ACADEMIC SCIENCE, INDUSTRIAL R&D, AND THE GROWTH OF INPUTS*

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Abstract

This paper is a theoretical and empirical investigation of the connection between science, R&D and the growth of capital. Studies of high technology industries and recent labor studies agree in assigning a large role to science and technology in the growth of human and physical capital, although direct tests of these relationships have not been carried out. This paper builds on the search approach to R&D of Ecenson and Kislev (1976) to unravel the complex interactions between science, R&D, and factor markets suggested by these studies. In our theory lagged science increases the retruns to R&D, so that scientific advance later feeds into growth of R&D. In turn, product quality improvements and price declines lead to the growth of industry by shifting out new product demand, perhaps at the expense of traditional industries. All this tends to be in favor of the human and physical capital used intensively by high technology industries. This is the source of the factor bias which is implicit in the growth of capital per head. Our empirical work overwhelmingly supports the contention that growth of labor skills and physical capital are linked to science and R&D. It also supports the strong sequencing of events that is a crucial feature of our model, first from science to R&D, and later to output and factor markets.

Keywords: Technical Change, R&D, Factor Demand, Growth

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I. Introduction

Studies of high technology industries assign to science a pivotal role in the conduct of R&D and the subsequent growth of business capital, while labor economists have pointed to technology as a key force behind the recent rise in the return to skills[1]. Together these findings imply strong links between knowledge and capital in its many forms, and yet the links have been elusive. In seeking a remedy for this situation we are led in two principal directions.

First, we apply Evenson and Kislev's (1976) search approach to R&D to the relation between scientific and industrial progress[2]. A fundamental advantage of this approach is that the results of R&D are stochastic, thereby allowing for failure as well as success in the quest for new technologies, with science tilting the odds towards success.

Second, we carry the link between knowledge and growth beyond total factor productivity[3]. The additional link with growth "explained" by factors follows from the dependence of input growth on technology. The topic clearly touches on the role of embodiment in growth[4]. Knowledge is almost surely biased towards human and physical capital because of the embodying function of capital[5]. And though we cannot identify embodiment, still we can probe the relation between knowledge and particular inputs for pertinent evidence[6]. Indirect evidence for our perspective is already present in studies of capital deepening. General growth of human and physical capital per head has been documented by Schultz (1961), Denison (1962), Griliches and Jorgenson (1967), Becker (1975), Kendrick (1976), and Jorgenson, Gollop, and Fraumeni (1987).

The theory proceeds from the assumption that science is helpful in the R&D search process, so that advances in science increase R&D. Furthermore, it assumes that human and physical capital are employed intensively by R&D intensive industries, and that demand curves for the output of such industries are shifted out in response to quality improvements from new technology even while costs decline, provoking entry and growth in input demand. Factor bias then follows from the intensity assumptions.

In the empirical work we find that science and technology are biased in favor of physical capital, especially equipment. We also find powerful effects in favor of college trained labor, and from science to R&D. We employ two sets of manufacturing production data. The first is Jorgenson, Gollop, and Fraumeni's (1987). Their data include growth in labor, physical capital, and intermediate goods. The second is from the Bureau of Labor Statistics (Gullickson and Harper [1987]). It consists of distinct categories of labor and capital plus intermediate goods. We study growth in two kinds of physical capital, equipment and all other, and two labor categories, college-educated workers and less than college.

Each has its advantages. The Jorgenson et alia data express growth in the quantity and quality of inputs in convenient summary form. But key avenues of technical change are concealed by this aggregation. The BLS data are able to capture some of these through the disaggregation of factor categories.

The paper is arranged as follows. Section II models the link between knowledge and R&D, derives industry factor demand curves in growth rate form, and draws implications for these demands. Section III discusses the data we have collected to study this problem. Estimates of input growth equations are reported in section IV, section V concludes, and an Appendix spells out the derivations.

II. Analytical Framework

A. Heterogeneous Firms and Technologies

This paper relates factor growth and factor bias to industrial R&D and academic science. To account for this behavior we consider heterogeneous firms using distinct processes. We depart from the idea of production as one process and use a mixture of simple production functions to generate observed factor biases. Our approach tallies closely with Census data, which reveal large differences in plants within and between firms (see Dunne, Roberts, and Samuelson [1989]).

Industries use a mix of processes, but most are unprofitable and inactive at any one time. A key parameter that determines activity is the productivity state, defined as best practice in that process. In this paper, productivity evolves stochastically with current R&D but stays the same when R&D is zero[7]. And since process and product R&D are often inseparable, technology raises both the demand curve and productive efficiency.

We sharply distinguish R&D spillovers and science in their effects on the time path of the firm's R&D. Spillovers accelerate productivity gains through imitation but have little or no effect on technological opportunity. Spillovers tend to replace future R&D with present R&D since less remains to be discovered if opportunities are held constant. In contrast science improves the distribution of returns to R&D. Otherwise R&D eventually ceases because search over a fixed distribution encounters falling payoffs as higher productivities are reached. In this manner science sustains future as well as present R&D.

We proceed comparatively simply, leaving Section II.D to informally extend our arguments to other cases. There are two processes, 1 and 2. Identical type 1 firms specialize in process 1 and conversely for type 2s. Specialization follows from a comparative advantage argument. Firms stay type 1s even when profits are higher for incumbent type 2s because they lack inputs that would render them profitable as type 2s.

The scientific foundations of 1 stay the same, no R&D is performed, and productivity stays the same. Since 1 relies on old technology it uses unskilled labor intensively[8]. In contrast, the science underlying 2 changes rapidly, R&D is large, and technology rises apace. Type 2 firms use skilled labor heavily in line with rapid changes in their technology.

To keep matters simple there are two inputs, skilled and unskilled labor. We could, at this stage, include several forms of physical capital, but the analytical gains would not equal the resulting notational complexity. Per firm quantities are output q_{it}, unskilled labor l_{it}, skilled labor h_{it}, and productivity A_{it}, all type i (i=1,2). Production is Cobb-Douglas:

$$q_{it}=A_{it}^{\alpha_{Ai}} l_{it}^{\alpha_{li}} h_{it}^{\alpha_{hi}}. \tag{1}$$

Diminishing returns prevail given A_{it}, so $\alpha_{li}+\alpha_{hi}<1$. Assumed factor intensity differences imply $\alpha_{l1}>\alpha_{l2}$ and $\alpha_{h1}<\alpha_{h2}$, while the static technology of 1 means that $A_{1t}=A_1$ for all t. Now, process 2 employs R&D scientists and engineers (hereafter S&Es, or R_t) whose purpose is to raise <u>future</u> productivity. Thus R_t is not an argument of (1), though past values of it influence the expected value of A_{2t}. p_{it} is the price of output i, s_{jt} is the price of input j, the wage of S&Es is w_t, and amortized fixed costs are c_{it}. In terms of our notation profits are

$$\pi_{it}=p_{it}q_{it}-\sum_{z=l,h}^{k} s_{zt}z_{it}-w_t\ell_{it}-c_{it}, \qquad (i=1,2) \tag{2}$$

where $R_{1t}=0$, since there is no R&D in process 1. (2) is concave in labor and S&Es. Let E_t be the expectation at time t and β be the discount factor ($0<\beta<1$). Present value is then

$$EV_{it}=E_t\sum_{j=0}^{\infty}\beta^j\pi_{it+j}, \qquad (i=1,2). \tag{3}$$

Market conditions are that process 1 is competitive so p_{1t} is fixed to individual firms. We assume that skills required of innovative firms are limited in supply, so 2 is an oligopoly limited to R&D firms with market power.

Outputs of 1 and 2 are substitutes in consumption. Also, type i technology raises demand for good i and lowers demand for j (i,j=1,2). Reflecting this, market demand is

$$Q_{it}=b_{it}A_1^{\varepsilon_{i1}}A_{2t}^{\varepsilon_{i2}}p_{1t}^{\eta_{i1}}p_{2t}^{\eta_{i2}}, \tag{4}$$

where Q_{it} is type i industry output. We have $\eta_{ii}<0$ but $\eta_{ij}>0$, $i\neq j$, since i and j are price substitutes; and we have $\varepsilon_{ii}>0$, but $\varepsilon_{ij}<0$, $i\neq j$, since i and j are "quality" substitutes. Technical change in good 2, the only active technology, lowers demand for 1 by improving 2's quality and perhaps by reducing p_2. The demand for 2 is increased by the same forces, and this is at the heart of our explanation of factor bias within and between industries. (1)-(4) comprise the production and revenue side of the industry.

B. Factor Demands at the Firm Level

Type 1 Firms

Decisions of type 1 firms are essentially static, involving repeated choice of l_{1t} and h_{1t} to maximize (3) subject to (1) and (2). First order conditions are

$$\alpha_{l1}\frac{p_{1t}q_{1t}}{l_{1t}}=s_{lt},\ \alpha_{h1}\frac{p_{1t}q_{1t}}{h_{1t}}=s_{ht}. \qquad (5)$$

Part A of the Appendix derives factor demand curves from (5). In log differential form these are

$$D\ln z_{1t}=\sum_{j=l,h}^{k}\phi_{zj}\left(\frac{s_{jt}}{p_{1t}}\right), \qquad (6)$$

where all coefficients N_{ij} are negative because of the Cobb-Douglas assumption.

Type 2 Firms

Type 2 firms solve an inherently dynamic problem, since R&D involves search and the forecasting of future rewards. By hiring appropriately trained S&Es, R&D firms learn about science and R&D spillovers, apply that learning to industrial designs, and produce goods embodying the designs whose lower cost and higher quality are reflected in (1) and (4) above. For R&D to be profitable firms must have property rights in their inventions and market power despite imitation and entry. Imitation seems to occur more rapidly than the acquisition of science (Griliches, ed. [1984], Adams [1990]), and we emphasize this with lags of 0 and M on spillovers and science respectively.

S&Es (R_t) perform two functions (Bernstein and Nadiri [1989], Cohen and Levinthal [1989]). They improve productivity by increasing n_t, aided by R&D spillovers, and by searching the science literature for ways to raise quality and productivity. We express these considerations in the rule,

$$n_t = SP_t^{\lambda_{SPt}} \ell_t^{\lambda_{\ell t}}, \qquad \textbf{(7)}$$

where SP_t is R&D spillovers and n_t is concave. R_t and SP_t are clearly complementary in this formulation[9].

Future productivity is a random variable which we call a_2, as opposed to current productivity A_{2t}. We assume that a_2 is exponentially distributed with parameters 1_t and 6[10]:

$$g_{2t}(a_2) = \theta_t e^{-\theta_t (a_2 - K)}. \qquad \textbf{(8)}$$

The mean and variance of the exponential are $E_t(a_2)=6+1/1_t$ and $V_t(a_2)=1/1_t^2$. Let the stock of scientific results be KN_{t-M}. R_t and KN_{t-M} increase the mean and variance by decreasing 1_t and they are again complementary, so $1_t= 1(R_t,KN_{t-M})$, where 1_1, 1_2, $1_{12}<0$. In this simple world a_2 is identically and independently distributed over projects. We assume that spillovers increase projects but not the productivity distribution, while science shifts the distribution but not projects. Though it is exaggerated we believe in the asymmetry for the following reasons. Since firms perform similar R&D spillovers are unlikely to change research opportunities very much. Science does improve the distribution, through well-founded departures from received knowledge.

We now proceed to the probabilities of failure and success in R&D. Let G_{2t} be the cumulative of a_2 and let A_{2t} be actual productivity. Then a project fails with probability

$$G_{2t}(\boldsymbol{A}_{2t}) = \int_0^{\boldsymbol{A}_{2t}} \theta_t \boldsymbol{e}^{-\theta_t(\boldsymbol{a}_2 - K)} \boldsymbol{da}_2 . \qquad \textbf{(9)}$$

The R&D program of a firm includes n_t projects and fails because none of these succeed in raising productivity. Given independence over projects, the probability of failure is

$$\boldsymbol{Pr}(F\boldsymbol{ai}lur\boldsymbol{e}) = G_{2t}^{n_t}(\boldsymbol{A}_{2t}) . \qquad \textbf{(10)}$$

and the probability of success is the complement,

$$\boldsymbol{Pr}(Success) = 1 - G_t^{n_t}(\boldsymbol{A}_{2t}) . \qquad \textbf{(11)}$$

The density for productivity improvements is therefore

$$\left| \frac{\boldsymbol{dPr}(Success)}{\boldsymbol{da}_2} \right| = n_t G_{2t}^{n_t - 1} \boldsymbol{g}_{2t} \equiv h_{2t}(n_t, \boldsymbol{A}_{2t}) . \qquad \textbf{(12)}$$

In summary, (7)-(12) specify the R&D side of type 2 firms.

Type 2s maximize (3) subject to (1),(2),(4), and (7)-(12). Controls are conventional labor and S&Es (l_{2t}, h_{2t}, and R_t). State variables are productivity, the stock of academic science, R&D spillovers (A_{2t}, KN_{t-M}, SP_t), and prices, suppressed here for simplicity. The optimization method is Dynamic Programming.

The value of the firm equals current profit plus the expected value next period. This is the value if productivity stays the same times the probability of it staying the same, plus the expected value given varying degrees of improvement.

Bellman's equation for this problem is

$$EV_t(\mathbf{A}_{2t},KN_{t-M},SP_t)=\max[\ \pi_t+\beta G_{2t}^{n_t}EV_{t+1}(\mathbf{A}_{2t},KN_{t-M+1},SP_{t+1}) + \beta\int_{\mathbf{A}_{2t}}^{\infty} h_{2t}EV_{t+1}(\mathbf{a}_2,KN_{t-M+1},SP_{t+1})\,d\mathbf{a}_2]. \quad \mathbf{(13)}$$

We assume that (13) is concave in the states and controls. First order conditions for l and h equate marginal revenue product with factor price:

$$\alpha_{l2}\frac{mr_{2t}\mathbf{q}_{2t}}{l_{2t}}=s_{lt},\quad \alpha_{h2}\frac{mr_{2t}\mathbf{q}_{2t}}{h_{2t}}=s_{ht}, \quad \mathbf{(14)}$$

where $mr_{2t}=(1-f_t/|O_{22}|)p_{2t}$, f_t is market share, and $1>f_t/|O_{22}|$. For later reference, in our symmetric case f_t equals 1 over the number of firms N_{2t}. Note that l and h depend <u>retrospectively</u> on technology since marginal product depends on A_{2t}.

The first order condition for S&Es, reflecting their forward-looking aspect, equates marginal benefit with earnings:

$$\beta\left[\frac{\partial\left(G_{2t}^{n_t}\right)}{\partial \ell_t}EV_{t+1}(\mathbf{A}_{2t},\bullet)+\int_{\mathbf{A}_{2t}}^{\infty}\frac{\partial h_{2t}}{\partial \ell_t}EV_{t+1}(\mathbf{a}_2,\bullet)\,\mathbf{a}_2\right]=w_t. \quad \mathbf{(15)}$$

The right hand terms of (15) are signed as follows. Using (7) and (10) the effect of S&Es on the probability of failure is

$$\frac{\partial\left(G_{2t}^{n_t}\right)}{\partial \ell_t}=\left[\frac{\lambda_{\ell t}\ell n G_{2t}}{\ell_t}+\frac{1}{G_{2t}}\frac{\partial G_{2t}}{\partial \ell_t}\right]n_t G_{2t}^{n_t}<0. \quad \mathbf{(16)}$$

(16) is less than zero[11]. This follows from $G_{2t}<1$, so $RnG_{2t}<0$, and from the fact that R_t shifts the productivity distribution to the

right, so $MG_{2t}/MR_t<0$. This last result implies that the integral term in (15) is positive. From (11) the integrand is

$$\frac{\partial h_{2t}}{\partial \ell_t}=\frac{\lambda_{\ell t}n_t}{\ell_t}G_{2t}^{n_t-1}g_{2t}+n_t\left\{\left[\frac{\lambda_{\ell t}n_t}{\ell_t}\ln G_{2t}+(n_t-1)\,\frac{1}{G_{2t}}\,\frac{\partial G_{2t}}{\partial \ell_t}\right]\cdot G_{2t}^{n_t-1}g_{2t}+G_{2t}^{n_t-1}\frac{\partial g_{2t}}{\partial \ell_t}\right\}. \tag{17}$$

By (16) this is positive on average[12]. Put differently, S&Es increase the firm's value given that A_{2t} is surpassed.

(15) shows that the demand for S&Es depends <u>prospectively</u> on technology and the market and that the probability that R&D fails goes to 1 given KN_{t-M}, since A_{2t} rises against fixed opportunities. Thus S&Es go to zero under static conditions of knowledge.

(14) implies a system of demands for l_{2t} and h_{2t}. The system is nonlinear because mr_{2t} is a nonlinear function of firm output. Part B of the Appendix derives the following linear approximation in factor growth rates:

$$D\ln z_{2t}\approx \phi_{20}+\sum_{j=l}^{h}\phi_{2zj}D\ln\left(\frac{s_{jt}}{mr_{2t}}\right)+\phi_{2A}D\ln A_{2t}. \qquad (z=l,h) \tag{18}$$

where N_{2zj} is the jth factor price elasticity for z, and N_{2A} is the technology elasticity. Given the Cobb-Douglas assumption, it comes as no surprise that price elasticities are negative and that the technology elasticity is positive and neutral.

While a detailed analysis is beyond this paper, we comment briefly on the demand for S&Es. Qualitative properties can be derived from the value function. The value function is concave in S&Es and the effect of S&Es increases as spillovers and science increase. Using these properties part C of the Appendix shows that R_t decreases with scientific earnings and increases with R&D spillovers and stocks of academic science:

$$D\ell n \ell_t = \Phi_{\ell 0} + \Phi_{\ell w} D\ell n w_t + \Phi_{\ell KN} D\ell n KN_{t-M} + \Phi_{\ell SP} D\ell n SP_t + \Phi_{\ell X} D\ell n X_t, \quad \textbf{(19)}$$

X_t= a vector of future prices. From what has gone before N_{Rw}<0, N_{RSP}>0, and N_{RKN}>0. Effects of future prices are as follows. Growth in output price increases growth of S&Es, but increases in real interest lower growth. Comparison of (18) with (19) shows that science cascades through time, affecting S&Es with lag M, only later affecting l and h through A_{2t} .

C. Industry Factor Demands

In our representative firm setting, industry input growth equals growth in the number of firms plus employment growth per firm in each process. As before let z_t stand for any input. Since N_{it} is the number of firms and z_{it} is employment of z per firm in process i, process employment is $Z_{it}=N_{it}z_{it}$, while industry employment is $Z_t=Z_{1t}+Z_{2t}$. Log differentiating Z_t, percentage growth in industry employment is the weighted sum of employment growth per firm and growth in the number of firms,

$$D\ell n Z_t \equiv (1-\nu_{2Z})(D\ell n z_{1t} + D\ell n N_{1t}) + \nu_{2Z}(D\ell n z_{2t} + D\ell n N_{2t}), \quad \textbf{(20)}$$

where $<_{2z}$ is the type 2 share in the employment of Z.

Employment growth per firm derives from the input growth equations (6) and (18). However, these depend on <u>equilibrium</u> growth in output price, marginal revenue, and entry. Thus entry, output price, and per firm employment growth are simultaneously determined by factor prices and technology.

Part D of the Appendix isolates the effects of changes in A_{2t} by holding factor prices and thus p_{1t} constant[13]. In this case, reduced form, equilibrium growth of p_{2t} and mr_{2t} is

$$D\ell n p_{2t} = \frac{\epsilon_{22} - d_2}{d_1 - \eta_{22}} D\ell n A_{2t} \equiv \phi_{2pA} D\ell n A_{2t}$$

$$D\ell n mr_{2t} = \left[(k_1 h_1 + k_2) \frac{\epsilon_{22} - d_2}{d_1 - \eta_{22}} + k_1 h_2 \right] D\ell n A_{2t} \equiv \phi_{2mrA} D\ell n A_{2t}. \qquad \textbf{(21)}$$

The signs of d_i, h_i, k_i-- these "supply" terms are defined in the Appendix-- are all positive. Furthermore, $,_{22}>0$, and $O_{22}<0$, and the denominators are strictly positive. The numerator of the expression for $DRnp_{2t}$, on the other hand, combines two opposing effects of technical progress. $,_{22}$ expresses the rightward shift in demand due to higher quality, which tends to raise price. d_2 reflects entry and increased output per firm, which tend to lower price. The expression for $DRmr_{2t}$ includes these two effects and adds a third, the direct effect on entry from lower average cost.

Equilibrium entry, which is determined by price-average cost margins (see Bresnahan and Reiss [1991]) is given by

$$\Delta \ell n N_{1t} = \left[\frac{\eta_{12}(\epsilon_{22} - \delta_2)}{\delta_1 - \eta_{22}} + \epsilon_{12} \right] \Delta \ell n A_{2t} = \phi_{1NA} \Delta \ell n A_{2t}$$

$$\Delta \ell n N_{2t} = \left[\frac{h_1(\epsilon_{22} - \delta_2)}{\delta_1 - \eta_{22}} + h_2 \right] \Delta \ell n A_{2t} = \phi_{2NA} \Delta \ell n A_{2t}. \qquad \textbf{(22)}$$

The equation for $\Delta \ell n N_{1t}$ reflects price and quality substitution as does that for $\Delta \ell n N_{2t}$. However, the latter also includes cost reductions that encourage entry. Since $\eta_{12}>0$, exit from 1 occurs given that p_{2t} declines ($\epsilon_{22}<\delta_2$), and quality substitution increases the rate of exit from 1, since $\epsilon_{12}<0$. The reverse occurs in process 2. Note that it is quite possible to observe exit from 1 in spite of a rise in p_{2t}, and entry into 2 despite a fall in p_{2t}. Hereafter we shall take the pattern of exit from 1 and entry into 2 as the leading case for analysis, because industries with growing technologies often seem to show entry despite falling product price.

Combining (6), (18), (20)-(22) we obtain industry growth in Z_{2t} due to technology,

$$\Delta \ell n Z_t = [(1-\nu_{2Z})\phi_{1NA} + \nu_{2Z}(\phi_{2mr}\phi_{2mrA} + \phi_{2A} + \phi_{2NA})] \Delta \ell n A_{2t}. \qquad \textbf{(23)}$$

where ϕ_{2mr} and ϕ_{2A} are common effects of marginal revenue and technology on l and h in process 2 (see the Appendix). In our leading case, growth in A_{2t} causes entry in 2, so that $\phi_{2NA}>0$, and exit from 1, so that $\phi_{1NA}<0$. Now, there are two forces at work in our model that generate growth of particular inputs. First there is the rightward shift of demand for type 2 output due to rising product quality. Second, there is the concentration of particular inputs in process 2, the growing sector. With this in mind we are ready to discuss factor biases.

We consider within and between industry effects in turn. Within industry factor bias is measured by the difference in growth rates of high and low skilled labor. Evaluating (23) for H_t and L_t and taking the difference yields

$$D\ln H_t - D\ln L_t = (\nu_{2H}-\nu_{2L})\,[(\phi_{2mr}\phi_{2mrA}+\phi_{2A})+(\phi_{2NA}-\phi_{1NA})]\,D\ln A_{2t}. \qquad \textbf{(24)}$$

Since the high technology sector is skill intensive, $<_{2H}><_{2L}$. And because of entry into 2 and exit from 1, $N_{2NA}-N_{2NA}>0$. If incumbents in process 2 share the expansion ($N_{2mr}N_{2mrA}+N_{2A}>0$) then growth of high skilled labor exceeds that of low skilled.

Between industry effects are complicated by differing demand conditions, but the same key elements should serve a similar role. Factors should grow faster in more rapidly changing industries, provided that product demand shifts and entry are dominant. Simply treat 1 and 2 as homogeneous industries rather than processes. In that case industry 1 contracts due to price and quality substitution, while 2 expands. Our framework accomodates factor bias both within and between industries. Both effects seem to favor high skilled labor in the U.S. during the 1963-1988 period (Katz and Murphy [1992]).

Our theory traces technology back to its origins at different levels of the science and technology system, since productivity growth can be traced to science, R&D spillovers, S&Es, and a component reflecting luck in R&D. To see this, note that actual productivity growth equals expected growth plus the difference between actual and expected:

$$D\ell n\boldsymbol{A}_{2t} \equiv ED\ell n\boldsymbol{A}_{2t} + (D\ell n\boldsymbol{A}_{2t} - ED\ell n\boldsymbol{A}_{2t}) . \qquad \textbf{(25)}$$

We approximate the first term on the right using $EDℓnA_{2t}.(EA_{2t+1}-EA_{2t})/EA_{2t}$. Supposing that the flow of R&D activity depends on the stock of scientific knowledge, and as in Bartel and Lichtenberg [1989], on recent changes in the stock, and on S&Es, we can futher decompose expected productivity growth. Expanding EA_{2t+1} around EA_{2t} to the first order using rates of growth in science, R&D spillovers, and S&Es, and expressing the result in elasticity form we find

$$\frac{E\boldsymbol{A}_{2t+1} - E\boldsymbol{A}_{2t}}{E\boldsymbol{A}_{2t}} \approx \Phi_{\boldsymbol{A}KN} D\ell nKN_{t-M} + \Phi_{\boldsymbol{A}SP} D\ell nSP_{t-1} + \Phi_{\boldsymbol{A}\ell} D\ell n\ell_{t-J} \qquad \textbf{(26)}$$

Differences in lags reflect shorter lags on technology as compared with science and the idea that knowledge must first be acquired before it can be applied to the search for productivity gains. Substituting (26) in (25) yields

$$D\ell n\boldsymbol{A}_{2t} \approx \Phi_{\boldsymbol{A}KN} D\ell nKN_{t-M} + \Phi_{\boldsymbol{A}SP} D\ell nSP_{t-1} + \Phi_{\boldsymbol{A}\ell} D\ell n\ell_{t-J} + (D\ell n\boldsymbol{A}_{2t} - ED\ell n\boldsymbol{A}_{2t}) . \qquad \textbf{(27)}$$

To a first approximation (27) shows that productivity growth is due to current luck in R&D search, recent R&D spillovers, S&Es at a somewhat earlier time, and knowledge still further back. Substituting (27) into (23) we see that the same factors tend to accelerate growth of inputs in process, or industry, 2.

D. Extensions

Allowing for more processes and more dynamic technologies would allow us to generate a richer set of factor biases. Similar to the breakdown by types of labor, we could consider multiple forms of capital, especially equipment versus other capital, in which equipment represents the particular embodiment of new technologies (DeLong and Summers [1991]). Equipment would exhibit faster growth than other capital since it conveys new technology. We could allow, thirdly, for direct effects of S&Es on production. This extension would break the separability of the input demand systems and subject S&Es to realized productivity shocks, though to a lesser degree than ordinary labor. Since we are interested in the research function of S&Es, we are consigning their human capital function to high skilled labor. For this reason the extension would address measurement of true research activity rather than any substantive change.

III. Description of the Knowledge Data

Our production data are discussed with considerable clarity in Jorgenson et al. (1987) and Gullickson and Harper (1987), so we focus on our measures of knowledge and R&D in industry.

Knowledge is a stock that is increasingly based on academic science, despite the dominance of trial and error in earlier times (Rosenberg [1982]). Presumably this change reflects increasing division of labor in knowledge production: see Rosen (1983), and Becker and Murphy (1992) for related analyses.

But different industries draw upon science differently, and we assume that the result of their absorption is to create two stocks of applied knowledge. One represents externalities generated within an industry. This is the own stock. The other is the externality between industries, or spillover stock. The destination of the externalities is controlled by imitative R&D, as in Rosenberg (1976) and Schmitz (1989). Each depends on academic science and includes a repackaging-imitation mechanism mapping science into industry.

Since the knowledge stocks depend on underlying science and applied R&D resources, it should come as no surprise that they turn out to be index numbers of interactions between lagged industry scientists and stocks of academic papers. Two assumptions underlie the indexes: that scientific papers are units of theoretical innovation in the same sense as patents are units of applied innovation; and that industrial S&Es index the value of science to industry through willingness to pay. Moreover, the theory tells us that lagged scientists, even interacted with lagged science stocks in the absorbed stock of knowledge, are predetermined variables in input demand curves.

Our index of the own stock of knowledge in an industry is

$$KN_{t-L} = \sum_{j=1}^{F} \ell_{ijt-D} N_{jt-L}, \tag{28}$$

in which R_{jt-D} is the employment of scientists in industry i and field j at time t-D and the N_{jt-L} are article count stocks in field j at time t-L. This statistic requires distributions of industrial scientists by field and stocks of scientific papers. The industrial distribution of scientists derives from U.S. Department of Labor (1973), National Science Foundation (various years), and unpublished National Science Foundation tabulations. These sources yield R_{jt-D} in (28), which we introduce by itself in differenced form in the regressions below.

Sources for the article count stocks are described at length in Adams (1990). Annual data on scientific papers are drawn from major abstracting journals in their respective fields. These are world-wide flows of publications usually beginning early in the 20th century and ending in 1983. Flows are accumulated into stocks at various rates of obsolescence. Weighting the stocks by industry scientists and summing yields (28). In the regressions below we sometimes enter the difference of (28) in the recent past to capture impact effects of newer academic research.

Advantages of the scientific papers entering the stock are that they stand for the underlying science rather than industrial development; that they cover a wide range of studies; that the series begin earlier than R&D and offer greater flexibility in testing lags in effect; that, given their world-wide scope, they are more exogenous than R&D; and that, while papers vary in value, the mean value is captured in large samples.

The interindustry spillover stock is defined as

$$SP_{it} = Cos\Theta_{it}\sum_{j=1}^{F} \ell_{jt}N_{jt}. \quad \textbf{(29)}$$

Cos 1_{it} is the uncentered correlation between S&Es in industry i in different fields and their counterparts in the rest of industry. The remainder of (29) is the absorbed stock elsewhere, defined as in (28), but using as weights R_{jt}, S&Es in field j in the rest of industry.

We also employ estimates of R&D stocks and flows by applied product field-- industry of use-- from 1950 to 1986. The flow data were linked to research laboratory data classified by industry in 1960 and before, at intervals extending back to 1921. The resulting series extend from 1921-1986[14].

This concludes the description of the technology data.

IV. Empirical Results

A. Transition to Empirical Work

Our theory imposes a tight sequencing of events running from sceince to R&D in which percentage growth of inputs is treated as an approximate log linear function of percentage growth in input prices, percentage growth of nearly contemporaneous R&D expenditures, recent percentage growth of S&Es, percentage growth in the stock of knowledge somewhat further in the past, and the stock of knowledge, perhaps extending from the distant past. We follow this approximation, testing over various lags for the sequencing of events described, and finding, on usual criteria of statisticial significance, that effects of R&D are indeed the most recent, followed by growth in S&Es, and lastly by the stock of knowledge and its growth. Thus the sequencing argument receives considerable support in the pretests.

We depart from the elasticity form of the factor demands (see eq. (23), (25), and (26) above) in the case of our technology variables. Since we use pooled data across industries and time, we hesitate to force constant technology elasticities across industries. Instead we convert products of elasticities and technology growth rates into products of derivative effects on factors and of technology divided by input levels. Considering one technology term, and letting J be a technology indicator,

$$\eta_{Z_t\tau} D\ln\tau_t = \frac{\partial Z_t}{\partial \tau_t}\frac{\Delta\tau}{Z_{t-2}}. \qquad \textbf{(30)}$$

Z_t is lagged on the right to avoid division error bias with factor growth DRnZ_t in the demand equation. The reason for conversion to intensity form is that effects of technology on inputs are more nearly equal across industries than are the elasticities. And the fit of the intensity regressions judged by adjusted R^2 is in fact superior to the fit of the constant elasticity regressions.

Table 1 offers a description of the technology variables in intensity form. In the pretesting significant effects were found only for very short lags on R&D of 1-2 years. Somewhat stronger results were found on lags of 1-10 years on S&Es, lags of 5-10 years on academic research in computer science and engineering, and 20-30 years on basic science research in chemistry, physics, and the like. Our choice of technology indicators is conditioned on collinearity diagnostics (Belsley, Kuh, and Welsch [1980]), which strongly suggested that growth in the industry knowledge intensity be replaced by growth in the knowledge intensity per S&E. With that substitution, collinearity is no longer a major issue in our data. Tables 2 and 3 display descriptive statistics on rates of input growth and the main science and technology indicators for each of our two samples. From the factor growth rates in Table 2 we observe that capital and intermediate goods rise relative to labor. But Table 3 shows that college trained labor rises quite rapidly, noncollege hardly at all. The large size of the spillover intensity in either Table reveals the large number of sectors entering this variable and an average cosine between scientific employments (see (30)) of about 0.6. Finally, variation in the same intensity across factors is due to differences in factor employments. Since college employment is atypically low, though fast growing, its intensities are unusually large.

Table 1
Description of Technology Indicators

Concept	Formula	Lags Selected in Pretest	Industry Coverage
Intensity of Own Knowledge Stock in an Industry; Intensity Relative to Input Z)	KN_t/Z_{t-2}; see (28) of the text for the numerator	5 years on S&E weights; 5-20 years on article counts	14-15 manuf. industries
Growth of the Own Knowledge Intensity	$(KN_t-KN_{t-5})/5Z_{t-2}$	past 5-10 years of growth	14-15 manuf. industries
Growth of R&D Spending Intensity	$(RD_{t-1}-RD_{t-2})/Z_{t-2}$	last period's growth	14-15 manuf. industries
Growth of Industry S&Es	$(SE_t-SE_{t-10})/10$	growth over past 10 years	14-15 manuf. industries
Spillover Stock of Knowledge Between Industries	SP_t/Z_{t-2}; see (29) of the text for the numerator	5 years on S&E weights; 10-30 years on article counts	18 manuf. industries; 9 sectors outside manuf.

Table 2
Means and Standard Deviations of
Input Growth and Selected Science and Technology Indicators
Jorgenson, Gollop, and Fraumeni Data
(Standard Deviations in Parentheses)

Variable	Labor	Capital	Intermediate Goods[a]
Rate of Growth	0.014 (0.066)	0.041 (0.046)	0.038 (0.117)
Own Stock of Knowledge Intensity	8.1 (6.7)	5.4 (5.0)	5.9 (6.4)
Spillover Stock of Knowledge Intensity	297.2 (210.6)	177.9 (130.7)	213.9 (225.8)
Change in Real R&D Intensity	3.1 (11.0)	3.2 (10.9)	2.9 (10.1)

[a] Intermediate goods include materials, services, and energy.

Table 3
Means and Standard Deviations of
Input Growth and Selected Science and Technology Indicators
Bureau of Labor Statistics Data
(Standard Deviations in Parentheses)

Variable	College Trained Labor	Non-College Labor	Equip-ment Capital	Other Cap.[a]	Intermed-iate Goods
Rate of Growth	0.038 (0.063)	0.0003 (0.054)	0.038 (0.031)	0.029 (0.038)	0.032 (0.074)
Own Stock of Knowledge Intensity	55.5 (29.3)	12.1 (12.5)	13.6 (14.9)	8.9 (8.2)	7.5 (7.4)
Spillover Stock of Knowledge Intensity	2849.3 (2382.5)	407.6 (351.7)	427.5 (372.9)	301.8 (228.2)	258.5 (189.1)
Change in Real R&D Intensity	21.0 (52.5)	3.9 (10.6)	6.5 (21.3)	4.2 (12.7)	3.2 (8.8)

Notes. [a] All other capital includes buildings, land, and inventories.

B. Findings from the Jorgenson, Gollop, and Fraumeni Data

Tables 4 to 6 present estimated factor growth equations using the Jorgenson data. Dependent variables in all these tables are annual percentage rates of growth in labor, capital, and intermediate goods, just as in Table 2.

Since we are regressing small growth rates on technology intensities which are large in the case of the knowledge stocks (see Table 2), the estimated coefficients are rather small. Furthermore, the factors entering the denominators of the intensities vary in size, causing movements in the coefficients in the opposite direction. This suggests that mean effects should be reported, the product of means of the independent variables and their regression coefficients. Also, besides indicators of science and technology, all equations include growth in the three factor prices, the Federal Reserve Board's capacity utilization index, and growth in the price of energy. The last two variables control for the business cycle and energy price shocks. However, to save space, and since the other variables typically behave as expected, we limit our reporting to the science and technology indicators and summary goodness of fit statistics.

Table 4 reports regressions omitting industry dummies. This means that the estimated coefficients combine within and between industry effects. Table 4 shows generally positive and significant effects of science and technology on the growth of capital and labor, and very little for intermediate goods, but with some differences. Stocks of knowledge favor the growth of labor and capital, particularly capital. "Shock" effects of growth in the stock of knowledge and R&D spending are the reverse, promoting growth of labor but not capital. One interpretation is that the shock effects result in capital obsolescence, even though knowledge builds capital in the long run, as is shown by the significant effects of the knowledge stocks on the growth of capital. As in Bartel and Lichtenberg (1989), shocks may promote human capital to assist in the adjustment to new technology.

Table 5 includes industry dummies. Curiously, the resulting within industry effects, although similar to before, are even more favorable to science and technology. Notice that shock effects of knowledge continue to be strong in the labor equation, but not for capital. It seems strange that when cross industry variation is discarded the findings should increase in significance. The reason is probably that industries decline for reasons that are outside our hypothesis, for example increased foreign competition, and that this biases cross industry effects downward.

Table 6 revisits the setup of Table 4 allowing for endogeneity of the factor prices. The method of estimation is 3SLS. The system contains six equations corresponding to prices and quantities for the inputs[15]. Though the results for capital are somewhat weaker, generally the findings are similar to Table

4. This is because the second stage equations explain much of the variation in growth of the factor prices.

Table 4

Academic Science, Industrial R&D, and the Growth of Inputs
Findings from the Jorgenson, Gollop, and Fraumeni Data
Within and Between Industry Regressions
Dependent Variable: % Growth of Factors
(t statistics in parentheses)
[mean effects in brackets]

Variable or Statistic	Labor 4.1	Capital 4.2	Intermediate Goods 4.3
Industry Dummies	No	No	No
Growth in R&D Spending	0.79×10^{-3} (2.9) [0.0022]	0.38×10^{-3} (1.9) [0.0012]	0.89×10^{-3} (1.6) [0.0026]
Own Stock of Knowledge	1.18×10^{-3} (2.4) [0.0095]	2.15×10^{-3} (3.8) [0.0115]	1.79×10^{-3} (1.3) [0.0053]
Growth in Own Stock of Knowledge per S&E	1.44 (2.8) [0.0055]	-1.84 (-2.6) [-0.0026]	1.36 (1.0) [0.0023]
Annual Growth in S&Es over the past 10 years	-0.03 (-1.0) [-0.0026]	-0.04 (-1.9) [-0.0039]	-0.06 (-1.0) [-0.0053]
Spillover Stock of Knowledge	-0.01×10^{-4} (-0.0) [-0.0002]	0.83×10^{-4} (5.1) [0.0149]	0.15×10^{-4} (0.5) [0.0033]
Estimation Method	OLS	OLS	OLS
Root MSE	0.058	0.040	0.105
Adjusted R^2	0.235	0.249	0.190
F Statistic	13.9	14.9	10.8

Notes. Sample is 15 manufacturing industries. Period is 1952-1979. Other variables in the regression include growth in all 3 factor prices, growth in the price of energy, and the Federal Reserve Board index of capacity utilization.

Table 5

Academic Science, Industrial R&D, and the Growth of Inputs
Findings from the Jorgenson, Gollop, and Fraumeni Data
Within Industry Regressions
Dependent Variable: % Growth of Factors
(t statistics in parentheses)
[mean effects in brackets]

Variable or Statistic	Labor 5.1	Capital 5.2	Intermediate Goods 5.3
Industry Dummies	Yes	Yes	Yes
Growth in R&D Spending	0.62×10^{-3} (2.6) [0.0019]	0.53×10^{-3} (2.7) [0.0017]	0.58×10^{-3} (1.1) [0.0017]
Own Stock of Knowledge	2.30×10^{-3} (2.4) [0.0185]	4.48×10^{-3} (2.8) [0.0240]	4.93×10^{-3} (1.5) [0.0292]
Growth in Own Stock of Knowledge per S&E	1.82 (4.2) [0.0070]	-0.40 (-0.5) [-0.0006]	4.45 (3.1) [0.0075]
Annual Growth in S&Es over the past 10 years	0.03 (1.2) [0.0032]	-0.03 (-1.2) [-0.0025]	0.07 (1.2) [0.0064]
Spillover Stock of Knowledge	0.56×10^{-4} (2.0) [0.0167]	2.54×10^{-4} (4.6) [0.0452]	0.81×10^{-4} (0.8) [0.0174]
Root MSE	0.047	0.037	0.094
Adjusted R^2	0.488	0.353	0.357
F Statistic	17.6	10.5	10.7

Notes. Sample is the same as in Table 1.

Table 6

Academic Science, Industrial R&D, and the Growth of Inputs
Findings from the Jorgenson, Gollop, and Fraumeni Data
3SLS Between and Within Industry Regressions
Dependent Variable: % Growth of Factors
(asymptotic t-statistics in parentheses)
[mean effects in brackets]

Variable or Statistic	Labor 6.1	Capital 6.2	Intermediate Goods 6.3
Industry Dummies	No	No	No
Growth in R&D Spending	0.71×10^{-3} (2.8) [0.0022]	0.24×10^{-3} (1.5) [0.0008]	1.05×10^{-3} (2.0) [0.0031]
Own Stock of Knowledge	0.94×10^{-3} (2.2) [0.0075]	1.16×10^{-3} (2.6) [0.0062]	0.80×10^{-3} (0.7) [0.0047]
Growth in Own Stock of Knowledge per S&E	1.29 (3.0) [0.0050]	-0.45 (-0.8) [-0.0006]	1.62 (1.4) [0.0027]
Annual Growth in S&Es over the past 10 years	-0.01 (-0.4) [-0.0009]	-0.01 (-0.8) [-0.0013]	-0.02 (-0.3) [-0.0015]
Spillover Stock of Knowledge	-0.03×10^{-4} (-0.2) [-0.0009]	0.42×10^{-4} (3.2) [0.0076]	-0.06×10^{-4} (-0.2) [-0.0012]
Estimation Method	3SLS	3SLS	3SLS

Notes. Sample is 15 manufacturing industries. Period is 1953-1979. The system to which 3SLS is applied includes the 3 input growth equations and the 3 input price growth equations.

Finally, we estimated equations relating percentage growth in R&D to science intensity. A representative equation, where the intensities are relative to R&D stock, is the following (t-statistics in parentheses):

% change in R&D stock= 0.045+ 0.363*(own knowledge intensity)+
(7.2)
13.209*(change in knowledge intensity per S&E)-
(2.1)
0.0001*(spillover knowledge intensity)+...+
(-0.5)
Adj. R^2=0.248.

Other variables in the equation included input price growth, growth in energy price, and capacity utilization. The preferred lags resembled closely those in the input growth equations. This too suggests the sequencing notion of Section II.C between science and R&D.

C. Findings from the BLS Data

Table 7 reports findings from BLS data that separate college trained from noncollege trained labor and equipment capital from other capital[16]. The idea of this table is that high skilled labor embodies the knowledge required by fast growing processes, and that equipment capital is more likely to embody the fruits of sectoral R&D than is other capital. The results for college trained labor are supportive, even though they are downward biased due to the large errors in the college trained series[17]. As far as equipment capital is concerned, mean effects for the own industry science and technology variables are somewhat in its favor. But interindustry knowledge effects are the reverse, suggesting that disembodied spillovers between industries also promotes growth of capital and industry. The generally strong links between human and physical capital are consistent with Dertouzos, et al. (1989), which promotes the wisdom of technical sophistication, and bureaucratic attneuation, in successful plant retoolings.

Table 8 presents results with industry dummies. In some ways the findings for the college trained are weaker, but knowledge spillovers are stronger, and the bias against noncollege labor continues to prevail. In relative terms the results for equipment and other capital remain unchanged, though links with technology in both sets of results are generally stronger than in Table 7. Thus the results for capital strengthen at the expense of labor. The unavoidable time series errors in the college trained series very likely play a role in this.

Table 9 presents 3SLS results which treat input prices as endogenous[18]. These are counterparts to Table 7 since industry dummies are omitted. As was the case with the Jorgenson data, findings for the most part stay the same. This concludes the presentation of the empirical work.

Table 7

Academic Science, Industrial R&D, and the Growth of Inputs
Findings from the Bureau of Labor Statistics Data
Within and Between Industry Regressions
Dependent Variable: % Growth of Factors
(t statistics in parentheses)
[mean effects in brackets]

Variable or Statistic	Labor: College	Labor: Noncollege	Capital: Equipment	Capital: Other	Intermediate Goods
	7.1	7.2	7.3	7.4	7.5
Industry Dummies	No	No	No	No	No
Growth in R&D Spending	0.16×10^{-3} (2.9) [0.0034]	0.28×10^{-3} (1.6) [0.0011]	0.14×10^{-3} (2.3) [0.0009]	-0.04×10^{-3} (-0.3) [-0.0002]	-0.41×10^{-3} (-1.1) [-0.0013]
Own Stock of Knowledge	0.32×10^{-3} (3.0) [0.0177]	0.09×10^{-3} (0.5) [0.0011]	0.95×10^{-3} (8.4) [0.0129]	1.40×10^{-3} (5.6) [0.0116]	1.28×10^{-3} (2.7) [0.0096]
Growth in Own Stock of Knowledge per S&E	0.02 (0.7) [0.0011]	0.14 (1.0) [0.0017]	-0.34 (-3.2) [-0.0024]	-0.78 (-4.0) [-0.0045]	-0.63 (-1.6) [-0.0034]
Annual Growth in S&Es over the past 10 years	0.01 (2.0) [0.0063]	0.03 (2.8) [0.0031]	-0.01 (-2.3) [-0.0023]	0.01 (0.7) [0.0008]	0.03 (1.3) [0.0031]
Spillover Stock of Knowledge	0.04×10^{-4} (2.9) [0.0114]	-0.04×10^{-4} (-0.5) [-0.0016]	0.04×10^{-4} (1.3) [0.0019]	0.34×10^{-4} (4.9) [0.0103]	0.36×10^{-4} (2.2) [0.0094]
Estimation Method	OLS	OLS	OLS	OLS	OLS
Root MSE	0.056	0.037	0.024	0.032	0.059
Adjusted R^2	0.208	0.528	0.412	0.308	0.361
F Statistic	11.4	45.2	29.5	19.2	24.0

Notes. Sample is 14 manufacturing industries. Period is 1953-1986.

Table 8

Academic Science, Industrial R&D, and the Growth of Inputs
Findings from the Bureau of Labor Statistics Data
Within Industry Regressions
Dependent Variable: % Growth of Factors
(t statistics in parentheses)
[mean effects in brackets]

Variable or Statistic	Labor		Capital		Intermediate Goods
	College	Noncollege	Equipment	Other	
	8.1	8.2	8.3	8.4	8.5
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Growth in R&D Spending	0.14×10^{-3} (2.5) [0.0029]	0.29×10^{-3} (1.6) [0.0011]	0.19×10^{-3} (3.2) [0.0012]	-0.02×10^{-3} (-0.2) [-0.0009]	-0.55×10^{-3} (-1.5) [-0.0017]
Own Stock of Knowledge	0.32×10^{-3} (1.6) [0.0177]	0.12×10^{-3} (0.4) [0.0014]	1.66×10^{-3} (5.2) [0.0224]	2.2×10^{-3} (3.6) [0.0196]	0.83×10^{-3} (0.8) [0.0062]
Growth in Own Stock of Knowledge per S&E	0.05 (1.5) [0.0027]	0.06 (0.4) [0.0007]	-0.40 (-3.4) [-0.0030]	-0.79 (-3.9) [-0.0045]	-0.98 (-2.3) [-0.0053]
Annual Growth in S&Es over the past 10 years	0.01 (1.7) [0.0063]	0.03 (2.0) [0.0031]	-0.01 (-2.3) [-0.0021]	0.01 (1.0) [0.0013]	0.02 (0.8) [0.0021]
Spillover Stock of Knowledge	0.14×10^{-4} (4.5) [0.0399]	0.14×10^{-4} (1.0) [0.0057]	0.02×10^{-4} (0.2) [0.0010]	0.34×10^{-4} (4.9) [0.0130]	1.55×10^{-4} (3.5) [0.0399]
Estimation Method	OLS	OLS	OLS	OLS	OLS
Root MSE	0.055	0.036	0.023	0.032	0.059
Adjusted R^2	0.244	0.559	0.475	0.330	0.369
F Statistic	7.1	25.1	18.7	10.6	12.5

Notes. Sample is 14 manufacturing industries. Period is 1953-1986.

Table 9

Academic Science, Industrial R&D, and the Growth of Inputs
Findings from the Bureau of Labor Statistics Data
3SLS Between and Within Industry Regressions
Dependent Variable: % Growth of Factors
(asymptotic t-statistics in parentheses)
[mean effects in brackets]

Variable or Statistic	Labor		Capital		Intermediate Goods
	College	Noncollege	Equipment	Other	
	9.1	9.2	9.3	9.4	9.5
Industry Dummies	No	No	No	No	No
Growth in R&D Spending	0.14×10^{-3} (2.5) [0.0029]	0.36×10^{-3} (2.1) [0.0014]	0.13×10^{-3} (2.2) [0.0008]	0.00×10^{-3} (0.1) [0.0000]	0.18×10^{-3} (0.5) [0.0006]
Own Stock of Knowledge	0.28×10^{-3} (2.6) [0.0155]	0.12×10^{-3} (0.8) [0.0015]	0.74×10^{-3} (6.5) [0.0100]	0.71×10^{-3} (3.2) [0.0063]	0.43×10^{-3} (0.9) [0.0032]
Growth in Own Stock of Knowledge per S&E	0.01 (0.2) [0.0005]	0.23 (1.9) [0.0028]	-0.25 (-2.3) [-0.0020]	-0.63 (-3.4) [-0.0038]	-0.19 (-0.5) [-0.0011]
Annual Growth in S&Es over the past 10 years	0.01 (1.9) [0.0063]	0.03 (2.8) [0.0031]	-0.01 (-1.4) [-0.0019]	0.02 (1.7) [0.0024]	0.04 (1.7) [0.0036]
Spillover Stock of Knowledge	0.03×10^{-4} (2.8) [0.0114]	-0.06×10^{-4} (-1.0) [-0.0024]	0.01×10^{-4} (0.3) [0.0004]	0.16×10^{-4} (2.6) [0.0048]	-0.00×10^{-4} (-0.0) [-0.0001]
Estimation Method	3SLS	3SLS	3SLS	3SLS	3SLS

Notes. Sample is 15 manufacturing industries. Period is 1953-1986. The system to which 3SLS is applied includes 10 equations: 5 for input growth and 5 for input price growth.

V. Conclusion

This paper has presented a new model of industry growth with factor bias that is a synthesis of a large body of earlier research. The theory exposits the connections between science and technology by assuming that science plays a critical role in the R&D search process, and by assuming that human and physical capital are employed intensively by technologically dynamic processes and industries. Precisely because of their growing technology the latter experience large and favorable shifts in product demand, and considerable growth in diverse forms of capital. Our empirical findings are supportive of this idea, and also of the idea that science and technology cascade through time, with the results of science leading the results of R&D. Science and technology matter to the growth of inputs and industries, and they appear to be a potent force responsible for capital deepening in the U.S. and other economies. They are a powerful mover of the entire structure of production, with consequences no doubt mostly unforeseen by the originators of the underlying science.

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Appendix

Part A. Derivation of Derived Demands by Type 1 Firms

Taking logs of (5) yields

$$\begin{bmatrix} \alpha_{l1}-1 & \alpha_{h1} \\ \alpha_{l1} & \alpha_{h1}-1 \end{bmatrix} \begin{bmatrix} \ell n l_{1t} \\ \ell n h_{1t} \end{bmatrix} = \begin{bmatrix} \ell n s_{lt} - \ell n \boldsymbol{p}_{1t} - \alpha_{\boldsymbol{A}1} \ell n \boldsymbol{A}_1 \\ \ell n s_{ht} - \ell n \boldsymbol{p}_{1t} - \alpha_{\boldsymbol{A}1} \ell n \boldsymbol{A}_1 \end{bmatrix}. \tag{A.1}$$

Solving (A.1) we reach

$$\begin{aligned} \ell n l_{1t} &= \boldsymbol{b}_1 \left[(1-\alpha_{h1}) \ell n \left(\frac{s_{lt}}{\boldsymbol{p}_{1t}} \right) + \alpha_{h1} \ell n \left(\frac{s_{ht}}{\boldsymbol{p}_{1t}} \right) - \alpha_{\boldsymbol{A}1} \ell n \boldsymbol{A}_1 \right] \\ \ell n h_{1t} &= \boldsymbol{b}_1 \left[\alpha_{l1} \ell n \left(\frac{s_{lt}}{\boldsymbol{p}_{1t}} \right) + (1-\alpha_{l1}) \ell n \left(\frac{s_{ht}}{\boldsymbol{p}_{1t}} \right) - \alpha_{\boldsymbol{A}1} \ell n \boldsymbol{A}_1 \right]. \end{aligned} \tag{A.2}$$

Diminishing returns ("$_{l1}$+"$_{h1}$<1) imply

$$\boldsymbol{b}_1 = \frac{1}{\alpha_{l1}+\alpha_{h1}-1} < 0.$$

$$\boldsymbol{D} \ell n z_{1t} = \phi_{1zl} \boldsymbol{D} \ell n \left(\frac{s_{lt}}{\boldsymbol{p}_{1t}} \right) + \phi_{1zh} \boldsymbol{D} \ell n \left(\frac{s_{ht}}{\boldsymbol{p}_{1t}} \right). \tag{A.3}$$

First differencing yields the derived demands in growth rate form,

Part B. Derivation of Derived Demands by Type 2 Firms

We approximate factor growth rates for type 2 firms. Consider (14) at t+1 and expand around period t values to the first order. The result is

$$\begin{bmatrix} \dfrac{\partial VMP_{2lt}}{\partial l_{2t}} & \dfrac{\partial VMP_{2lt}}{\partial h_{2t}} \\ \dfrac{\partial VMP_{2ht}}{\partial l_{2t}} & \dfrac{\partial VMP_{2ht}}{\partial h_{2t}} \end{bmatrix} \begin{bmatrix} l_{2t+1} - l_{2t} \\ h_{2t+1} - h_{2t} \end{bmatrix} \simeq \begin{bmatrix} \boldsymbol{e}_{2lt+1} \\ \boldsymbol{e}_{2ht+1} \end{bmatrix} \tag{B.1}$$

where zero order terms vanish by (14) and the vector on the right is

$$\begin{bmatrix} e_{21t+1} \\ e_{2ht+1} \end{bmatrix} = \begin{bmatrix} (s_{1t+1}-s_{1t}) - \frac{\partial VMP_{12t}}{\partial mr_{2t}}(mr_{2t+1}-mr_{2t}) - \frac{\partial VMP_{12t}}{\partial A_{2t}}(A_{2t+1}-A_{2t}) \\ (s_{ht+1}-s_{ht}) - \frac{\partial VMP_{h2t}}{\partial mr_{2t}}(mr_{2t+1}-mr_{2t}) - \frac{\partial VMP_{h2t}}{\partial A_{2t}}(A_{2t+1}-A_{2t}) \end{bmatrix} \quad \textbf{(B.2)}$$

Note that changes in mr_{2t} are exogenous changes on the right.

Factors are complements so off-diagonal terms on the left of (B.1) are positive. Diagonal terms are negative since marginal product is diminishing. Multiplying by the inverse of the matrix on the left of (B.1) we arrive at the expression

$$\begin{bmatrix} l_{2t+1}-l_{2t} \\ h_{2t+1}-h_{2t} \end{bmatrix} = \frac{1}{|A|}\begin{bmatrix} c_{11t} & c_{21t} \\ c_{12t} & c_{22t} \end{bmatrix} \cdot \begin{bmatrix} e_{21t+1} \\ e_{2ht+1} \end{bmatrix}. \quad \textbf{(B.3)}$$

where c_{iit} and *A*, the determinant of the left hand matrix of (A.3), are positive and negative by the second order conditions. Further, factor complementarity implies that $c_{ijt}>0$, since

$$D\ell n z_{2t} = \phi_{2z0} + \phi_{2z1} D\ell n\left(\frac{s_{1t}}{mr_{2t}}\right) + \phi_{2zh} D\ell n\left(\frac{s_{ht}}{mr_{2t}}\right) + \phi_{2zk} D\ell n\left(\frac{s_{kt}}{mr_{2t}}\right) + \phi_{2A} D\ell n A_{2t}. \quad \textbf{(B.5)}$$

$$c_{ijt} = -\left[\frac{\partial VMP_i}{\partial j}\frac{\partial VMP_k}{\partial k} - \frac{\partial VMP_i}{\partial k}\frac{\partial VMP_k}{\partial j}\right], \quad \textbf{(B.4)}$$

The growth rate form of (B.3), which is (18), is:

The signs, negative except for N_{2A}, follow from signs of the c_{ijt}. Furthermore, N_{2A} is positive and the same for l_{2t} and h_{ht}, as can be shown by expanding (B.3) in the percentage change form of A_{2t}.

Part C. Derivation of Derived Demands for S&Es by Type 2 Firms

We apply a similar procedure to part B to the derived demand for S&Es. Index (15) at time t+1, and expand in Taylor's Series to the first order around period t values:

$$\frac{\partial^2 EV_t}{\partial \ell_t^2}(\ell_{t+1}-\ell_t) \cong \boldsymbol{d}_{t+1} \tag{C.1}$$

where the zero order term vanishes by (15). On the right we have

$$\begin{aligned} \boldsymbol{d}_{t+1} \equiv\ & (w_{t+1}-w_t) - \frac{\partial^2 EV_t}{\partial \ell_t \partial KN_{t-M}}(KN_{t-M+1}-KN_{t-M}) - \\ & \frac{\partial^2 EV_t}{\partial \ell_t \partial SP_t}(SP_{t+1}-SP_t) - \frac{\partial^2 EV_t}{\partial \ell_t \partial X_t}(X_{t+1}-X_t) \end{aligned} \tag{C.2}$$

Solving (C.1) we obtain

$$\ell_{t+1}-\ell_t \cong \left(\frac{\partial^2 EV_t}{\partial \ell_t^2} \right)^{-1} \boldsymbol{d}_{t+1}. \tag{C.3}$$

The term M^2EV_{t+1}/MR_t^2 is negative by the concavity of the value function in R_t. (C.3) in log differential form is (19).

D. The System of Industry Relationships

Equilibrium expressions for entry and percent change in price and marginal revenue are derived as follows. Fixing factor prices pegs p_{1t} in constant cost competitive markets.

By (4) growth in final demand for type 1 and 2 output is

$$\Delta \ln Q_{1t}^{d} = \eta_{12} \Delta \ln p_{2t} + \epsilon_{12} \Delta \ln A_{2t}$$
$$\Delta \ln Q_{2t}^{d} = \eta_{22} \Delta \ln p_{2t} + \epsilon_{22} \Delta \ln A_{2t}. \qquad \textbf{(D.1)}$$

Here $\eta_{12}>0$, $\eta_{22}<0$, while $\epsilon_{12}<0$, $\epsilon_{22}>0$.

Output in each process is $Q_{it}=q_{it}N_{it}$. q_{1t} stays the same so changes in Q_{1t} and N_{1t} are equal. Change in Q_{2t} is split between q_{2t} and N_{2t}. Thus percentage changes in Q_{1t} and Q_{2t} are

$$\Delta \ln Q_{1t}^{s} = \Delta \ln N_{1t}$$
$$\Delta \ln Q_{2t}^{s} = \Delta \ln q_{2t} + \Delta \ln N_{2t}. \qquad \textbf{(D.2)}$$

Market equilibrium requires $\Delta \ln Q_{it}^{d} = \Delta \ln Q_{it}^{s}$.

q_{2t} depends on mr_{2t} and mc_{2t}, the latter declining with A_{2t}; entry depends on p_{2t} versus ac_{2t}, also declining in A_{2t}. Therefore,

$$\Delta \ln q_{2t} = g_1 \Delta \ln mr_{2t} + g_2 \Delta \ln A_{2t}$$
$$\Delta \ln N_{2t} = h_1 \Delta \ln p_{2t} + h_2 \Delta \ln A_{2t}. \qquad \textbf{(D.3)}$$

Signs are g_1, $g_2>0$ and h_1, $h_2>0$ from what has gone before.

Percent change in mr_{2t} completes the system. Since $mr_{2t}=(1-f_t/|\eta|)p_{2t}$, and $f_t=1/N_{2t}$ in the symmetric case, we obtain,

$$\Delta \ln mr_{2t} = k_1 \Delta \ln N_{2t} + k_2 \Delta \ln p_{2t}, \qquad \textbf{(D.4)}$$

where k_1, $k_2>0$ from the definition of mr_{2t}.

Solving (D.1)-(D.4) we reach

$$\boldsymbol{D}\ln \boldsymbol{p}_{2t} = \frac{\epsilon_{22} - \boldsymbol{d}_2}{\boldsymbol{d}_1 - \eta_{22}} \boldsymbol{D}\ln \boldsymbol{A}_{2t}$$

$$\boldsymbol{D}\ln mr_{2t} = \left[(k_1 h_1 + k_2) \frac{\epsilon_{22} - \boldsymbol{d}_2}{\boldsymbol{d}_1 - \eta_{22}} + k_1 h_2 \right] \boldsymbol{D}\ln \boldsymbol{A}_2 t. \tag{D.5}$$

The coefficients d_1 and d_2 are

$$\boldsymbol{d}_1 = h_1 (1 + \boldsymbol{g}_1 k_1) + \boldsymbol{g}_1 k_2,$$

$$\boldsymbol{d}_2 = h_2 (1 + \boldsymbol{g}_1 k_1) + \boldsymbol{g}_2. \tag{D.6}$$

Both are positive. Similarly, equilibrium entry is given by

$$\boldsymbol{D}\ln N_{1t} = \left[\frac{\eta_{12} (\epsilon_{22} - \boldsymbol{d}_2)}{\boldsymbol{d}_1 - \eta_{22}} + \epsilon_{12} \right] \boldsymbol{D}\ln \boldsymbol{A}_{2t}$$

$$\boldsymbol{D}\ln N_{2t} = \left[\frac{h_1 (\epsilon_{22} - \boldsymbol{d}_2)}{\boldsymbol{d}_1 - \eta_{22}} + h_2 \right] \boldsymbol{D}\ln \boldsymbol{A}_{2t}. \tag{D.7}$$

(D.5) and (D.7) are (21) and (22) of the text.

Footnotes

1. See Nelson (1982), Hounshell and Smith (1988), and Mowery and Rosenberg (1989) among other industry studies. Notable labor studies include Murphy and Welch (1992), Bound and Johnson (1992), and Murphy and Katz (1992).

2. Search theory in its general form was developed by Stigler (1961, 1962) and McCall (1970).

3. By total factor productivity we mean the Divisia index consisting of percentage output growth between periods minus the weighted average of input growth between periods, where the weights are cost shares. The latter weighted average is often refered to as "explained" output growth.

4. See Griliches and Jorgenson (1967) and Denison (1969). We are aware that breaking the effect of knowledge into an "explained" part embodied in factors and an "unexplained" productivity part linked to research spillovers does require knowledge of embodiment. If all prices and quantities were correctly measured then productivity would reflect only disembodied knowledge and explained growth would capture only embodiment. In such a world the effects of knowledge would be additive. But true productivity is unobserved so the decomposition is impossible.

5. For a compelling study of this effect, see Horowitz and Sherman [1980]).

6. We do not mean that the observed rate of growth is independent of embodiment. In new growth theory models observed growth falls short of optimal growth to the extent that growth is disembodied. See Romer (1986, 1990), and Lucas (1988).

7. The term productivity state distinguishes stochastically evolving productivity from deterministic R&D capital stock. The concept of productivity state separates R&D output from R&D inputs. Productivity state need not increase with R&D expenditures, whereas R&D stock does. This view is close to that of Evenson and Kislev (1976).

8. The factor intensity ordering can be motivated by appealing to the demands for an influx of human and physical capital imposed adjustments to changes in technology, as in Nelson and Phelps (1966) and Bartel and Lichtenberg (1989). We do not pursue this connection in detail.

9. Concavity means that 8_{SPt} and 8_{Rt} lie between zero and 1 and sum to less than 1.

In this formulation spillovers have a stochastic effect on productivity. Let the firm's current productivity state be A_{2t}. A deterministic effect of spillovers could be obtained by defining the new productivity state, $A'_{2t}=g(R_t,SP_t)$, where g is an increasing function oF S&Es and spillovers. In this case $A'_{2t}>A_{2t}$ and $G_{2t}=0$ once the number of scientists and spillovers exceed a critical mass, but $A'_{2t}<A_{2t}$ if spillovers are small, regardless of the number of S&Es. We do not pursue this alternative approach here, in part because adaptive invention is probably not a sure bet.

10. The exponential distribution is commonly used to descibe continuous non-negative random variables. In our case it is an approximation, since productivity has a finite upper bound while the domain of an exponential variate is unbounded above. We bound productivity at a high level so that the resulting truncated distribution is approximated by the exponential.

11. The derivative in (16) follows from differentiation of the exponent as well as the base. To see this, use the formula $y=f(x)^{g(x)}/e^{g(x)\ln f(x)}$, make the appropriate substitutions for y, f(x), and g(x), and differentiate.

12. Recall that $h_{2t}=n_t g_{2t} G_{2t}^{nt-1}$. Repeated application of the product rule and application of the result in fn. 10 yields (17).

13. Type 1 is a competitive activity with identical firms, changes in p_{1t} are entirely driven by factor prices, and changes in mr_{2t} partly so. Though we worked out this more general case, we opted for the simpler presentation in the text.

14. Estimates of research and development expenditures from 1921 to 1960 were based on information on employment in individual research laboratories included in directories published by the National Research Council. Individual laboratories were assigned to product fields based on their stated areas of research.

Directory information for 1921, 1927, 1933, 1940, 1946, 1950, 1955, and 1960 was used in these calculations. Since the wartime pattern of research cannot reasonably be determined from data for 1940 and 1946 alone, estimates of the wartime pattern of R & D expenditures were constructed from <u>The Government's Wartime Research and Development, 1940-44</u>, a report from the Subcommittee on War Mobilization to the Senate Committee on Military Affairs, and from other sources.

The 1921-1960 data were benchmarked to national data on research and development expenditures published in BLS Bulletin 2331, <u>The Impact of Research and Development on Productivity Growth</u>. The individual industry estimates were linked to the standard National Science Foundation applied product field data in 1960. Data were collected from both the directories and NSF sources in 1960, and linked; this adjustment procedure made it possible to modify the directory data to allow for the fact that research laboratories of the type covered by the directories account for a larger proportion of the total research effort in some industries (chemicals) than in others (aircraft).

The NSF applied product field data have not been published on a comparable basis after 1983. Therefore, estimates of applied product field data were constructed for 1984 to 1986 using an alternative NSF industry series for these years. Subsequently, the 1921-1960 data from the directories, the NSF applied product field data for 1960-1983, and the further estimates for 1984-1986 were combined to create the 1921-1986 time-series analyzed here.

15. The factor quantity growth equations are specified as before. The factor price growth equations include growth in the price of that factor in other industries, growth in the price of that factor in the industry lagged one and two periods, and growth in real GNP. The labor price growth equation also includes population growth, the capital price equation includes the savings rate, and the intermediate goods price equation includes growth of energy price. This system satisfies both the rank and order conditions for identification.

16. The separation of college from noncollege labor by 2 digit manufacturing industry is nontrivial, because industry data distinguish only white and blue collar workers. To obtain estimates of college and noncollege workers by industry it is first necessary to derive college and noncollege proportions of white and blue collar workers by industry. The only source for this between Census years is the CPS, but the CPS sample is thin when it is divided up by industry. Thus the estimates of the college proportions exhibit large sampling variability from year to year. To combat this problem we take 3 year moving averages of the college proportions. The smoothed proportions are multiplied by white and blue collar employees. We note that data on white and blue collar employment are relaible since they are drawn from the comprehensive 790 survey of manufacturing employers. Adding together the estimated college numbers derived from college proportions in each of white and blue collar employment, we obtain total college employment by industry. This exhibits movements due to the business cycle, and some remaining sampling variability. The latter biases our results for the college trained downward. Noncollege trained are a residual after subtraction of college employment from total employment.

17. The attenuation bias for our data is as follows. Let $y_t = \alpha + \beta q_t$, where q_t is the true technology intensity. However, the

divisor of the intensity is erroneous so we have not q_t but $z_t=q_t+e_t$, and the bias as usual is $-\$F_e^2/(F_e^2+F_z^2)<0$. See Greene (1990) among others.

18. The system is the same as in the Jorgenson data, except that there are 5 input quantity growth equations and 5 input price growth equations.