R&D, innovation, and technological progress: a test of the Schumpeterian framework without scale effects

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Abstract. I use U.S. manufacturing industry data to estimate a system of three equations implied by a model of R&D-induced growth in steady state. These equations relate R&D intensity to patenting, patenting to technological progress, and technological progress to economic growth. In each case, I find evidence of positive impact. Thus, I reject the null hypothesis that growth is not induced by R&D in favour of the Schumpeterian endogenous growth framework without scale effects. I also find strong support for technological spillovers from aggregate research intensity to industry-level innovation success. JEL Classification: O40, O30

R&D, innovation, et progrès technologique: un test du cadre schumpétérien en l'absence-d'effets d'échelle. L'auteur utilise des données de l'industrie manufacturière pour calibrer un système de trois équations émergeant d'un modèle de croissance en régime permanent induite par le R&D. Ces équations relient l'intensité de R&D à l'obtention de brevets, l'obtention de brevets au progrès technologique, et le progrès technologique à la croissance économique. Dans chaque cas, on trouve un impact positif. En conséquence, l'auteur rejette l'hypothèse nulle que la croissance n'est pas engendrée par le R&D en faveur de l'hypothèse de croissance endogène à la Schumpeter sans effets d'échelle. L'auteur confirme fortement l'hypothèse d'effets de retombées technologiques sur le succès de l'innovation au niveau de l'industrie en conséquence d'une forte intensité de recherche.

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1. Introduction

In this paper, I implement a direct test of endogenous growth theory based on a Schumpeterian endogenous growth model without scale effects. This framework, which includes Dinopoulos and Thompson (1998), Howitt (1999), and Segerstrom (2000), emphasizes the growth-enhancing effects of research expenditures undertaken by profit-making entrepreneurs. Unlike exogenous or semi-endogenous growth models, these models are consistent with policy's having a long-run impact on economic growth so that empirical testing of Schumpeterian growth models can be informative about the potential for policy to influence technological progress and economic growth in the long run.

The Schumpeterian framework implies a positive relation between R&D intensity, the rate of patenting, technological change, and the growth rate of output per worker. My approach relies on a system of equations and restrictions implied by this endogenous growth framework in steady state. I derive and estimate the implications of the Schumpeterian framework of endogenous growth as a system of equations examining the impact of (i) R&D intensity on the rate of patenting, (ii) the rate of patenting on technological progress, and (iii) technological progress on economic growth. Consistent with the model's assumption that individual industries can draw from an aggregate pool of knowledge, I also consider the effect of total manufacturing innovative activity variables on the average industry's innovation success.

In the paper I utilize data from a panel of industries at the 2-digit SIC classification of U.S. manufacturing for the period 1963–88. The manufacturing sector accounted for more than 90% of R&D expenditures in the United States until the late 1980s. Thus, this sector offers a natural laboratory in which to examine the validity of models of R&D-based growth. Moreover, the U.S. manufacturing sector is a useful benchmark for studying the link between innovation and economic growth, since the United States is arguably at the world technological frontier.

The evidence presented in this paper provides support for the Schumpeterian endogenous growth framework without scale effects. I show that R&D intensity has a positive impact on the rate of patenting. The rate of patenting is then shown to drive technological progress which in turn drives the growth rate of output per worker. Moreover, the evidence points to technological spillovers from aggregate research intensity to industry-level innovation success.

The endogenous growth framework considered here is free of the scale effects implication of first-generation endogenous growth models such us Romer (1990), Segerstrom, Anant, and Dinopoulos (1990), and Aghion and Howitt (1992.) A scale effect arises in these models because they predict that a higher level of R&D expenditures (or a more populous economy) will be associated with higher rates of economic growth in steady state. This prediction does not fare well in the data. Accordingly, these models were criticized by

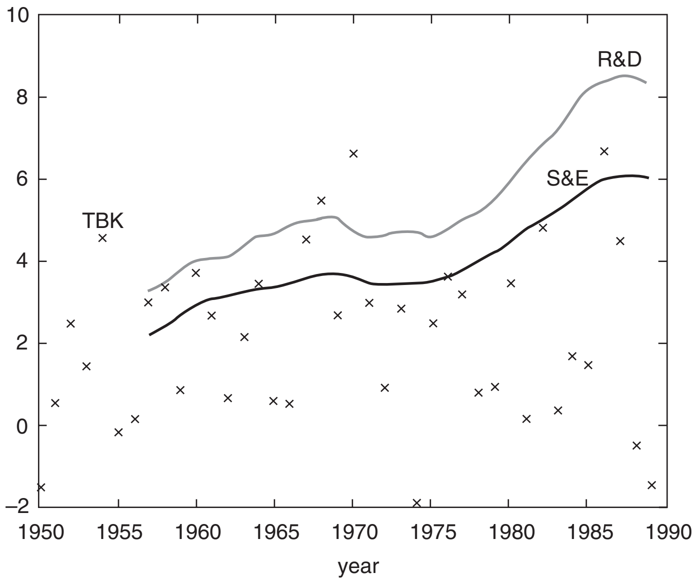

FIGURE 1 R&D expenditures, scientists and engineers, and the rate of technological progress
NOTES: The U.S. manufacturing sector research and development expenditures shown in figure 1 as 'R&D,' are total industry research and development expenditures in constant dollars from table 4.2 of the BEA R&D Satellite accounts. In the above figure, this is given in billions of 1987 $US. The series of scientists and engineers for the U.S. manufacturing sector shown in figure 1 as 'S&E,' is the annual average full-time-equivalent number of research and development scientists and engineers from table 4.3 of the BEA R&D Satellite accounts. In figure 1, this is given in hundreds of thousands. Technological progress (TBK) refers to the Basu, Fernald, and Kimball (1998) fully corrected estimate of technological progress, here given in percentages. This accounts for imperfect competition and removes spurious procyclicality from total factor productivity growth.

Jones (1995b), who pointed out rising R&D expenditures and rising numbers of scientists and engineers in relation to the constancy of TFP growth as evidence against first-generation endogenous growth models.[1] His argument is portrayed in figure 1, which reproduces figure 1 from Jones (1995b) with U.S. manufacturing data. As is evident here, the rising levels of R&D expenditures and of the number of scientists and engineers have not been accompanied by an increase in the rate of technological progress, as would be predicted by early endogenous growth models.

Schumpeterian endogenous growth models without scale effects are essentially a response to the Jones critique. These models predict a positive relation between the fraction of GDP allocated to R&D expenditures (R&D intensity)

1 Jones (1995b) then proposes a 'semi-endogenous' growth theoretical framework where, in steady state, the growth rate of labour drives the rate of economic growth, and variables that can be influenced by policy have no effect. Similarly, Segerstrom (1998) considers a semi-endogenous growth setting. Both models imply a transition period which is several decades long.

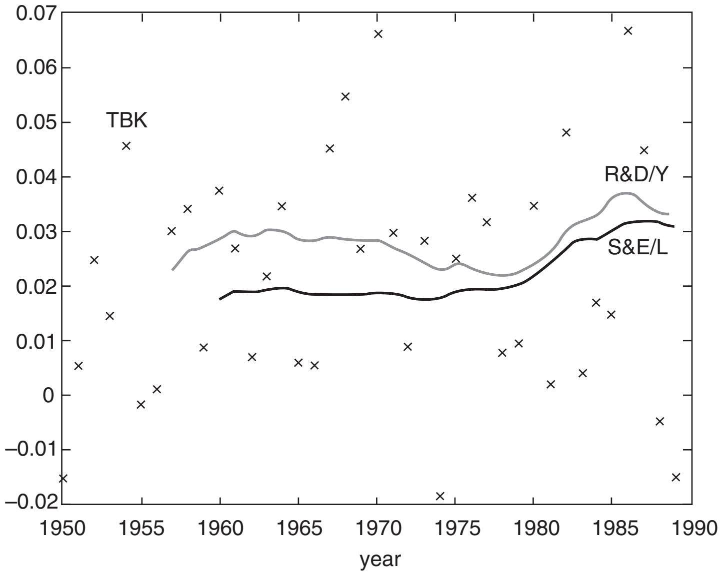

FIGURE 2 R&D intensity, scientists and engineers over employment, and the rate of technological progress
NOTES: The R&D intensity series for the manufacturing sector shown in figure 2 as 'R&D/Y,' is constructed by dividing R&D expenditures in current dollars by gross output in current dollars. R&D in current dollars is total industry research and development expenditures, including federally funded R&D, in millions of dollars from table 3.1 of the BEA R&D Satellite accounts. Gross output in current dollars is taken from the Jorgenson, Gollop, and Fraumeni database. The series for the fraction of the labour force engaged in R&D activities shown in figure 2 as 'S&E/L,' is constructed using the series for the number of scientists and engineers in the manufacturing sector from figure 1, divided by total employment in manufacturing. Total employment in manufacturing for the period 1960–92 is taken from the OECD Sectoral Database of 1994. Technological progress (TBK) refers to the Basu, Fernald, and Kimball (1998) fully corrected estimate of technological progress. This accounts for imperfect competition and removes spurious procyclicality from total factor productivity growth.

and technological progress but do not presume a relation between the latter and the level of R&D expenditures, as was implied by first-generation models. As a result, these models suggest that the rate of technological progress remains constant during periods when R&D intensities are constant. Figure 2 illustrates the behaviour of R&D intensity and technological progress for aggregate U.S. manufacturing during the period 1957–89. Unlike the R&D expenditures levels shown in figure 1, the fraction of GDP allocated to R&D shown in figure 2 appears to be relatively constant. Figure 2 also presents the share of labour devoted to R&D activities, S&E/L, in the manufacturing sector for the period 1960–89. To the extent that figure 2 shows this variable exhibiting similar time-series behaviour with R&D intensity, then the positive relation between R&D intensity and technological progress documented in this paper would suggest a similar positive relation between technological progress and the share of labour devoted to R&D activities.[2]

In this paper, I utilize empirical measures corresponding closely to the theoretical concepts of the R&D input, the rate of innovation, and the rate of technological progress that arise in the above framework. First, Aghion and Howitt (1998, 418) suggest that R&D intensity, rather than the R&D stock or the number of scientists and engineers, is the proper measure for the R&D input in the innovation function within the context of the endogenous growth model without scale effects I consider here. Thus, I construct R&D intensities as the fraction of output devoted to R&D expenditures. Second, Kortum (1993) shows that the rate of patenting is the relevant measure for quality-ladder models like the one examined here. Thus, I construct measures of the rate of patenting to proxy for the rate of innovation. Finally, I use the Basu, Fernald, and Kimball (1998) fully corrected estimate of technological progress which is consistent with the imperfect competition assumption of this endogenous growth framework and removes spurious[3] procyclicality from TFP growth. My approach is also consistent with Kirchhoff's (1994) and Geroski's (1994) discussions on innovative activity: R&D is considered to be an input into the production of patents or inventions, and patents as intermediates into the production of innovations that bring about gains in productivity. To capture the chain of events leading to technological progress, I explicitly take into account the relationship between R&D intensity and the rate of patenting as implied by the production function of inventions and use the rate of patenting to proxy for the rate of innovation.[4]

The paper deviates from the earlier empirical literature as documented below. That literature typically has examined the relation between R&D and patenting, or between R&D and productivity in isolation from one another

2 Jones (1995b) argues against his specification (3) on p. 762, which relates TFP growth to the share of labour devoted to R&D. He presents the rising share of labour devoted to R&D in his figure 2 on p. 764 as evidence against this relation. The importance of this relation lies in the fact that 'With a specification such as (3), it is easy to see that R&D drives TFP growth and that subsidies to R&D . . . will raise the steady-state growth rate.' To make a conclusive statement on the relation of technological progress to the fraction of labour employed in R&D activities, further investigation is needed. I do not attempt to estimate the latter relation because R&D intensity corresponds more closely to the theoretical model under study and because data on scientists and engineers are more fragmented at the industy level, compared with R&D data.

3 'Spurious' in the sense that such cyclicalities are unrelated to technical change, which is what TFP growth aims to measure when used in growth applications.

4 In related work, Caballero and Jaffe (1993) develop an empirical framework consistent with a Schumpeterian model of creative destruction but do not estimate the overall system of equations implied by the model as a whole, as I do here. Crepon, Duguet, and Mairesse (1998) investigate the channels through which R&D impacts on innovation and productivity growth for French manufacturing firms and report evidence for a positive relation between research effort and innovation output as proxied by patent numbers, as well as between the latter and productivity growth. My paper complements their work, since I study these relations at a more aggregate level over a longer time dimension and by providing a direct link to long-run economic growth.

within a partial equilibrium framework. Instead, I explore a theoretically implied system of equations in which all the stages of the innovation process are considered simultaneously. In this sense, the approach adopted here provides a unifying framework where the interrelations at different stages of the innovation process are explicitly taken into account. Estimating such a system improves the efficiency of estimation relative to estimating individual relations implied by partial equilibrium analysis and can provide more accurate estimates of the impact of R&D on technological progress and economic growth, accounting for the specific mechanics that link these concepts together.

Pakes and Griliches (1984) study the relationship between R&D and patenting for a large number of firms over a short time period. They consider contemporaneous effects as well as lags of R&D and find that the sum of the contemporaneous and lagged effects is positive and significant. Griliches (1990) points out that the latter result is driven by a large contemporaneous effect and explains that this might well be due to reverse causality. To address this problem, I employ an instrumental variables approach, instrumenting contemporaneous values of the explanatory variables with their lags. On the other hand, studies of the direct partial equilibrium relation between R&D and productivity, reviewed in Nadiri (1993), give mixed results, with the significance of the relation being sensitive to the time period under study and the level of disaggregation.[5] More recent work on the direct link between R&D and productivity includes Zachariadis (forthcoming), who provides evidence for R&D-induced growth in OECD countries; Keller (2002), who documents the role of international spillovers on the relation between R&D and productivity growth in the OECD; and Griffith, Redding, and Van Reenen (2000), who use OECD data to show that R&D can enhance the ability of firms to learn as well as stimulate innovation directly. In this paper, I provide support for a direct as well as an indirect relationship between R&D intensity and productivity growth.

To summarize: the endogenous growth framework considered here implies in steady state a positive impact of R&D intensity on the rate of patenting, of the rate of patenting on the rate of technological change, and of the latter on the growth rate of output per worker. I find that a positive impact exists in each case and that aggregate manufacturing R&D has a strong positive impact on industry patenting rates consistent with technology spillovers across manufacturing industries. These findings lead to a rejection of the null hypothesis that growth is not induced by R&D, in favour of the Schumpeterian endogenous growth framework without scale effects.

Next, I provide the theory behind the empirical specification. In the third section, I describe the data, in section 4 I describe the empirical analysis and results, and section 5 briefly concludes.

5 These studies, which include Griliches (1980a,b), Mansfield (1988), and Griliches and Mairesse (1990), have typically used broad cross-sections of firms or disaggregated industry data over small periods of time.

2. Theoretical motivation

I consider a model from Aghion and Howitt (1998) and Howitt (1999) in order to study the implications of the Schumpeterian endogenous growth framework without scale effects. This framework is best viewed in the context of developed economies that perform R&D. Below, I provide a brief and non-rigorous description of the model's main components.

Growth in this model is driven by vertical drastic innovations that improve the quality of goods and displace previous incumbents. The model includes a final goods sector with constant returns to scale, Q_t monopolistic intermediate industries, and a research sector that develops new generations of inputs targeted at specific intermediate industries. The model provides a set of testable implications comprising (1) a positive relation between the arrival rate of innovations and R&D intensities, (2) a positive relation between the average rate of productivity growth and the arrival rate of innovations, and (3) a positive relationship between the growth rate of output per worker and the rate of productivity growth. As shown below, the first two implications are a direct consequence of the production function of knowledge in the research sector, while the third implication follows from the final output equation and the intermediate inputs production function.

Output of the single final good, Y_t, at time t is produced as $Y_t = (L_t/Q_t)^{1-\alpha} \int_0^{Q_t} A_{it} x_{it}^{\alpha} di$ with A_{it} a productivity parameter attached to the latest version of intermediate product i, x_{it} the output flow of intermediate product i, Q_t the number of intermediates which grows as a result of imitation (not deliberate innovation), and L_t the labour input in the final goods sector growing at an exogenous population rate. Division of L_t by Q_t eliminates any productivity gain resulting from product proliferation. The assumption here is that population and product variety (the number of intermediate sectors) grow at the same rate, so that the market size for any one intermediate product remains constant as population grows. This deals with the 'demand-driven scale effects' implied by earlier endogenous growth models.[6] Each intermediate sector is monopolized and sells its product to the competitive final sector at a price equal to the marginal product of that intermediate input in producing the final good. Capital is used as an input in the production of intermediate goods, so that the output flow of intermediate input in sector i in period t is given by $x_{it} = K_{it}/A_{it}$ where K_{it} is the capital input for sector i, and A_{it} is the sector-specific productivity parameter attached to the latest version of intermediate product i. Division of the capital input by this productivity parameter indicates that successive vintages of the intermediate product i are produced

6 Jones (1999) shows that a proportionate relation between product variety and population is needed for the Dinopoulos and Thompson (1998) or the Howitt (1999) models to avoid the scale effects problem. If product variety increases more than proportionately with population, then one is left with the Jones (1995b) model, where long-run growth is simply proportional to the rate of population growth and does not depend on other endogenous variables. If product variety increases less than proportionately with population, then the implication is that Howitt's (1999) model still exhibits scale effects in growth.

by increasingly capital-intensive techniques. As a result, in a steady state, capital and productivity will have to grow at the same rate for the output flow of intermediate product x_{it} to be constant.

Turning now to the research sector looking to develop the next generation of an intermediate input i, the flow of innovation output, ϕ_{it}, is given as

$$\phi_{it} = \lambda\phi(n_{it}) = \lambda\phi\left(\frac{R_{it}}{A_t^{\max}}\right), \phi' > 0, \phi'' < 0, \tag{1}$$

where $\lambda > 0$ is the flow probability of an innovation and indicates R&D productivity, the function ϕ exhibits decreasing returns to R&D as a result of a research congestion externality within any one product associated with duplication and overlap, and $n_{it} = R_{it}/A_t^{\max}$ is the research intensity, with R_{it} the total amount of final output invested in R&D at date t. The same equilibrium flow of research input R_{it} is used for any intermediate input i, so that $R_{it} = R_t$. Finally, $A_t^{\max}$ is the leading-edge productivity parameter at date t, and division by this indicates that the cost of further advances increases proportionately to technological advances as a result of increasing complexity. That is, research expenditures should increase at the same rate as the technology frontier shifts outwards just to keep the flow of innovations constant. Equation (1) implies a positive relationship between the rate of innovation arrival (the rate of patenting) and the productivity-adjusted level of R&D at time t given by n_t. As Aghion and Howitt (1998) argue, in a steady state, the latter can be measured by the fraction of output allocated to R&D.[7]

The arrival rates of innovations in different sectors draw from the same pool of knowledge whose state is represented by the leading-edge technology parameter $A_t^{\max}$. An important characteristic of this framework is that growth in the leading-edge technology occurs as a result of the knowledge spillovers produced by innovations. Each innovation is implementable only in the intermediate industry in which it is used, but increases the knowledge stock depending on the innovation size σ, so that the next innovator in any intermediate industry can draw from an expanded pool of knowledge. Finally, the ratio of the average to leading-edge technology is $A_t^{avr} = A_t^{\max}/(1+\sigma)$ which, with constant σ, implies $\dot{A}_t^{avr}/A_t^{avr} = \dot{A}_t^{\max}/A_t^{\max}$. From the above, productivity growth, g_t, will depend on the size of innovations, σ, and the innovation rate, ϕ_t, so that

$$g_t = \frac{\dot{A}_t^{avr}}{A_t^{avr}} = \sigma\phi_t. \tag{2}$$

7 The rate at which the technology frontier improves drives the rate of output growth. Thus, in a steady state, the ratio R_t/Y_t, where Y_t stands for output, behaves similarly to $R_t/A_t^{\max}$.

This equation suggests a positive relationship between productivity growth and the rate of patenting.[8]

Finally, we need to obtain a relation between the growth rate of output per worker and technological progress. With some manipulation, the output equation for the final good can be rewritten in the standard per capita form as $Y_t/L_t = A_t^{avr} k_t^{a}$.[9] Taking logs and differentiating with respect to time, the latter expression then implies that the growth rate of output per worker, G_t, is given by

$$G_t = g_t + \alpha \frac{\dot{k}_t}{k_t}. \qquad (3)$$

In a steady state, the growth rate of capital, $\dot{k}_t/k_t$, is equal to zero and economic growth depends solely on the rate of technological progress. In the system estimation in the next section, I consider the relationship of the growth rate of output per person with the rate of technological progress in steady state.

3. A preliminary look at the data

I use annual data on patents, R&D expenditures, gross output, and productivity growth. These data are available for the period 1963–88 for the manufacturing sector and 10 2-digit industries of this same sector. These are 20: Food and Kindred Products, 28: Chemicals and Allied Products, 30: Rubber and Plastics Products, 32: Stone, Clay, and Glass Products, 33: Primary Metal Industries, 34: Fabricated Metal Products, 35: Machinery Except Electrical, 36: Electrical Machinery, 37: Transportation Equipment, and 38: Instruments and Related Products.

8 When $\phi(n_t) = n_t^{\gamma}$, then $\dot{A}_t^{avr}/A_t^{avr} = v(R_t)^{\gamma}(A_t^{avr})^{-\gamma}$ with $v = \sigma\lambda(1+\sigma)^{-\lambda}$, and the equation for the growth rate of average productivity resembles the research technology in Jones (1995b), the main difference being that now R_t includes capital inputs.

9 The derivation steps follow. First, the condition for equilibrium in the capital market gives $K_t = \int_0^{Q_t} K_{it} di$, which combined with the condition for intermediate output gives $K_t = \int_0^{Q_t} A_{it} x_{it} di = x_t Q_t A_t^{avr}$. Output for intermediates is thus given by $x_t = K_t / A_t^{avr} Q_t$. Noting that $x_{it} = x_t$, and plugging the latter in the output equation, we see that

$$Y_t = \left(\frac{L_t}{Q_t}\right)^{1-\alpha} \int_0^{Q_t} A_{it}(K_t/A_t^{avr} Q_t)^{\alpha} di$$

$$= \left(\frac{L_t}{Q_t}\right)^{1-\alpha} A_t^{avr} Q_t (K_t/A_t^{avr} Q_t)^{\alpha} \text{ or}$$

$$Y_t = (A_t^{avr} L_t)^{1-\alpha} K_t^{\alpha} = A_t^{avr} L_t k_t^{\alpha}.$$

Since the theoretical model is consistent with stationarity of the variables utilized here – namely, the rate of patenting, R&D intensity, the growth rate of productivity, and the growth rate of output per worker – the starting point should be to test for the null of stationarity rather than the null of a unit root. More specifically, I apply the $G(p, q)$-tests from Park (1990.) Under the null that a variable is stationary after removing the maintained deterministic time trends of time polynomial of order p, the $G(p, q)$-test has asymptotic chi-square distribution with q-p degrees of freedom. These tests are based on spurious regression results. Consider a regression:

$$x_t = \sum_{t=0}^{p} \mu_\tau t^\tau + \sum_{t=p+1}^{q} \mu_\tau t^\tau + \eta_t.$$

The maintained hypothesis is that the variable x possesses deterministic time polynomials up to the order of p, and additional time polynomials are spurious time trends. Kahn and Ogaki (1992) perform Monte Carlo experiments on Park's $G(p, q)$-tests and conclude that a small q is advisable for small samples. Thus, I use the $G(p, q)$-tests for $q = 1$, 2, and 3. I consider the case of $p = 0$ (no deterministic trend) and $p = 1$ (with deterministic trend.) I report the results for both $p = 0$ and $p = 1$ which are, in general, very similar. Nevertheless, the literature suggests that a prior based on independent information regarding the presence or absence of a deterministic trend is useful. For example, institutional changes negatively affecting the propensity to patent over time suggest the presence of a negative deterministic trend, whereas no such prior information about the presence of a trend exists for R&D intensity, productivity growth, or the growth rate of output per worker. Moreover, a deterministic trend does not enter significantly into the univariate analysis of the latter three series but is significant and negative for the rate of patenting.[10] Thus, even though I report results for the stationarity tests with a deterministic trend as well as without one, I favour the $G(0, q)$-tests for the latter three variables and the $G(1, q)$-test for the rate of patenting. For all the variables, I present the results of Park's $G(p, 2)$, $G(p, 3)$, and $G(p, 4)$ stationarity tests for $p = 0$ or $p = 1$ in table 1. A panel test that uses the Bonferroni bound is also performed for each variable. In general, using a Bonferroni bound, one would reject the null

10 The null hypothesis that the deterministic trend coefficient is zero in a regression of the form $y = c + \beta t + \gamma y_{t-1}$ cannot be rejected for these three series at a 5% level of significance using a Bonferroni Bound, but is rejected for the rate of patenting. I also tested for the presence of a split trend term that allows for a change in the slope of the trend. The split trend term is the coefficient γ in a regression resembling the first step of Perron's (1989) model B: $y_t = \mu + \beta t + \gamma DT_t^* + error_t$, with $DT_t^* = t - T_B$, where T_B is the 'break' period. The null that γ is zero is not rejected at the 5% level of significance for the three dependent variables of equations (1), (2), and (3): the rate of patenting, productivity growth, and the growth rate of output per worker. Thus, a split trend is not included in the empirical specification of section four.

TABLE 1
P-values for the stationarity null (*G*-test; Park 1990)

	$G(0, 2)$	$G(0, 3)$	$G(0, 4)$	$G(1, 2)$	$G(1, 3)$	$G(1, 4)$
R&D Intensity						
Total Manufacturing	0.363	0.283	0.253	0.172	0.167	0.176
Food & Kindred Products	0.031*	0.084	0.160	0.216	0.263	0.238
Chemicals & Allied Products	0.363	0.266	0.152	0.164	0.094	0.157
Rubber & Plastics Products	0.066	0.078	0.165	0.035*	0.108	0.170
Stone, Clay & Glass Products	0.059	0.137	0.262	0.246	0.494	0.319
Primary Metal Industries	0.767	0.296	0.375	0.118	0.208	0.036*
Fabricated Metal Products	0.218	0.415	0.149	0.492	0.024*	0.057
Machinery Except Electrical	0.033*	0.075	0.159	0.037*	0.109	0.159
Electrical Machinery	0.066	0.137	0.254	0.214	0.406	0.180
Transportation Equipment	0.656	0.569	0.359	0.317	0.196	0.154
Instruments & Products	0.033*	0.098	0.188	0.257	0.253	0.234
Rate of patenting						
Total Manufacturing	0.109	0.269	0.213	0.677	0.036*	0.071
Food & Kindred Products	0.182	0.349	0.263	0.433	0.121	0.232
Chemicals & Allied Products	0.092	0.162	0.139	0.139	0.027*	0.059
Rubber & Plastics Products	0.114	0.286	0.208	0.952	0.036*	0.034*
Stone, Clay & Glass Products	0.118	0.284	0.218	0.609	0.033*	0.051*
Primary Metal Industries	0.086	0.228	0.216	0.843	0.042*	0.096
Fabricated Metal Products	0.101	0.226	0.212	0.302	0.033*	0.064
Machinery Except Electrical	0.070	0.188	0.221	0.558	0.051*	0.101
Electrical Machinery	0.163	0.327	0.217	0.414	0.055	0.079
Transportation Equipment	0.076	0.204	0.234	0.685	0.087	0.180
Instruments & Products	0.368	0.659	0.194	0.856	0.061	0.131
Rate of technological progress						
Total Manufacturing	0.957	0.477	0.685	0.224	0.476	0.638
Food & Kindred Products	0.387	0.608	0.434	0.614	0.359	0.556
Chemicals & Allied Products	0.309	0.589	0.529	0.873	0.539	0.701
Rubber & Plastics Products	0.668	0.502	0.648	0.274	0.479	0.669
Stone, Clay & Glass Products	0.479	0.531	0.679	0.381	0.603	0.656
Primary Metal Industries	0.289	0.522	0.722	0.665	0.897	0.975
Fabricated Metal Products	0.606	0.499	0.669	0.288	0.523	0.729
Machinery Except Electrical	0.014*	0.046*	0.093	0.722	0.778	0.859
Electrical Machinery	0.331	0.282	0.469	0.198	0.436	0.233
Transportation Equipment	0.143	0.275	0.234	0.493	0.318	0.514
Instruments & Products	0.257	0.118	0.136	0.074	0.104	0.025*
Growth rate of output per worker						
Total Manufacturing	0.687	0.409	0.602	0.200	0.425	0.634
Food & Kindred Products	0.118	0.145	0.053*	0.205	0.051*	0.082
Chemicals & Allied Products	0.680	0.703	0.265	0.462	0.147	0.273
Rubber & Plastics Products	0.740	0.219	0.385	0.088	0.233	0.369
Stone, Clay & Glass Products	0.538	0.499	0.587	0.314	0.459	0.439
Primary Metal Industries	0.118	0.145	0.053*	0.205	0.051*	0.082
Fabricated Metal Products	0.239	0.242	0.387	0.207	0.405	0.342
Machinery Except Electrical	0.678	0.886	0.965	0.793	0.950	0.837

(*continued*)

TABLE 1 *concluded*

	G(0, 2)	G(0, 3)	G(0, 4)	G(1, 2)	G(1, 3)	G(1, 4)
Electrical Machinery	0.945	0.843	0.917	0.562	0.777	0.906
Transportation Equipment	0.133	0.188	0.218	0.264	0.286	0.411
Instruments & Products	0.248	0.306	0.457	0.276	0.483	0.672

NOTES: *Reject the Null of stationarity at the 5% level of significance for the individual industry. R&D intensity is the fraction of output spent on research and development. This is available for 1957–89. The rate of patenting is the number of patents over the stock of patents. This is available for 1963–88. The growth rate of output per worker is available for 1951–89. This is the growth rate of the ratio of gross output over labour quantity using Jorgenson's gross output data and labour quantity data. The rate of technological progress is the Basu, Fernald, and Kimball (1998) measure (TBK) and is available for 1951–89.

hypothesis at the 10% level of significance for a panel of *n* industries if one can reject the null hypothesis at the $10/n$ level of significance for any of the *n* industries.

U.S. R&D data for 1957–92 were compiled by Bruce Grimm and Carol Moylan at the BEA as part of the R&D Satellite Accounts in 1994. They are available for 1957 to 1992. These R&D data account for research and development expenditures by 'Federally Funded Research and Development Centers' (FFRDC), which are administered by industry, as well as private business R&D expenditures. R&D intensities at the industry level are constructed as the ratio of R&D expenditures in current dollars over gross output in current dollars.[11] In table 1, I present the results of the stationarity tests for the R&D intensities in manufacturing and its 2-digit industries for which data are available. The individual industry variables appear to be stationary,[12] and a panel test that uses the Bonferroni bound implies that the null of stationarity cannot be rejected even at the 10% level of significance.

The available patents data consist of patents granted allocated in the year in which the application was filed with the U.S. patent office. These are available at the industry level for the period 1963–88. I obtained these data from the ESRC Data Archive. These data were collected by the U.S. Department of Commerce and compiled by R.A. Wilson in 1991. I construct the stock of patents as a measure of the knowledge stock using a knowledge obsolescence rate of 7% and the average annual rate of technological obsolescence over the past century as estimated by Caballero and Jaffe (1993). The benchmark year

11 Specifically, R&D expenditures in current dollars is total industry Research and Development Expenditures by performing industry in millions of dollars from table 3.1 of the BEA R&D Satellite accounts. Gross output for the period 1950–89 is taken from the database constructed by Jorgenson and his associates.

12 The null of stationarity is rejected at the 5% level of significance using Park's $G(0, 2)$-test for industries 20, 35, and 38, using the $G(1, 2)$-test for industries 30 and 35, using the $G(1, 3)$-test for industry 34, and using the $G(1, 4)$-test for industry 33. Overall, the null of stationarity is never rejected for an industry by more than one of the three tests for $p = 0$ or $p = 1$.

(1963) stock is given by the number of patents over the depreciation rate.[13] I accumulate this up to 1988 using $(Stock\ of\ Patents)_t = (Stock\ of\ Patents)_t + (1 - 0.07) \times (Stock\ of\ Patents)_{t-1}$. The rate of patenting is then given by the ratio of the number of patents for any one year over the stock of patents up to that year. Given that the model is consistent with a stationary rate of patenting in steady state, I test this series for the null of stationarity. Table 1 presents the results of the stationarity tests for the rate of patenting in manufacturing and its 2-digit industries with available data. A panel test using the Bonferroni bound implies that the null of stationarity cannot be rejected even at the 10% level of significance.[14]

The rate of technological progress is usually proxied by total factor productivity (TFP) growth. Under the assumptions of constant returns to scale, perfect competition in the inputs and outputs markets, instantaneous adjustment of all inputs (long-run equilibrium), correct aggregation, and correct measurement of the several inputs and outputs, TFP growth measures exactly the exogenous shifts in the production function and thus is identical to the 'true' technology shock. In the presence of non-constant returns to scale, imperfect competition, factor adjustment costs, aggregation bias, and measurement errors for input and output quantity and quality, the degree of cyclicality and persistence of measured TFP growth generally will not coincide with the cyclicality and persistence of the technology shock. Basu, Fernald, and Kimball provide estimates of the technological change component of TFP growth for U.S. manufacturing for 1950–89 and the Jorgenson input and output data for the U.S. economy for 1948–89. They use Jorgenson's quality-adjusted gross output data[15] and consider adjustments for non-constant returns to scale, imperfect competition, cyclical factor utilization, and aggregation effects. The resulting fully corrected estimate of technological change (TBK) removes the contemporaneous procyclical bias. This measure is consistent with the imperfect competition assumption of endogenous growth models. Moreover, it enables an improved (cyclicality-free) assessment of the relation between technological change and innovative activity. Thus, I use this fully corrected technological progress measure, TBK, throughout the paper. In table 1, I present the results of the stationarity tests for the rate of technological progress. The individual industry variables appear stationary in the great majority of industries,[16] and a panel test that uses the Bonferroni bound

13 The growth rate of patents ranged from positive to negative values over the period, so that the average was close to zero.

14 Looking at each individual industry, there are six rejections of the null of stationarity at the 5% level of significance using Park's (1990) $G(1, 3)$-test. These are for industries 28, 30, 32, 33, 34, and 35. The $G(1, 4)$-test rejects the stationarity null only for industries 30 and 32, while Park's $G(1, 2)$-, $G(0, 2)$-, $G(0, 3)$-, and $G(0, 4)$-tests never reject the null of stationarity at the 5% level of significance.

15 For a detailed description of this dataset see Jorgenson, Gollop, and Fraumeni (1987).

16 The null of stationarity is rejected at the 5% level of significance using Park's $G(0, 2)$- and $G(0, 3)$-tests for industry 35, and using the $G(1, 4)$-test for industry 38.

implies that the null of stationarity cannot be rejected even at the 10% level of significance.

Finally, I use Jorgenson's gross output data and labor quantity data for U.S. manufacturing industries for the period 1950 to 1989 to calculate the growth rate of output per worker. In table 1, I also present results of stationarity tests for the growth rate of output per worker. Once again, the individual industry variables appear stationary in the great majority of industries[17] and a panel test that uses the Bonferroni bound implies that the null of stationarity cannot be rejected at the 10% level of significance.

4. Empirical analysis and results

Equations (1S), (2S), and (3S) follow from equations (1), (2), and (3) and form the basis of a system that in turn relates R&D intensity to the rate of patenting, the rate of patenting to the rate of technological progress, and, finally, the rate of technological progress to the growth rate of output per worker. This system is essentially the value-added from the use of an endogenous growth model in asking the questions relating to R&D, patents, and productivity. The restrictions implied by the model allow us to exclude other explanatory variables in the equations of the system and to get a relatively simple structure as follows:

$$\log \phi_{it} = \lambda_i + \tau t + \gamma \log n_{it} + u_{it} \tag{1S}$$

$$g_{it} = \psi_i + \sigma \phi_{it} + v_{it} \tag{2S}$$

$$G_{it} = \alpha_i + \xi g_{it} + e_{it}, \tag{3S}$$

where u_{it}, v_{it}, and e_{it} are stationary errors.[18] Here, n_{it} stands for R&D intensity, ϕ_{it} for the rate of patenting, g_{it} for the rate of technological change, and G_{it} for the growth rate of output per worker.

I estimate this system of equations for a panel of 10 industries during the period 1963–88,[19] by instrumenting the contemporaneous explanatory variables using their lagged values and applying three-stage least squares.

Equation (1S) is a logarithmic linearization of equation (1), which assumes $\phi(n_t) = n_t^{\gamma}$ as the functional form for the R&D production function, where n_{it}

17 The null of stationarity is rejected at the 5% level of significance using Park's $G(0, 4)$- and $G(1, 3)$-tests for industries 20 and 33.

18 As shown in section 3, we do not reject the stationarity null for the variables used in the above estimation. Keller (2002) also chooses a trend stationary specification for the relation between R&D and productivity and argues that whether or not a time series is deemed to be stationary depends on the level of heterogeneity in the data generation processes across industries that one allows for.

19 This gives us 230 observations. We have 23 annual observations after taking three lags for each of the three main explanatory variables of the system to be used as instruments for their contemporaneous values. Using the second lag or a combination of the lags to instrument the RHS variables does not change the results qualitatively.

stands for R&D intensity and ϕ_{it} for the rate of patenting in industry i at period t. The industry-specific constants λ_i capture an industry's research productivity but might also be capturing industry-specific differences in the propensity to patent. I also consider a common trend in equation (1S) to capture possible changes of the propensity to patent over time. This is consistent with the results of the univariate analysis regarding the presence of a deterministic trend for the rate of patenting. Indeed, changes in the propensity to patent are well documented – see, for example, Pakes and Griliches (1984) – and constitute an idiosyncrasy of this empirical measure of the rate of innovation.[20] These changes in the propensity to patent can be thought of as exogenous to the theoretical model and unrelated to the 'true' rate of innovation that the theoretical specification from equation (1) relates to. Accounting for changes in the propensity to patent extends the specification to better capture the 'true' rate of innovation.

For model II, I impose the restriction $n_{it} = n_t$ on equation (1S) in order to capture spillover effects from aggregate manufacturing R&D to the individual industries innovation production. This is consistent with the model's implication that R&D performed by any one firm increases the innovation success of other firms. The results are not sensitive to the inclusion or exclusion of own-industry R&D along with the aggregate measure in equation (1S.)

In going from the theoretical equation (2) to the empirical specification (2S), we suppose that the aggregate relation from the former equation is reflected in the behaviour of the average manufacturing industry. The hypothesis that the size of innovations is equal across industries, $\sigma_i = \sigma$, cannot be rejected at the 10% level of significance, and thus is imposed on equation (2S) to limit the number of parameters to be estimated. Industry-specific effects ψ_i added to equation (2S) capture the effect on technological change of heterogeneity among the industries due to factors other than the rate of innovation. Finally, preliminary testing suggested that a time trend need not be included in equation (2S). The univariate analysis for technological progress suggests that this does not possess a deterministic or other trend. When included, a time trend was estimated to be statistically indistinguishable from zero.

In model III, I allow for a direct effect of R&D on technological change by adding R&D intensity to the right-hand side of equation (2S). This direct effect of R&D on technology is in addition to the indirect effect through the impact of R&D on patents, which in turn enter equation (2S.) Some innovations are not patented, and for such cases the link between R&D and technological change will not be captured by the indirect effect of R&D on technological change through its effect on patenting. It is thus advisable to add a term for the direct effect of R&D to account for those cases in which innovations are not patented. This both serves as a robustness check of the results as well as

20 Griliches (1990) also suggests rising costs of patenting over time as an explanation for a decline in the number of patents.

TABLE 2
Regression results

Equations	Coefficients	I	II	III
1S: $\log \phi_{it} = \lambda_i + \tau t + \gamma \log n_{it} + u_{it}$	γ	0.206 (3.85)***	0.603 (9.04)***	0.189 (3.56)***
2S: $g_{it} = \psi_i + \sigma\phi_{it} + sn_{it} + v_{it}$	s			0.131 (2.03)**
	σ	0.369 (2.43)**	0.305 (2.45)**	0.462 (3.00)***
3S: $G_{it} = \alpha_i + \xi g_{it} + e_{it}$	ξ	1.049 (2.13)**	1.314 (2.41)**	0.715 (1.39)
p-value of hypothesis test that $\xi = 1$		0.920	0.577	0.580
Total R&D impact on economic growth		0.083	0.656	0.159
Total R&D impact on productivity growth		0.079	0.499	0.222

NOTES: *p-value of hypothesis test < 0.10; **p-value < 0.05; ***p-value < 0.01; t-tests of the hypothesis that the parameter equals zero given in brackets employing robust standard errors. There are 230 observations for 10 manufacturing industries × 23 years (1966–88). The parameters reported above are defined as follows: γ: parameter for the impact of R&D intensity on the Rate of Patenting. s: parameter for the direct impact of R&D intensity on Technological Change. σ: parameter for the impact of the Rate of Patenting on Technological Change. ξ: parameter for the impact of Technological Change on Economic Growth. The models estimated are as follows: I: basic model from equations (1S), (2S), and (3S). II: imposes $n_{it} = n_t$ on equation (1S). III: adds n_{it} to right-hand side of equation (2S.) The total impact on the growth rate of output per worker is $dG/dn = (\partial G/\partial g \cdot \partial g/\partial\phi \cdot \partial \log\phi/\partial \log n \cdot \bar{\phi}/\bar{n}) + (\partial G/\partial g \cdot \partial g/\partial n)$ ($\partial g/\partial n$ set to zero for models I and II.) The total impact on the growth rate of productivity is $dg/dn = \partial g/\partial\phi \cdot \partial \log\phi/\partial \log\phi/\partial \log n \cdot \bar{\phi}/\bar{n} + \partial g/\partial n$ (again, $\partial g/\partial n$ set to zero for models I and II).

addresses possible shortcomings of the patenting rate as a measure of the innovation rate.[21]

Finally, the variable G_{it} in equation (3S) stands for the growth rate of gross output per worker in industry i at time t. This equation captures the relationship between the growth rates of technological progress and output per worker in steady state. The industry-specific effects, α_i, in equation (3S) are meant to capture time-invariant heterogeneity among the industries that affects their output growth. The univariate analysis of the growth rate of output per worker suggests that a time trend need not be added.[22]

4.1. Results

In table 2, I present results for the basic system of equations (1S), (2S), and (3S) in column I as well as results for modifications of these equations in columns II and III.

21 Pakes and Griliches (1980, 378) argue that 'patents are a flawed measure (of innovation output); particularly since not all innovations are patented.'

22 When a time trend was added, this was estimated to be statistically indistinguishable from zero, while all other estimates remain unchanged.

The estimates from the first equation of the system relating R&D intensity to the rate of patenting are reported in the first row of table 2 and show that the former has a positive impact on the rate of innovation. The finding of a positive relationship between R&D and patenting over time complements the existing literature summarized in Griliches (1990), which reports evidence of a strong positive relationship between R&D and patenting at the cross-sectional level.[23] As we can see from the first row of column II, the impact of aggregate R&D, 0.603, is much greater than the impact of own-industry R&D shown in column I to be 0.206. The estimate of the impact of aggregate R&D is not sensitive to the inclusion of own-industry R&D in the regression.[24]

The estimates from the second equation, (2S), are reported in the second and third rows of table 2. As shown in the third row of the table, the impact of the rate of patenting on technological progress is estimated to be positive and statistically significant at 0.369, 0.305, and 0.462 for models I, II, and III, respectively. The finding of a positive relation here deviates from Kortum (1993). The direct impact of R&D intensity shown in the second row for model III is also estimated to be positive, at 0.131. This confirms the findings of some of the earlier work summarized in Nadiri (1993.)

Finally, the estimates for equation (3S), relating technological progress to economic growth, suggest a positive impact of technological progress on the growth rate of output per worker equal to 1.049, 1.314, and 0.715 for models I, II, and III. The hypothesis that there is a one-to-one relation between technological progress and economic growth cannot be rejected for any of the three models with p-values ranging from 0.92 to 0.58.

Using the estimates from each of the three equations in the system, we can estimate an overall impact of R&D intensity on technological progress and on economic growth. The overall impact of own-industry R&D intensity on technological progress in that industry is estimated to be 0.08 for model I and 0.22 when we include the direct impact of R&D on technological progress in model III. Combined with the estimated coefficient for the impact of productivity on economic growth, this implies that increasing an industry's R&D intensity by 1 percentage point increases the growth rate of output per worker in that industry by 0.08 or 0.16 percentage points for models I and III, respectively.

The return of aggregate R&D is much higher. Now, increasing aggregate R&D intensity by 1 percentage point increases the rate of technological progress by half a percentage point and increases the growth rate of output per

23 Moreover, the trend coefficient in equation (1S) is estimated to be negative at −0.022 (t-stat = −13.1), −0.026 (t-stat = −18.2), and −0.022 (t-stat = −13.2) for models I, II, and III, respectively. This is consistent with Pakes and Griliches (1984), who report a negative trend coefficient suggesting a falling propensity to patent.

24 When we include both aggregate manufacturing R&D and individual industry R&D in equation (1S) in model II, the former is virtually unchanged – remaining positive and statistically significant at 0.611 – whereas the latter is now statistically indistinguishable from zero.

worker by 0.66 percentage points. Thus, spillovers from aggregate R&D are shown to be important for the technological success of individual industries and for economic growth. It appears that the benefits of individual firms from R&D performed in the manufacturing sector as a whole far outweigh the benefits from R&D performed in their specific industry. This is consistent with the Aghion and Howitt growth-theoretical framework, where once an innovation is in place it is readily available to all R&D-performing firms irrespective of which industry that innovation came from.

Taken together, the parameter estimates from the three equations imply that the null hypothesis that economic growth is not induced by R&D can be rejected. This suggests the plausibility of R&D-induced growth for the United States.

4.2. Relationship with other evidence

The results reported above provide support for the Schumpeterian endogenous growth framework without scale effects presented in Aghion and Howitt (1998) and Howitt (1999.) In particular, R&D intensity is shown to be positively related to technological progress and the growth rate of output per worker. Moreover, there is a positive impact of aggregate R&D activity on an industry's innovation success. These findings also support the models of Dinopoulos and Thompson (1998) and Segerstrom (2000) and are consistent with the empirical findings of Dinopoulos and Thompson (2000), who provide evidence in favour of an augmented version of Romer's (1990) model for a cross-section of countries.

In a review of the literature on the relation between R&D and patents, Griliches (1990) concludes that there is a strong and positive relationship between R&D and patents at the cross-sectional level across firms and industries, but only a weak relationship in the within-firms time series dimension. My paper provides evidence for this relationship across a panel of industries over a 23-year period. Kortum (1993) looks at the patents-productivity relation using a panel of industries and finds a positive and significant coefficient for the growth rate of the patent stock and that the rate of patenting, which is the relevant measure for quality-ladder models like that of Aghion and Howitt (1998), does not perform as well. Here, I find a relationship between the rate of patenting and productivity growth, consistent with quality-ladder models. The finding of a positive relation between innovation inputs and technological change also deviates from Shea (1998.) Shea (1998) uses an unrestricted VAR approach to look at the relation between R&D and Patents on the one side and TFP on the other side, finding no evidence for a positive relationship. Instead, I obtain the relation between R&D intensity, patenting, and productivity growth, imposing restrictions on the structure as implied by the Schumpeterian framework of endogenous growth. Another difference is the use of an improved measure of technological progress here instead of the spuriously procyclical measure of annual TFP growth rates used in the earlier paper. Finally, Coe and Helpman (1995) estimate the relation between R&D stocks and productivity levels at the aggregate economy level for G7 countries during 1971–1990 and report returns on R&D expenditures in excess of 100%. Using industry R&D intensities rather than aggregate R&D stocks, I find lower returns for R&D in industries of the manufacturing sector.

Finally, by considering the mechanics of the relationship between technological change and output, this paper also makes a contribution to the literature on economic fluctuations. I demonstrate that innovative activity is important in explaining movements in productivity and output. This is consistent with Fatas (2000), who stresses the interrelation between cyclical fluctuations and long-term growth.[25]

5. Conclusion

Growth theory has made significant advances over the last decade or so. An important contribution is the Schumpeterian model, which predicts a higher rate of long-run economic growth for societies that generate higher R&D intensities. This framework emphasizes the role of endogenous R&D and patenting activity on productivity and ultimately economic growth. I estimate the implications of this Schumpeterian framework of endogenous growth in steady state as a system of interrelated equations linking R&D, patenting, technological change, and economic growth. The theoretically implied system estimation approach improves the efficiency of estimation and allows us to estimate the impact of R&D on economic growth, while accounting for the specific mechanics of this relationship. Consistent with the model's assumption that individual industries can draw from the aggregate pool of knowledge, I also consider the effect of total manufacturing innovative activity variables on the average industry's innovation success.

The evidence presented in the paper provides support for the Schumpeterian endogenous growth framework without scale effects. Using industry data from U.S. manufacturing during the quarter-century from 1963 to 1988, I show positive impact of R&D intensity on innovation, technological progress, and economic growth. R&D intensity has a positive impact on the rate of patenting, the rate of patenting has a positive effect on technological progress, and, finally, technological progress has a one-to-one relation with the growth rate of output per worker. Moreover, the intensity of aggregate manufacturing R&D is shown to have a stronger impact on the rate of patenting than own-industry R&D, suggesting technological spillovers across manufacturing industries. Overall, I reject the hypothesis that long-run economic growth is not induced

25 A direct way to validate empirically the prediction of his model, that the time-series behaviour of R&D expenditures is responsible for the persistence of output fluctuations, is to estimate the effect of R&D expenditures on productivity growth. Citing evidence from Jones (1995a) and Shea (1998), Fatas (2000, 156) points out that 'the evidence on this issue is, however, very weak and inconsistent.'

by R&D, in favour of the Schumpeterian endogenous growth framework without scale effects. This suggests that the model is a useful template for studying growth in advanced economies like the United States.

A direct extension of this work would be to study the relation between R&D, patents, productivity, and economic growth in countries behind the world technology frontier, so as to assess the relevance of this class of models for countries other than the technological leader. The study of the impact of R&D performed by technological leaders on the economic success of countries further behind the frontier is likely to be a fruitful area for future research. Finally, an interesting extension would be to endogenize R&D by considering the role of profits, scale of operation, and the economic environment in which innovating firms operate in different countries. This would add to the findings regarding the importance of R&D for long-run economic growth and would go a long way towards explaining what is ultimately driving R&D-induced growth and what role, if any, policy can play in encouraging this.

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