP in the United States is just over twice as high as in Finland), less than half of the estimated effect is due to innovation—absorptive capacity is quantitatively more important.

Under the assumption that the association between productivity growth and R&D is causal, these estimated coefficients may be given a more structural interpretation. As discussed in the theoretical section above, the estimated coefficient on R&D corresponds to a social rate of return. Therefore, one implication of our analysis is that many existing studies, insofar as they have focused on the United States (which is typically the technological leader), will have underestimated R&D's social rate of return. In nonfron-

[28] See Krueger and Lindahl (2001) for a critical discussion and recent evidence.

[29] The specification in column (6) of table 2 was reestimated using the industry-level education data. The estimated coefficients (*standard errors*) on the linear and interaction education were 0.361 (*0.203*) and 0.439 (*0.549*), respectively. We also experimented with nonlinearities in human capital, but none of the terms were significant at conventional levels.

[30] In this specification the coefficients (*standard errors*) are: $TFPGAP_{t-1}$ 0.018 (*0.022*), $(R/Y)_{t-1}$ 0.689 (*0.301*), $(TFPGAP{\times}R/Y)_{t-1}$ 0.743 (*0.351*), H_{t-1} 0.270 (*0.137*), $(TFPGAP{\times}H)_{t-1}$ 0.448 (*0.139*), $(H{\times}R/Y)_{t-1}$ 0.840 (*1.052*).

[31] The results using imports from the whole world (not shown) are very similar to those with imports from the frontier, suggesting that it is openness per se that fosters technology transfer and not whether a country is directly importing from the most advanced nations. The results are weakest for imports from non-OECD countries, which does not seem consistent with the arguments of Wood (1994), who claims that trade with developing countries has resulted in large amounts of induced innovation (and so lowered the demand for less skilled workers).

[32] In the working paper version, we also show that our results are robust to including level and interaction terms in investment in fixed capital.

[33] The estimated coefficients (*standard errors*) were: $TFPGAP_{t-1}$ 0.000 (*0.022*), $(R/Y)_{t-1}$ 0.631 (*0.199*), and $TFPGAP_{t-1} \times (R/Y)_{t-1}$ 0.897 (*0.473*). Similar results are also obtained from treating both lagged R&D and lagged TFPGAP as endogenous (footnote 40). We also experimented with using policy changes such as the introduction of an R&D tax credit as instruments for the R&D intensity (see Bloom, Griffith, & Van Reenen, 2002). Unfortunately, there is only a small sample for which both the production data used to calculate TFP and the policy variables are available. The pattern of point estimates was similar, but the small sample size led to a large loss in precision.

TABLE 3.—TOTAL R&D AND HUMAN CAPITAL CONTRIBUTIONS TO PRODUCTIVITY GROWTH, TOGETHER WITH THE PERCENTAGE DUE TO TECHNOLOGY TRANSFER, BASED ON THE AVERAGE *TFPGAP* IN TOTAL MANUFACTURING

Country	(1) R&D Total Effect	(2) R&D Technology Transfer (%)	(3) Human Capital Total Effect	(4) Human Capital Technology Transfer (%)
Canada	0.69	26	0.35	29
Denmark	0.81	35	0.42	38
Finland	1.05	54	0.56	58
France	0.67	25	0.34	28
Germany	0.64	23	0.33	26
Italy	0.88	40	0.46	44
Japan	0.83	36	0.43	39
Norway	0.98	48	0.52	52
Sweden	0.78	35	0.40	38
United Kingdom	0.77	36	0.40	39
United States	0.57	14	0.28	15

Notes: Column (1) shows R&D's total contribution to productivity growth is $\hat{\rho}_R \equiv \hat{\rho}_1 + \hat{\delta}_2 \ln (A_F/A_i)_{i\,j\,t-1}$ using the coefficient estimates from column (6) of table 2 ($\hat{\rho}_1 = 0.473$, $\hat{\delta}_2 = 0.815$). Column (2) reports the percentage share of technology transfer [$\hat{\delta}_2 \ln (\bar{A}_F/A_i)$] in R&D's total contribution ($\hat{\rho}_R$), based on a country's time-averaged *TFGAP* in total manufacturing [$\ln (\bar{A}_F/A_i)$]. Column (3) shows human capital's total contribution to productivity growth, and column (4) reports the analogous percentage share of technology transfer.

tier countries, R&D contributes to TFP growth not only through innovation but also through technology transfer. The estimated social rate of return to R&D from innovation ($\hat{\rho}_1$) in table 2 of around 40% is consistent with existing U.S.-based studies.[34] As shown in table 3, in nonfrontier countries, R&D-based technology transfer [$\hat{\delta}_2 \ln (A_F/A_i)$] may substantially increase the effect of R&D on productivity.[35]

B. Robustness of Results

There are a number of potential concerns about the results presented above. In this subsection we consider the robustness of our results to the following concerns: (i) bias due to measurement error, (ii) nonlinearities and diminishing returns to R&D, (iii) sensitivity to the definition of the frontier, (iv) inclusion of contemporaneous frontier TFP growth as in equation (8), and (v) parameter heterogeneity.[36]

Measurement Error: Our first concern is with measurement error. If we measure TFP with error, then the weak exogeneity assumption will not be valid. The left-hand side of our regression is the measured TFP growth [$\ln (A_{ijt}/A_{i\,j\,t-1})$], whereas the right-hand side is the measured relative TFP [$\ln (A_{F\,j\,t-1}/A_{i\,j\,t-1})$]. If A_{ijt}, $A_{i\,j\,t-1}$, and $A_{F\,j\,t-1}$ are each subject to errors of measurement, the OLS estimate of the coefficient on relative TFP will be biased. To deal with this potential problem we use IV estimation. In the absence of serial correlation (conditional on the country-industry fixed effect and the other covariates), longer-lagged values of relative TFP are valid instruments. In columns (1) to (3) of table 4, we replicate the results from columns (5) to (7) of table 2 but instrument the relative TFP term with lags of itself ($t - 2$ and $t - 3$). The results are very similar to those presented in table 2.[37]

A complementary approach uses data on some of the variables suggested as sources of measurement error in the TFP literature. Column (4) presents estimation results using a measure of relative TFP that controls for cross-country and cross-industry variation in the degree of imperfect competition using data on the markup of price over marginal cost in individual country-industries. In column (5), we present results using a measure of relative TFP that controls for both country-industry variation in the degree of imperfect competition and country-industry-time variation in capacity utilization.[38] In both cases, the conclusions from the IV estimation are confirmed, and the finding of a second face of R&D activity is robust. The coefficients on the R&D level and interaction terms remain of similar magnitude and statistically significant at the 5% level. The human capital interaction is positively signed and statistically significant. Neither the international trade level nor the interaction

[34] For example, Sveikauses (1981) estimates a social rate of return to R&D of 50%, and Griliches and Lichtenberg (1984) estimate a social rate of return to R&D of 41%–62%. See Jones and Williams (1998) for a discussion of existing estimates of the social rate of return to R&D and their relation to the endogenous growth literature.

[35] This conclusion receives independent support from Eaton, Gutierrez, and Kortum (1998), who calibrate a computable general equilibrium model of endogenous innovation and growth to economy-wide data from 21 OECD countries. With the exception of Portugal, research productivity in all other OECD countries is found to be higher than in the United States.

[36] We show robustness of the results to other tests (such as interindustry spillovers) in Griffith et al. (2000).

[37] We considered two tests of the validity of the instruments in addition to the serial correlation tests. First, the Sargan test at the bottom of the columns is a test of the model's overidentifying restrictions. We are unable to reject the null hypothesis that the excluded exogenous variables are uncorrelated with the second-stage residuals. Second, we consider an F-test of the excluded instruments in the first-stage equations (IV estimates will be biased toward OLS in finite samples if the instruments are weakly correlated with the endogenous variables). In fact the excluded instruments were always highly significant. For example, in column (1) of table 4 the F-test of the joint significance of $RTFP_{i\,j\,t-2}$, $RTFP_{i\,j\,t-3}$, and $RTFP_{i\,j\,t-2} \times R/Y_{i\,j\,t-1}$, in the reduced form for $RTFP_{i\,j\,t-1}$, is significant at the 1% level.

[38] See the appendix for further details concerning the construction of these measures.

TABLE 4.—ROBUSTNESS OF THE MAIN RESULTS

ΔTFP_{ijt} Estimation	(1) IV	(2) IV	(3) IV	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS
ΔTFP_{Fjt}	—	—	—	—	—	—	—	0.121 (0.030)
$RTFP_{i\,j\,t-1}$	0.061 (0.019)	0.024 (0.024)	0.029 (0.025)	0.006 (0.022)	0.017 (0.020)	0.021 (0.021)	0.017 (0.024)	0.024 (0.021)
$R/Y_{i\,j\,t-1}$	0.432 (0.186)	0.432 (0.182)	0.461 (0.183)	0.495 (0.175)	0.343 (0.153)	0.857 (0.327)	0.394 (0.170)	0.427 (0.174)
$(R/Y_{i\,j\,t-1})^2$	—	—	—	—	—	−1.582 (1.214)	—	—
$(TFPGAP \times R/Y)_{i\,j\,t-1}$	1.336 (0.406)	1.131 (0.411)	1.046 (0.410)	0.900 (0.346)	0.950 (0.338)	0.682 (0.353)	1.008 (0.384)	0.815 (0.348)
$H_{i\,t-1}$	—	0.241 (0.125)	0.268 (0.125)	0.250 (0.131)	0.200 (0.120)	0.222 (0.124)	0.232 (0.123)	0.225 (0.124)
$(TFPGAP \times H)_{i\,j\,t-1}$	—	0.420 (0.175)	0.399 (0.176)	0.409 (0.143)	0.317 (0.140)	0.452 (0.137)	0.546 (0.165)	0.459 (0.136)
$IMPS_{i\,j\,t-1}$	—	—	0.003 (0.009)	0.003 (0.027)	0.015 (0.032)	—	—	—
$(TFPGAP \times IMPS)_{i\,j\,t-1}$	—	—	0.063 (0.034)	0.048 (0.046)	0.041 (0.047)	—	—	—
Serial correlation (p-value)	0.358	0.881	0.341	0.817	0.633	0.371	0.278	0.356
Sargan (p-value)	0.206	0.126	0.121	—	—	—		
Adjustments to TFP	s,h	s,h	s,h	s,h,m	s,h,m,c	s,h	s,h	s,h
Definition of frontier	One	One	One	One	One	One	Two	One

Notes: Sample contains 1801 observations, 1974–1990; numbers in ( ) are robust standard errors; all regressions include full set of time and country-industry dummies (within-group estimator); observations are weighted using initial industry share of total manufacturing employment; ΔTFP is growth in TFP; R/Y is R&D divided by value added; H is human capital; $IMPS$ is imports from the frontier; serial correlation is LM test for first-order serial correlation; Sargan is test for validity of overidentifying restrictions; TFP adjustments are s: skills; h: hours; m: markup; and c: capacity utilization (see appendix for details); instruments in columns (1) through (3) are $TFPGAP_{i\,j\,t-2}$, $TFPGAP_{i\,j\,t-3}$, $R/Y_{i\,j\,t-1}$, $(TFPGAP_{i\,j\,t-2} \times R/Y_{i\,j\,t-1})$; in column (2) we include as extra instruments: $H_{i\,j\,t-1}$, $(TFPGAP_{i\,j\,t-2} \times H_{i\,j\,t-1})$, $(TFPGAP_{i\,j\,t-3} \times H_{i\,j\,t-1})$; in column (3) we include $IMPS_{i\,j\,t-1}$, $(TFPGAP_{i\,j\,t-2} \times IMPS_{i\,j\,t-1})$, $(TFPGAP_{i\,j\,t-3} \times IMPS_{i\,j\,t-1})$; $TFPGAP$ is distance to frontier: One indicates that the potential for technology transfer is measured by TFP relative to the frontier, Two indicates that it is measured relative to the average of the two countries with the highest TFP levels.

term is statistically significant at conventional critical values.[39]

A related concern is that the output Y is subject to errors of measurement, which will not only affect the measured TFP but also the R&D intensity (R/Y). To address this concern, we reestimated the model using instrumental variables, including the the second and third lags of R&D intensity, *TFPGAP,* and their interactions in the instrument set. As discussed in section V A, (in particular, footnote 33), a very similar pattern of results was observed.[40]

Nonlinearities and Diminishing Returns to R&D: We have interpreted the interaction term between R&D and relative TFP as indication of technology transfer associated with R&D. An alternative interpretation, however, is that there are sharply diminishing returns to R&D and that countries further behind the frontier have a higher rate of return simply because they perform less R&D and are therefore higher up the marginal productivity curve for R&D. The empirical implication of this alternative story is that higher-order terms in R&D intensity should be included in our specifications and this should drive out the interaction of R&D with relative TFP. We tested for such nonlinearities in the R&D term and found that these higher-order terms in R&D were always insignificant. Column (6) shows a representative example; we include a squared R&D intensity term. Although it is negative (suggesting diminishing returns), it is insignificant. The interaction terms with relative TFP (both of human capital and of R&D) were basically unchanged by the addition of this variable.

Definition of the Frontier: How sensitive are our results to the definition of the frontier? In our model what matters for the regressions is not the identity of the frontier per se, but the measure of distance from the technological frontier that we use to capture the potential for technology transfer. We have already shown that our results are robust to a series of different adjustments to TFP measures. In column (7) of table 4 we also report results using the average of the top two countries as an indicator of the frontier, and the results are similar to column (6) of table 2. As a further robustness check we ran the same regression as shown in column (5) of table 2, but using TFP relative to the median. The idea is that, if our model is correct, this should not be meaningful, as it does not contain information about distance to the technological frontier. Indeed, that is what we see: the coefficients on distance to the median and the interaction between R&D and distance to the median were both statistically insignificant.[41]

Contemporaneous Frontier TFP Growth: Augmenting the specification for nonfrontier countries with an additional term in contemporaneous frontier TFP growth allows for a more flexible relationship between nonfrontier and frontier TFP within the context of an equilibrium correction model (ECM) [equation (8)]. The unattractive feature of this specification is that there is a discontinuity in the TFP growth process when a country becomes the frontier, in which case the contemporaneous frontier growth term is set equal to 0.

[39] We also experimented with using data on industry-specific purchasing power parities (PPPs). Once again, the conclusions were essentially unchanged: see Griffith et al. (2000) for further details.

[40] For example, in the specification of column (6) in table 2 we used $(R/Y)_{t-2}$, $(R/Y)_{t-3}$, $(TFPGAP)_{t-2}$, $(TFPGAP)_{t-3}$, $(TFPGAP \times R/Y)_{t-2}$, $(TFPGAP \times R/Y)_{t-3}$, $(TFPGAP \times H)_{t-2}$, and $(TFPGAP \times H)_{t-3}$ as instruments for $(R/Y)_{t-1}$, H_{t-1}, $(TFPGAP)_{t-1}$, $(TFPGAP \times R/Y)_{t-1}$, and $(TFPGAP \times H)_{t-1}$. The estimated coefficients (*standard errors*) on the key variables in the IV regressions were *TFPGAP* 0.026 (*0.022*), (R/Y) 0.693 (*0.191*), and $TFPGAP \times (R/Y)$ 1.382 (*0.473*).

[41] The coefficients (*standard errors*) were distance to median −0.012 *(0.009)*, R/Y 0.634 *(0.175),* and the interaction 0.141 *(0.125).*

TABLE 5.—HETEROGENEITY OF COEFFICIENTS

	(1) Pooled Coefficient	(2) Median Coefficient All Industries	(3) Median Coefficient Small Gap	(4) Median Coefficient Large Gap
$TFPGAP_{i\,j\,t-1}$	0.111	—	—	—
$(R/Y)_{i\,j\,t-1}$	0.491	1.261	0.118	2.327
$H_{i\,t-1}$	0.265	0.382	0.104	0.896

Notes: Country-industry fixed effects and common time effects are included in all specifications. Column (1) reports pooled coefficient from a model including *TFPGAP,* human capital, and R&D. Columns (2) to (4) report the median coefficient when we allow either the coefficient on R&D or human capital to vary across all 106 country-industry pairs (holding other coefficients constant). In column (2) we give the median across all industries. In column (3) we give the median coefficient in industries with a small gap (those industries near the frontier, defined as those above the median in each year), and in column (4) we give the median coefficient for industries far from the frontier (those below the median in each year).

In column (8) of table 4 we report a specification of this form and find a very similar pattern of results.

Parameter Heterogeneity: The specification in equation (12) allows the coefficient on the gap to vary with R&D, human capital, and international trade. This places a particular economic structure on parameter heterogeneity. We now consider the implications of allowing for more general forms of heterogeneity.[42] Table 5 reports the results from specifications that allow the coefficients to vary across each of the 106 country-industry cross-section units. We do this separately for R&D and for human capital.

To provide a benchmark against which to compare the results of the heterogeneous coefficient estimation, column (1) of table 5 estimates a regression with *TFPGAP,* the R&D level, and the level of human capital. The interaction terms are excluded, because they already constitute a method of allowing the coefficients on R&D and human capital to vary across industries. In the heterogeneous coefficient estimation we wish to allow the coefficients on these variables to vary across country-industries (as dictated by the data alone). In columns (2) to (4) we report the median coefficient when we allow either the coefficient on R&D or human capital to vary across all 106 industry-country pairs (holding the other coefficients constant). We report medians because the means can be sensitive to one or two extreme estimated values.

From our theoretical model and preferred specification we expect the impact of R&D and human capital to be higher in those countries that have lower levels of relative TFP and are further from the industry-specific technological frontier. In order to investigate whether this is the case, we split the sample by the median value of relative TFP into those country-industries that are far from the frontier ("large gap") and those that are closer to the frontier ("small gap"). As shown in columns (3) and (4), we find that the R&D and human capital coefficients are more important for those countries that are far from the industry technological frontier. In summary, this corroborates our qualitative findings from the more parsimonious models of table 2.

[42] See, for example, Pesaran and Smith (1995).

VI. Conclusions

This paper has produced econometric evidence on the importance of the two faces of R&D by examining the determinants of productivity growth in a panel of industries across twelve OECD countries. R&D stimulates growth directly through innovation and also indirectly through technology transfer. Thus R&D has played a role in the convergence of TFP levels within industries across OECD countries. This result was robust to a variety of tests, including measuring TFP in a number of different ways. We also identified a role for human capital in stimulating innovation and absorptive capacity. By contrast, trade had a statistically weak effect on productivity. The R&D and human capital effects were shown to be quantitatively important as well as statistically significant.

An implication of the results is that the social returns to investing in R&D and human capital may be underestimated in studies that focus solely on the U.S. economy, in that the United States is the technological frontier for a large number of industries. There is also an important spillover at the world level from advanced to less advanced countries. As a result of technology transfer, an increase in R&D at the frontier raises the steady-state rate of TFP growth of all countries.

One important question is why nonfrontier countries do not invest more in R&D if the social return is higher than in the frontier. As the incentive to invest in R&D is determined by the private return and not the social return, it may be the case that R&D is held back in many nonfrontier countries by underdevelopment of financial markets or inappropriate government policies. A future research priority should be to investigate these issues, through using firm-level data across a number of countries to estimate private and social rates of return in a framework that allows for the two faces of R&D.

Another avenue for future work would be to extend our framework to incorporate interindustry technology transfers. Despite the need for these further extensions, we believe the methods presented here provide a tractable and intuitive approach to understanding productivity dynamics across OECD countries and industries. The emphasis on human capital and R&D in modern growth theory is well placed.

REFERENCES

Abramovitz, M., "Catching Up, Forging Ahead, and Falling Behind," *Journal of Economic History* 46 (1986), 386–406.

Acemoglu, D., "A Microfoundation for Social Increasing Returns in Human Capital Accumulation," *Quarterly Journal of Economics* 111:3 (1996), 779–804.

Acemoglu, D., and F. Zillibotti, "Productivity Differences," *Quarterly Journal of Economics* 116 (2001), 563–606.

Aghion, P., and P. Howitt, "A Model of Growth through Creative Destruction," *Econometrica* (March 1992), 323–351.

——— *Endogenous Growth Theory* (Cambridge MA: MIT Press, 1997).

Arrow, K., "Classificatory Notes on the Production and Transmission of Technological Knowledge," *American Economic Review: Papers and Proceedings* 59:2 (1969), 29–35.

Barro, R., and J. Lee, "Sources of Economic Growth," *Carnegie-Rochester Conference Series on Public Policy* 40 (1994), 1–46.
Barro, R., and X. Sala-i-Martin, *Economic Growth* (New York: McGraw Hill, 1995).
Benhabib, J., and M. Spiegel, "The Role of Human Capital in Economic Development: Evidence from Aggregate Cross-Country Data," *Journal of Monetary Economics* 34 (1994), 143–173.
Berman, E., J. Bound, and S. Machin, "Implications of Skill-Biased Technological Change: International Evidence," *Quarterly Journal of Economics* (November 1998), 1245–1279.
Bernard, A., and S. Durlauf, "Convergence in International Output," *Journal of Applied Econometrics* 10 (1995), 97–108.
——— "Interpreting Tests of the Convergence Hypothesis," *Journal of Econometrics* 71:1–2 (1996), 161–173.
Bernard, A., and C. Jones, "Productivity across Industries and Countries: Time Series Theory and Evidence" this REVIEW, 78:1 (1996a), 135–146.
——— "Comparing Apples to Oranges: Productivity Convergence and Measurement across Industries and Countries," *American Economic Review* 86:5 (1996b), 1216–1238.
Bernstein, J., and M. Nadiri, "Inter-industry Spillovers, Rates of Return and Production in High Tech Industries," *American Economic Review* 78 (1989), 429–434.
Bloom, N., R. Griffith, and J. Van Reenen, "Do R&D Tax Credits Work: Evidence from an International Panel of Countries 1979–97," *Journal of Public Economics* 85 (2002), 1–31.
Brezis, E., P. Krugman, and D. Tsiddon, "Leapfrogging in International Competition: A Theory of Cycles in National Technological Leadership," *American Economic Review* 83 (1993), 1211–1219.
Cameron, G., "Catchup and Leapfrog between the USA and Japan," (chapter 6), in "Innovation and Economic Growth," Nuffield College, University of Oxford, DPhil thesis (1996).
——— J. Proudman, and S. Redding, "Productivity Convergence and International Openness," (chapter 6), in J. Proudman and S. Redding (Eds.), *Openness and Growth* (London: Bank of England, 1998).
Caves, D., L. Christensen, and E. Diewert, "The Economic Theory of Index Numbers and the Measurement of Input, Output and Productivity," *Econometrica* 50:6 (1982a), 1393–1414.
——— "Multilateral Comparisons of Output, Input, and Productivity Using Superlative Index Numbers," *Economic Journal* 92 (1982b), 73–86.
Cohen, W., and D. Levinthal, "Innovation and Learning: Two Faces of R&D," *Economic Journal* 99 (1989), 569–596.
Coe, D., and E. Helpman, "International R&D Spillovers," *European Economic Review* 39:5 (1995), 859–887.
Eaton, J., and S. Kortum, "International Patenting and Technology Diffusion: Theory and Evidence," *International Economic Review* 40:3 (1999), 537–570.
Eaton, J., E. Gutierrez, and S. Kortum, "European Technology Policy," *Economic Policy* 27 (1998), 403–438.
Geroski, P., S. Machin, and J. Van Reenen, "The Profitability of Innovating Firms," *Rand Journal of Economics* 24:2 (1993), 198–211.
Gerschenkron, A., *Economic Backwardness in Historical Perspective* (Cambridge, MA: Belknap Press, 1952).
Griffith, R., S. Redding, and J. Van Reenen, "Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries," CEPR discussion paper no. 2457 (2000).
Griliches, Z., "Returns to R&D Expenditures in the Private Sector," in K. Kendrick and B. Vaccara (Eds.), *New Developments in Productivity Measurement* (Chicago: University of Chicago Press, 1980).
——— "The Search for R&D Spillovers," *The Scandinavian Journal of Economics* 94 (1992), 29–47.
Griliches, Z., and F. Lichtenberg, "R&D and Productivity Growth at the Industry Level: Is There Still a Relationship?" in Z. Griliches (Ed.), *R&D, Patents, and Productivity* (Chicago: NBER and University of Chicago Press, 1984).
Hall, R., "The Relation between Price and Marginal Cost in US Industry," *Journal of Political Economy* 96 (1988), 921–947.
Harrigan, J. "Technology, Factor Supplies, and International Specialisation," *American Economic Review* 87 (1997), 475–494.
Hendry, D., *Dynamic Econometrics* (Oxford: Oxford University Press, 1996).
Howitt, P., "Endogenous Growth and Cross-Country Income Differences," *American Economic Review* 90:4 (2000), 829–846.
Jaffe, A., "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits and Market Value," *American Economic Review* 75:6 (1986), 984–1002.
Jones, C., and J. Williams, "Measuring the Social Rate of Return to R&D," *Quarterly Journal of Economics* 113:4 (1998), 119–135.
Krueger, A., and M. Lindahl, "Education for Growth: Why and for Whom?" *Journal of Economic Literature* 39:4 (2001), 1101–1136.
Lach, S., and M. Schankerman, "The Dynamics of R&D Investment in the Scientific Sector," *Journal of Political Economy* 97 (1989), 80–94.
Lucas, R., "On the Mechanics of Economic Development," *Journal of Monetary Economics* 22:1 (1988), 3–42.
Machin, S., and J. Van Reenen, "Technology and Changes in Skill Structure: Evidence from Seven OECD Countries," *Quarterly Journal of Economics* 443 (1998), 195–226.
Martins, J., S. Scarpetta, and D. Pilat, "Mark-up Pricing, Market Structure and the Business Cycle," *OECD Economic Studies* 27 (1997), 71–105.
Nadiri, M., and S. Kim, "Sources of Growth of Output and Convergence of Productivity in Major OECD Countries," *IJPRODE* 52:1–2 (1997), 133–146.
Nelson, R., and E. Phelps, "Investment in Humans, Technological Diffusion and Economic Growth," *American Economic Review* 56 (1966), 69–75.
Nickell, S., "Biases in Dynamic Models with Fixed Effects," *Econometrica* 49:6 (1981), 1417–1426.
Parente, S., and E. Prescott, "Barriers to Technology Adoption and Development," *Journal of Political Economy* 102:2 (1994), 298–321.
Pesaran, H., and R. Smith, "Estimating Long-Run Relationships from Dynamic Heterogeneous Panels," *Journal of Econometrics* 68 (1995), 79–113.
Redding, S., "The Low-Skill, Low-Quality Trap: Strategic Complementarities between Human Capital and R&D," *Economic Journal* 106 (1996), 458–470.
Roeger, W., "Can Imperfect Competition Explain the Difference between Primal and Dual Productivity Measures? Estimates for US Manufacturing," *Journal of Political Economy* 103:2 (1995), 316–330.
Romer, P., "Endogenous Technological Change," *Journal of Political Economy* 98:5 (1990), S71–S102.
Sveikauskas, L., "Technology Inputs and Multifactor Productivity Growth" this REVIEW, 63 (1981), 275–282.
Wood, A., *North-South Trade, Employment, and Inequality: Changing Fortunes in Skill-Driven World* (Oxford: Clarendon Press, 1994).

APPENDIX

1. Data Sources

Our sample consists of twelve countries over the period 1971–1990. For some of the countries, information is available for nine two-digit industries (ISIC 31–39); for others, ISIC 38 is additionally broken down into five three-digit industries. Where the more disaggregated information is available for the three-digit industries, we use it. At the same time, careful attention is paid to the robustness of the results to alternative samples of countries and industries. After cleaning and deleting missing values, we have 1801 observations across countries and industries. See Griffith et al. (2000) for details. Data are used from the following sources:

OECD International Sectoral Database (ISDB): Data on real value added, real capital stock, employment, hours worked, labor compensation, and real gross output.
OECD ANBERD/ANRSE (Research and Development in Industry: Expenditure and Researchers, Scientists and Engineers) Database: Data on business enterprise expenditure on research and development (BERD), includes all sources of funding (industry and business, domestic and overseas).
OECD Bilateral Trade Database (BTD): Data on the value of each OECD country's bilateral imports from all other OECD countries.
United Nations General Industrial Statistics Database (UNISD): Data on the numbers and wage bills of nonproduction and production

workers[43] available for Canada, Denmark, Finland, Japan, Sweden, the United Kingdom, and the United States; for all other countries we use the mean employment and wage bill shares in that industry across countries.

Industry-specific markups: From Martins, Scarpetta, and Pilat (1996), reported for 36 three- and four-digit industries, estimated using Roeger's (1995) methodology, which builds on Hall (1988); we aggregate to the two- and three-digit industry level using value-added shares.

Educational attainment: "Percentage of higher school attained in the total population" from Barro and Lee (1994); reported for the whole economy at five-year intervals; we interpolate missing observations; industry-specific education proportions are from Machin and Van Reenen (1998), which is aggregated from individual-level data sources (such as the CPS in the United States). These numbers are available only for France, Germany, Japan, Sweden, the United Kingdom, and the United States.

2. TFP Measures

Much attention has been paid to how to measure TFP accurately and how to obtain comparable numbers across countries. We measure TFP in a number of ways and test whether our results are robust to the various corrections. We do four main types of corrections: (a) adjustments to the measure of labor inputs for differences in hours worked and skill levels, (b) adjustments to factor shares due to imperfect competition, (c) adjustments to the capital stock for differences in capacity utilization, and (d) the use of manufacturing-industry-specific rather than economy-wide PPPs. Our baseline measures are described in section IV, and were constructing using the data as reported in the ISDB.

2.a Adjusting labor input for differences in hours and skills

Our base measure is numbers employed in industry j of economy i. We adjust this by average annual hours actually worked per person in employment (from the ISDB). This is an economy-wide adjustment. We also control for differences in the quality of labor inputs. Employment in each country-industry-year is subdivided into the number of production and nonproduction workers. Aggregate labor input is expressed as an index of the two types of labor,

$$L_{ijt} = (h_{ijt})^{s_{ijt}}(u_{ijt})^{1-s_{ijt}},$$

where h_{ijt} denotes the number of nonproduction workers, u_{ijt} the number of production workers, and s_{ijt} the share of nonproduction workers in the wage bill. In making this adjustment, we use country-industry data on h_{ijt} and s_{ijt} where they are available (for Canada, Denmark, Finland, Japan, Sweden, the United Kingdom, and the United States) and mean values of h_{ijt} and s_{ijt} across these countries in each industry where the data are not available.

2.b Adjusting for markups

We allow for imperfect competition with country-industry-specific markups. The labor share parameter α_{ijt} in the superlative indices of TFP growth and relative TFP [equations (9) and (10)] is replaced by

$$\tilde{\alpha}_{ijt} = \mu_{ij}\alpha_{ijt},$$

where μ_{ij} is the country-industry-specific markup.

2.c Adjusting capital for capacity utilization

We adjust for the fact that countries may have different economic cycles, and that during downturns capital may not be fully used, whereas during booms it may be overused. We construct a measure of capacity utilization by estimating a smoothed output series, $\hat{Y}_{ijt}$, which is predicted from a regression

$$Y_{ijt} = \delta_{ij} + t_t,$$

where t_t is a time trend. Adjusted capital input is then given by

$$(K \times CU)_{ijt} = K_{ijt}\left(1 + \frac{Y_{ijt} - \hat{Y}_{ijt}}{\hat{Y}_{ijt}}\right).$$

[43] This is a crude distinction, but is the only one available consistently across a large range of industries and countries over time. It has been analyzed extensively by other authors (such as Berman, Bound & Machin, 1998), who have found the occupational split highly correlated with alternative measures of human capital (such as education).