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 three 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 favor 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.

Keywords: Endogenous Growth, R&D, Patents, Technological Change.

JEL Classification: O40, O30

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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. The Schumpeterian framework implies positive relations 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.

The evidence presented in this paper provides support for the Schumpeterian endogenous growth framework without scale effects. This framework includes Dinopoulos and Thompson (1998), Howitt (1999), and Segerstrom (2000.) 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.)[1] These models were criticized by Jones (1995b) who pointed out to the rising R&D expenditures or the rising number of scientists and engineers in relation to the constancy of TFP growth as evidence against first-generation endogenous growth models.[2] His argument is portrayed in Figure 1 which reproduces Figure 1 from Jones (1995b) with U.S. manufacturing data.

Schumpeterian endogenous growth models without scale effects are essentially a response to the Jones critique and predict instead that the fraction of GDP allocated to R&D remains constant during periods of steady growth. That is, the framework of R&D-induced growth examined here points to a positive relation between R&D intensity with technological progress but does not presume a relation between the latter and

[1] These models predict a constant level of R&D expenditures or number of scientists and engineers during periods of steady growth.

[2] Jones (1995b) then proposes a "semi-endogenous" growth theoretical framework where, in steady state, the growth rate of labor 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.

the level of R&D expenditures as was implied by first-generation models. Figure 2 illustrates the behavior of R&D intensity and technological progress for aggregate U.S. manufacturing during the period 1957-1989. Figure 2 also presents the share of labor devoted to R&D activities, S&E/L, in the manufacturing sector for the period 1960-1989. To the extent that Figure 2 shows this variable exhibiting similar time-series behavior 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 labor devoted to R&D activities.[3]

This paper utilizes empirical measures corresponding closely to the theoretically-implied concepts. First, I construct R&D intensities as the fraction of output devoted to R&D expenditures. Aghion and Howitt (1998)[4] suggest that R&D intensity is the proper empirical measure for the R&D input of the innovation function in the context of the endogenous growth model without scale effects I consider here. This is because in this model, both capital and labor are included in R&D. Instead, the Jones (1995b) model includes labor but not capital as an input to the R&D equation and thus has no direct implications regarding R&D intensity since R&D intensity includes a large portion of capital expenditures as well as payments to labor in its numerator. Second, I construct measures of the rate of patenting to proxy the rate of innovation in U.S. manufacturing industries. Kortum (1993) shows that the rate of patenting is the relevant measure for quality-ladder models like the one examined here. 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[5] procyclicality from Total Factor Productivity growth.

My approach in this paper is consistent with Kirchhoff's (1994) and Geroski's (1994) discussions on innovative activity: R&D is considered as an input into the production of patents or inventions, and patents as intermediates into the production of innovations which bring about gains in productivity. 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 measure the rate of innovation. This approach captures

[3] Jones (1995b) argues against his specification (3) in page 762, that relates TFP growth to the share of labor devoted to R&D. He presents the rising share of labor devoted to R&D in his Figure 2 of page 764 as evidence against this relation. The importance of this relation lies in 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 with the fraction of labor 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 to R&D data.

[4] Chapter twelve, page 418, second paragraph.

[5] "Spurious" in the sence that such cyclicalities are unrelated to technical change which is what the TFP growth proxy is usually meant to measure when used in growth applications.

the chain of events leading to technological progress.

The paper utilizes data from a panel of industries at the two-digit SIC classification of U.S. manufacturing for the period 1963-1988. The manufacturing sector has accounted for more than ninety percent of R&D expenditures in the United States until the late eighties. Thus, this sector offers a natural laboratory in which to examine the validity of models of R&D-based growth.

To summarize: the endogenous growth framework considered here implies that in steady state there is a positive impact by R&D intensity on the rate of patenting, by the rate of patenting on the rate of technological change, and by the rate of technological change on the growth rate of output per worker. I find that a positive impact exists in each case. Thus, the null hypothesis that growth is not induced by R&D is rejected in favor of the Schumpeterian endogenous growth framework without scale effects. Furthermore, aggregate manufacturing R&D is shown to have a positive impact on industry patenting rates, implying technology spillovers across manufacturing industries.

Relationship with other evidence

During the second half of the last decade several papers have addressed the question of testing endogenous growth theory based on its implications about convergence (Evans 1996a), and the relation of economic growth with government-related variables (Kocherlakota and Yi 1997), money (Evans 1996b), investment, and R&D expenditures (Jones 1995a,b.) With the exception of Kocherlakota and Yi (1997) the evidence from these papers appears to be against the empirical relevance of endogenous growth theory. More recently, Dinopoulos and Thompson (2000) provide evidence in favor of an augmented version of Romer's (1990) model for a cross-section of countries. My findings regarding the empirical relevance of endogenous growth theory are in contrast to the majority of the previous literature, but consistent and complementary to the findings of Dinopoulos and Thompson (2000.) Using two different approaches and datasets, both papers nevertheless provide evidence for a growth model where policy can have a positive impact on economic growth.

The empirical industrial organization literature has also examined the relation between R&D and patenting and the relation between R&D and productivity, typically in isolation from one another. My work builds and improves upon the earlier pioneering work of Zvi Griliches. I explore a theoretically implied system of equations which considers all the stages of the innovation process simultaneously. In this sense, the approach adopted here provides a unifying framework where the inter-relations at different stages of the innovation process are explicitly taken into account. Estimating such a system greatly improves the efficiency of estimation and can provide accurate estimates of the impact of R&D on technological progress and economic growth, accounting for the specific mechanics which link these concepts together. Overall, the methodology and the findings of the paper differ from earlier work as documented below.

Pakes and Griliches (1984) study the relationship between R&D and Patenting using a short time period between 1968 and 1975 for a large number of firms. They consider contemporaneous effects as well as five 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.

Crepon, Duguet, and Mairesse (1998) investigate the channels through which R&D impacts on innovation and productivity growth for a cross-section of firms in the French manufacturing sector. They report evidence for a positive relation between research effort and innovation output as proxied by patent numbers, as well as a positive relation between innovation output and productivity growth. The current study complements that work by studying these relations at a more aggregated level over time in the case of the U.S. manufacturing sector, and by providing a direct link to economic growth. 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 twenty-three year period.

Kortum (1993) looks at the patents-productivity relation using a panel of industries. He finds a positive and significant coefficient for the growth rate of the patent stock. He also finds that the rate of patenting, which is the relevant measure for quality-ladder models like that of Aghion and Howitt(1998), performs worse than the growth rate of the patent stock. Here, I find a relationship between the rate of patenting and productivity growth, consistent with quality-ladder models.

In related work, Caballero and Jaffe (1993) develop an empirical framework consistent with a Schumpeterian model of creative destruction. They use a rich dataset of patent citations for a large number of U.S. firms over time to estimate rates of creative destruction, technological obsolescence, and diffusion, in an endogenous growth framework. They do not estimate the overall system of equations implied by the model as a whole. I do so in this paper.

Studies of the direct relation between R&D and productivity give mixed results. An excellent review of this literature is found in Nadiri (1993.) These studies include Griliches (1980a,b), Mansfield (1988), and

Griliches and Mairesse (1990). All of these authors use a Cobb-Douglas production function that includes R&D stock as one of three inputs, to derive a relation between productivity and R&D. Griliches (1980a) uses a panel of 3-digit manufacturing industry data and finds that the estimate of the R&D coefficient is sensitive to the time period under study; for the period 1959 to 1968 he estimates a positive and significant coefficient, 0.07, whereas for the period 1969 to 1977 the estimated R&D coefficient is close to zero. Griliches (1980b) uses a short time series between 1957 and 1963 for a large cross-section of firms and finds a positive relationship between company productivity and R&D intensity with the estimated R&D coefficient between 0.05 and 0.1, with an average about 0.07. Mansfield (1988) uses a cross-section of industries averaging the data for the period 1960 to 1979 for Japan and for the period 1948 to 1966 for the Unites States. He finds a high positive coefficient for applied R&D in Japan, 0.42, but a negative and statistically insignificant coefficient for basic research. In the United States, the coefficient for applied research is 0.07 and for basic research it equals 1.49. Finally, Griliches and Mairesse (1990) use a cross-section of firms for the United States and Japan for the short time period 1973 to 1980 and find mixed results; for a number of firms R&D-intensity coefficients are negative, for some firms this same coefficient is between zero and 0.05, and for other firms this is greater than 0.05.

More recent work on the link between R&D and productivity, includes Keller (1998) who uses a panel of industries and countries to document the role of international spillovers on the relation between R&D and productivity growth, and Griffith, Redding, and Van Reenen (2000) which use OECD data to show that R&D can enhance the ability of firms to learn as well as stimulate innovation directly. Moreover, Coe and Helpman (1995) estimate the relation between R&D stocks and productivity levels for 1971 to 1990 at the aggregate level and report a return on R&D expenditures of 123 percent for the G7 countries and a return of 85 percent for the remaining fifteen countries in their sample.

In this paper, I provide strong support for a direct as well as an indirect relationship between R&D intensity and productivity growth. The impact of own-industry R&D intensity on technological progress in that industry is estimated to be 0.08 for the most basic specification and 0.22 when we include the direct impact of R&D on technological progress as well. Combined with the estimated coefficient for the impact of productivity on economic growth, these imply that increasing an industry's R&D intensity by one percentage point increases the growth rate of output per worker in that industry by 0.08 or 0.16 percentage points depending on the preferred specification.

The return of aggregate R&D is much higher. Now, increasing aggregate R&D intensity by one percentage point increases the rate of technological progress by half a percentage point and increases the growth rate of output per worker by 0.66 percentage points. 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 idea in 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.

In the next section, I provide the theory behind the empirical specification and in the third section I take a preliminary look at the data. In section four, I describe the empirical analysis and results while section five briefly concludes.

2 THE SCHUMPETERIAN FRAMEWORK AND ITS IMPLICATIONS

I consider a model from Aghion and Howitt (1998) and Howitt (1999) in order to derive the implications of the Schumpeterian endogenous growth framework without scale effects. All growth in this model is driven by vertical drastic innovations which improve the quality of goods and displace previous incumbents. This framework should be seen as a model applicable to developed countries which perform R&D. Below, I provide a brief and non-rigorous description of the model's main components.

Output of the single final good, Y_t, at time t is produced as

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

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 existing intermediate products, and L_t the labor input in the final goods sector growing at the exogenous population rate, g_L. Division of L_t by Q_t eliminates any productivity gain resulting from product proliferation. The assumption here is that population and product variety grow at the same rate.[6] The implication here is 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.

Each intermediate sector is monopolized and sells its product to the competitive final sector at a price

[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 (1995) model where growth is simply proportional to the rate of population growth and does not depend on other endogenous variables. If product variety increases less that proportionately with population then the implication is that Howitt's (1999) model still exhibits scale effects in growth.

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 by increasingly capital-intensive techniques.

The model provides a set of testable implications comprising of: (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. These are implied by the respective equations (1), (2), and (3) below.

Equation (1) specifies the flow of innovation output, ϕ_{it}, in the research sector looking to develop the next generation of an intermediate input i as

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

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 anyone product associated with duplication and overlap, and $n_{it} = \frac{R_{it}}{A_t^{\max}}$ 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 $R_{it} = R_t$. $A_t^{\max}$ 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 arrival of innovations proxied by the rate of patenting and the productivity-adjusted level of R&D at time t given by n_t. The main difference from Jones (1995b) is that here the input R_t includes capital as well as labor.[7] In a steady state, R_t grows at the same rate as $A_t^{\max}$ and the rate at which the technology frontier improves is in turn the same as the rate of output growth. Thus, in steady state the ratio R_t/Y_t behaves similarly to $R_t/A_t^{\max}$, where Y_t stands

[7] When $\phi(n_t) = n_t^{\gamma}$ then $\frac{\dot{A}_t^{avr}}{A_t^{avr}} = \nu(R_t)^{\gamma}(A_t^{avr})^{-\gamma}$ with $\nu = \sigma\lambda(1+\sigma)^{-\gamma}$. This equation for the growth rate of average productivity resembles the research technology in Jones (1995b) with $0 < \gamma \leq 1$, except that here the input R_t includes capital as well as labor.

for output. That is, the current framework predicts that the fraction of output allocated to R&D remains constant during periods of steady growth.

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 $A_t^{\max}$. The ratio of the leading edge to average technology is $A_t^{\max}$=(1+σ)A_t^{avr} implying $\frac{\dot{A_t^{avr}}}{A_t^{avr}} = \frac{\dot{A_t}^{\max}}{A_t^{\max}}$ with σ, the size of innovations, constant. An important characteristic of the current framework is that growth in the leading edge technology, $A_t^{\max}$, occurs as a result of the knowledge spillovers produced by innovations. Each innovation is implementable only in the intermediate sector it is used in but it increases the knowledge stock so that the next innovator in any intermediate sector can draw from an expanded pool of knowledge. This suggests that any one industry can potentially benefit from R&D performed in the economy as a whole. Knowledge grows at a rate proportional to the average rate of innovations, A_t^{avr}, and is publicly available and costly.

The steady-state rate of technological progress, g_t, is then given by

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

where σ is the size of innovations and ϕ_t is the innovation rate. This equation implies a positive relationship between g_t and the innovation rate ϕ_t. In the empirical application in the next section the latter is proxied by the rate of patenting.

Finally, the growth rate of output per worker is given by equation (3):

$$G_t = g_t + \alpha\frac{\dot{k_t}}{k_t} \tag{3}$$

In a steady state, the growth rate of capital, $\frac{\dot{k_t}}{k_t}$, is equal to zero and economic growth depends solely on the rate of technological progress. In the system estimation of 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 to 1988 for the manufacturing sector and ten two-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.

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 impacting negatively 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 in the univariate analysis of the latter three series but is significant and negative for the rate of patenting.[8] [9] Thus, even though I report results for the stationarity tests with a deterministic trend as well as without one, I favor 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 hypothesis at the ten percent 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

[8] 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 five percent level of significance using a Bonferroni Bound, but is rejected for the rate of patenting.

[9] 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 five percent 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.

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.[10] In Table 1, I present the results of the stationarity tests for the R&D intensities in manufacturing and its two-digit industries for which data are available. The individual industry variables appear to be stationary[11] and a panel test that uses the Bonferroni bound implies that the null of stationarity cannot be rejected even at the ten percent 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 to 1988. I obtained these data from the ESRC Data Archive. These data were orininally collected by the US Department of Commerce and compiled by R. A. Wilson (1991.) I construct the stock of patents as a measure of the knowledge stock using a knowledge obsolescence rate of seven percent, the average annual rate of technological obsolescence over the past century as estimated by Caballero and Jaffe (1993). The benchmark year (1963) stock is given by the number of patents over the depreciation rate[12]. 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 two-digit industries with available data. A panel test using the Bonferroni bound implies that the null of stationarity cannot be rejected even at the ten percent level of significance.[13]

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

[10] 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 1950-1989 is taken from the database constructed by Jorgenson and his associates.

[11] The null of stationarity is rejected at the five percent level of significance using Park's G(0,2) test for industries 20, 35, and 38, using the G(1,2) test for industry 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.

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

[13] Looking at each individual industry, there are six rejections of the null of stationarity at the five percent 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 five percent level of significance.

function and is thus 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 will not generally 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[14] 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[15] and a panel test that uses the Bonferroni bound implies that the null of stationarity cannot be rejected even at the ten percent 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[16] and a panel test that uses the Bonferroni bound implies that the null of stationarity cannot be rejected at the ten percent 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 relates in turn 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:

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

[15] The null of stationarity is rejected at the five percent 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.

[16] The null of stationarity is rejected at the five percent level of significance using Park's G(0,4) and G(1,3) tests for industries 20 and 33.

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

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

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

where u_{it}, v_{it}, and e_{it} are stationary errors.[17] Here, n_{it} stands for R&D intensity, ϕ_{it} for the rate of patenting, g_{it} stands for the rate of technological change, and G_{it} stands for the growth rate of output per worker.

I estimate this system of equations for a panel of ten industries during the period 1963 to 1988,[18] 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} 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.[19] 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.)

[17] As shown in section 3, we do not reject the stationarity null for the variables used in the above estimation. Similarly, Keller (2001) chooses a trend stationary specification for the relation between R&D and productivity and argues that whether a time series is deemed to be stationary or not depends on the level of heterogeneity in the data generation processes across industries that one allows for.

[18] 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.

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

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 behavior of the average manufacturing industry. The hypothesis that the size of innovations is equal across industries, $\sigma_i = \sigma$, cannot be rejected at the ten percent level of significance, 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 serves as a robustness check of the results as well as addresses possible shortcomings of the patenting rate as a measure of the innovation rate.[20]

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 which affects their output growth. The univariate analysis of the growth rate of output per worker suggests that a time trend need not be added.[21]

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, III.

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

[20] Pakes and Griliches (1980, p.378) argue that, "patents are a flawed measure (of innovation output); particularly since not all innovations are patented."

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

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.[22] 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.[23]

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.[24]

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.[25] Combined with the estimated coefficient for the impact of productivity on economic growth, these imply that increasing an industry's R&D intensity by one 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.[26]

[22] 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.

[23] 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.

[24] I thank a referee of this journal for suggesting this simple but informative test.

[25] The overall impact on the rate of technological progress was calculated as $dg/dn = \partial g/\partial n + \partial g/\partial \phi \cdot \partial \log \phi / \partial \log n \cdot \bar{\phi}/\bar{n}$. with the first term set to zero for models I and II.

[26] The overall impact on the growth rate of output per worker is given by $dG/dn = (\partial G/\partial g \cdot \partial g/\partial n) + (\partial G/\partial g \cdot \partial g/\partial \phi \cdot \partial \log \phi / \partial \log n \cdot \bar{\phi}/\bar{n})$ where the first term is again set to zero for models I and II.

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

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.

Relating the above evidence to the literature

Taken as a whole, 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 are also consistent with the models of Dinopoulos and Thompson (1998) and Segerstrom (2000.)

The finding of a positive relation between innovation inputs and technological change 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. My paper differs from Shea (1998) in that I derive the relation between R&D intensity, patenting, and productivity growth, imposing restrictions on the structure as implied by the Schumpeterian framework of endogenous growth. An other important difference between the two papers, is the use of an improved measure of technological progress in place of the spuriously procyclical TFP measure used in the earlier paper.

Finally, by considering the mechanics of the relationship between technological change and output, this paper also makes a contribution to the literature on economic flactuations. The paper demonstrates that past innovative activity is important in explaining movements in productivity and output. This is consistent with Basu, Fernald, and Kimball (1998) and Gali (1999) who show that innovations have a positive effect on output with a lag, as well as with Fatas (2000) who stresses the interrelation between cyclical fluctuations and long-term growth.[27]

[27] A direct way to validate empirically the prediction of his model that the time-series behavior 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) points out (in page 156, second paragraph of Section 4) that "*t*he evidence on this issue is, however, very weak and inconsistent."

5 CONCLUSION

Growth theory has made significant advances over the last decade. One important contribution is the Howitt (1999) model that predicts a higher rate of 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 derive and 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 greatly the efficiency of estimation and allows us to estimate the impact of R&D on technological progress and economic growth while accounting for the specific mechanics of this relationship. 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.

The evidence presented in the paper provides support for the Schumpeterian endogenous growth framework without scale effects. Using two-digit industry data from U.S. manufacturing during the period 1963-1988, I show a positive impact of R&D intensity on innovation, technological progress and economic growth.

More specifically: 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. This implies technological spillovers across manufacturing industries.

Overall, we reject the null hypothesis that economic growth is not induced by R&D in steady state in favor of the Schumpeterian endogenous growth framework without scale effects. This suggests that the model considered here 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 close to the technology frontier, so as to assess the relevance of this class of models for countries other than the technological leader. Moreover, the study of the impact of R&D performed in advanced countries on the technological and 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 of this paper about the importance of R&D for technological progress and economic growth, and would go a long way towards explaining what is behind R&D-induced growth and what role, if any, policy can play in encouraging this.

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Table 1: P values for the stationarity null (G test, Park 1990)[28]

R&D Intensity	G(0,2)	G(0,3)	G(0,4)	G(1,2)	G(1,3)	G(1,4)
3: Total Manufacturing	0.363	0.283	0.253	0.172	0.167	0.176
20: Food & Kindred Products	0.031*	0.084	0.160	0.216	0.263	0.238
28: Chemicals & Allied Products	0.363	0.266	0.152	0.164	0.094	0.157
30: Rubber & Plastics Products	0.066	0.078	0.165	0.035*	0.108	0.170
32: Stone, Clay & Glass Products	0.059	0.137	0.262	0.246	0.494	0.319
33: Primary Metal Industries	0.767	0.296	0.375	0.118	0.208	0.036*
34: Fabricated Metal Products	0.218	0.415	0.149	0.492	0.024*	0.057
35: Machinery Except Electrical	0.033*	0.075	0.159	0.037*	0.109	0.159
36: Electrical Machinery	0.066	0.137	0.254	0.214	0.406	0.180
37: Transportation Equipment	0.656	0.569	0.359	0.317	0.196	0.154
38: Instruments & Products	0.033*	0.098	0.188	0.257	0.253	0.234

Rate of Patenting	G(0,2)	G(0,3)	G(0,4)	G(1,2)	G(1,3)	G(1,4)
3: Total Manufacturing	0.109	0.269	0.213	0.677	0.036*	0.071
20: Food & Kindred Products	0.182	0.349	0.263	0.433	0.121	0.232
28: Chemicals & Allied Products	0.092	0.162	0.139	0.139	0.027*	0.059
30: Rubber & Plastics Products	0.114	0.286	0.208	0.952	0.036*	0.034*
32: Stone, Clay & Glass Products	0.118	0.284	0.218	0.609	0.033*	0.051*
33: Primary Metal Industries	0.086	0.228	0.216	0.843	0.042*	0.096
34: Fabricated Metal Products	0.101	0.226	0.212	0.302	0.033*	0.064
35: Machinery Except Electrical	0.070	0.188	0.221	0.558	0.051*	0.101
36: Electrical Machinery	0.163	0.327	0.217	0.414	0.055	0.079
37: Transportation Equipment	0.076	0.204	0.234	0.685	0.087	0.180
38: Instruments & Products	0.368	0.659	0.194	0.856	0.061	0.131

Rate of technological progress	G(0,2)	G(0,3)	G(0,4)	G(1,2)	G(1,3)	G(1,4)
3: Total Manufacturing	0.957	0.477	0.685	0.224	0.476	0.638
20: Food & Kindred Products	0.387	0.608	0.434	0.614	0.359	0.556
28: Chemicals & Allied Products	0.309	0.589	0.529	0.873	0.539	0.701
30: Rubber & Plastics Products	0.668	0.502	0.648	0.274	0.479	0.669
32: Stone, Clay & Glass Products	0.479	0.531	0.679	0.381	0.603	0.656
33: Primary Metal Industries	0.289	0.522	0.722	0.665	0.897	0.975
34: Fabricated Metal Products	0.606	0.499	0.669	0.288	0.523	0.729
35: Machinery Except Electrical	0.014*	0.046*	0.093	0.722	0.778	0.859
36: Electrical Machinery	0.331	0.282	0.469	0.198	0.436	0.233
37: Transportation Equipment	0.143	0.275	0.234	0.493	0.318	0.514
38: Instruments & Products	0.257	0.118	0.136	0.074	0.104	0.025*

[28] I would like to thank Masao Ogaki for providing the programs for performing the G tests.

Table 1 (cont.):

Growth rate of output per worker	G(0,2)	G(0,3)	G(0,4)	G(1,2)	G(1,3)	G(1,4)
3: Total Manufacturing	0.687	0.409	0.602	0.200	0.425	0.634
20: Food & Kindred Products	0.118	0.145	0.053*	0.205	0.051*	0.082
28: Chemicals & Allied Products	0.680	0.703	0.265	0.462	0.147	0.273
30: Rubber & Plastics Products	0.740	0.219	0.385	0.088	0.233	0.369
32: Stone, Clay & Glass Products	0.538	0.499	0.587	0.314	0.459	0.439
33: Primary Metal Industries	0.118	0.145	0.053*	0.205	0.051*	0.082
34: Fabricated Metal Products	0.239	0.242	0.387	0.207	0.405	0.342
35: Machinery Except Electrical	0.678	0.886	0.965	0.793	0.950	0.837
36: Electrical Machinery	0.945	0.843	0.917	0.562	0.777	0.906
37: Transportation Equipment	0.133	0.188	0.218	0.264	0.286	0.411
38: Instruments & Products	0.248	0.306	0.457	0.276	0.483	0.672

Notes:

* Reject the Null of stationarity at the five percent 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 to 1989.

The rate of patenting is given by the number of patents over the stock of patents. This is available for 1963 to 1988.

The growth rate of output per worker is available for 1951 to 1989. This is the growth rate of the ratio of gross output over labor quantity using Jorgenson's gross output data and labor quantity data.

The rate of technological progress is the Basu etal measure (TBK) and is available for 1951 to 1989.

Table 2:

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:

t-tests of the hypothesis that the parameter equals zero given in brackets employing robust standard errors.

* p-value of hypothesis test <0.10, ** p-value<0.05, *** p-value<0.01

230 observations for 10 manufacturing industries× 23 years (1966-88).

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.

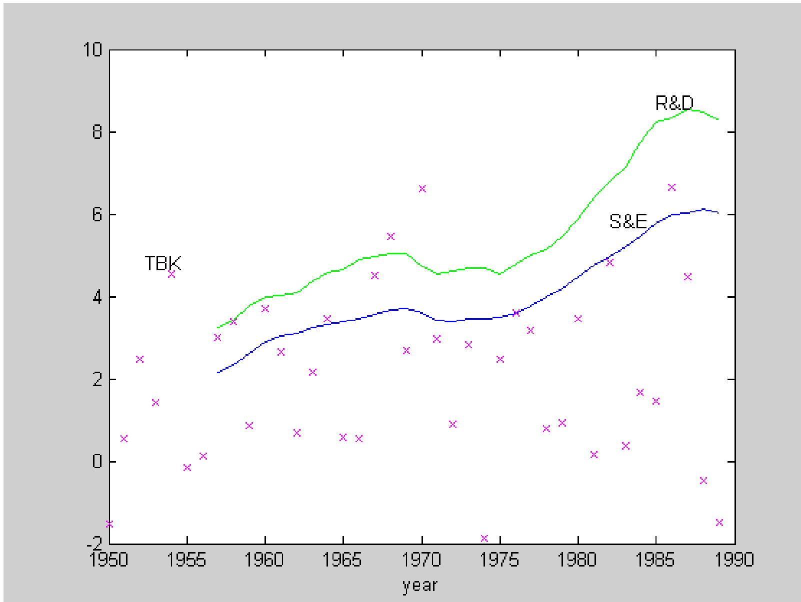
I: Basic model from equations (1S), (2S), and (3S).

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 $dg/dn = \partial g/\partial\phi \cdot \partial \log \phi/\partial \log n \cdot \bar{\phi}/\bar{n} + \partial g/\partial n$ (again $\partial g/\partial n$ set to zero for models I and II.)

Figure 1: R&D Expenditures, Scientists and Engineers, and the rate of Techological Progress



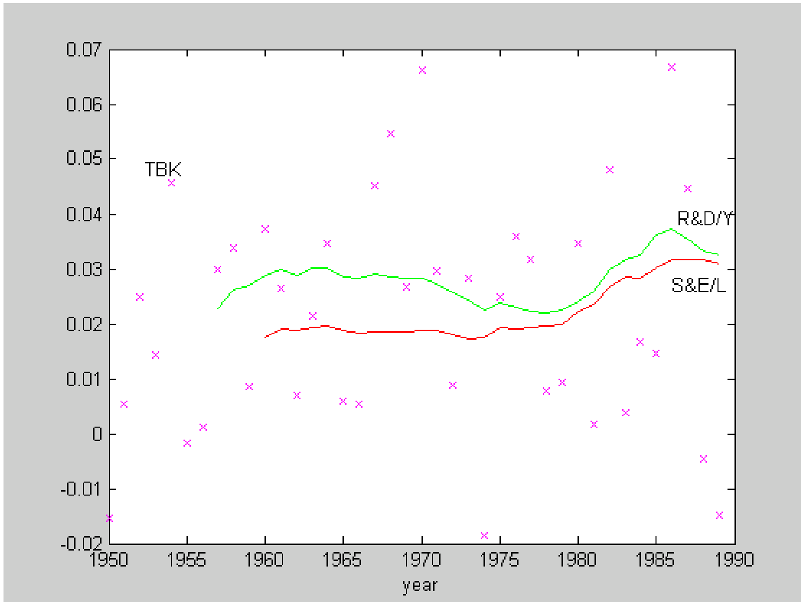
Notes:

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. This accounts for imperfect competition and removes spurious procyclicality from Total Factor Productivity growth.

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 etal database.

The series for the fraction of the labor 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 1960-1992 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.