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AN EXPLORATION INTO THE DETERMINANTS OF RESEARCH INTENSITY

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ABSTRACT

This paper explores the economic factors which determine the variation of research effort across firms. The intra-industry coefficient of variation of research intensity is much larger than those of traditional factors. We show that this important fact is consistent with the theoretical argument that knowledge possesses unique economic characteristics, and that the demand for research depends both on the parameters of the production function for knowledge and on the ability of the firm to appropriate the benefits from the knowledge it produces. We propose and implement a framework for decomposing the observed intra-industry variance in research intensity into three components: demand inducement, a firm-specific structural parameter, and errors in the observed variables. The main empirical findings are that errors in the variables (especially research) are important, that very little of the structural variance in research intensity is accounted for by demand inducement, and that the bulk of the variance is related to differences in the firm-specific parameter. Both the theoretical and empirical analysis indicate that it is not reasonable to treat the demand for research in a manner analogous to the demand for traditional inputs, including capital. Substantially richer models are required to provide insight into the structure of incentives driving the demand for research.

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AN EXPLORATION INTO THE DETERMINANTS OF RESEARCH INTENSITY*

Introduction

The recent interest of economists in the process of technological change derives in part from the unique economic characteristics of knowledge. These characteristics, discussed formally by Arrow (1962), indicate the likelihood of a divergence between the private and social rates of return to research resources devoted to producing new knowledge. It should not be surprising that these same characteristics also affect the derived demand for research by profit-oriented firms. This paper explores the economic factors which determine the distribution of research effort across firms. These factors are known as cross-sectional inducement mechanisms. There are three sets of competing explanations in the literature, each emphasizing a different aspect of the problem.

Schmookler (1966), and Griliches and Schmookler (1963), emphasize the importance of expected market size as an inducement to research effort. They recognize that the cost of reproducing the knowledge generated by research is low relative to the original cost of producing it, and that the private return to research therefore varies directly with the number of units of output in which the knowledge is embodied, or the size of the market. Differences across industries in the cost of producing knowledge are downplayed, on the argument that scientific knowledge is sufficiently well developed to make the supply for new industrial knowledge highly elastic at the same level of costs for all industries. Rosenberg (1963, 1969 and 1974), while granting the importance of market size, argues that the body of scientific and engineering knowledge grows at different rates in different areas and that the application of such knowledge to industries is more circumscribed than Griliches and Schmookler suggest. He concludes that these differences in the cost of producing industrial knowledge, or technological opportunity, are a major determinant of the observed distribution of research effort. Schumpeter (1950), on the other hand, argues that research effort generates temporary monopoly power for the innovating firm. Since knowledge has a low reproduction cost, any economic unit aware of the information embodied in an innovation can exploit it. Hence the private benefits from the production of knowledge must be a result of quasi-rents accruing to the producer of the innovation. The key to this process is the ability of the firm to appropriate the monetary benefits from the knowledge it produces. Schumpeter therefore emphasizes the determinants of the degree of appropriability, such as entrepreneurial ability, industrial market structure, and the general institutional framework (including patent rights) in which the firm operates. Finally, any study which specifies empirical measures of research effort and their relationship to economically useful knowledge must give careful attention to the influence of measurement and specification errors on the observed distribution of research expenditures.

These different issues in cross-sectional inducement remain unresolved and unintegrated into a general framework. This paper presents a unified framework for analyzing interfirm differences in research expenditures which takes account of the unique characteristics of knowledge as an economic commodity. The model postulates Cobb-Douglas production relationships and results in equations determining the intensity of use of all inputs. Traditional factor intensities in such a framework depend only on production function parameters. The optimum research intensity depends, in addition, on expected growth rates and appropriability. The intra-industry coefficient of variation in research intensity in the comprehensive cross-section of American manufacturing firms examined is more than seven times as large as the coefficient of variation in traditional factor intensities (1.81 compared with 0.24). This in itself supports the theoretical arguments which indicate that research demand is determined by a more complex set of factors than the demand for traditional inputs and suggests that the inducement mechanisms described in the literature do discriminate among firms.

The paper is organized as follows. Section 1 specifies the production function for knowledge which underlies the cost side of the determinants of research demand. In Section 2 a model of the private returns to new industrial knowledge is presented. It is shown that the cost of production and the returns from the use of new industrial knowledge jointly determine the private rate of return to research resources and, in a profit-oriented economy, the research intensity of the firm. Section 3 specifies the structure of the stochastic terms. Section 4 applies the model to an examination of the intra-industry variance in research intensity. Concluding remarks provide a brief summary of results and a discussion of implications.

1. Production Relationships

This paper is limited to an analysis of an extended Cobb-Douglas production function. Research resources enter the production process by raising the productivity of traditional factors of production in a disembodied manner. Problems involved in the construction of R & D variables have made this simple type of specification the most widely used framework in the empirical analysis of the role of research resources in production, and in this respect the data base used here is no exception.[1] The general limitations of this type of framework have been ably discussed by Griliches (1973 and 1975), and we will not repeat them here. Our specification differs from the one chosen by Griliches (1975) in two respects. First, we decompose "research resources" into its component inputs, research labor and research capital. Second, we explicitly incorporate both an R & D gestation lag and a rate of obsolescence of produced knowledge. Both of these parameters become determinants of the R & D intensity of the firm.

The following discussion sets out the basic set of production relationships. We begin with the traditional production function:

$$Q = \gamma_0 K N^{\gamma_1} H^{\gamma_2} \tag{1}$$

where

γ_0 = a constant, which may be both firm and time specific

K = stock of accumulated and still productive, own-produced knowledge

N = traditional labor services

H = traditional capital services

Q = output (value added)

and all firm and time subscripts have been omitted for convenience. Since the stock of knowledge K is an unobservable variable, its units are arbitrary. Hence, without loss of generality it has been normalized such that a one percent increase in K raises output by one percent.

The generation of knowledge is summarized by its production function:

$$\dot{K}_t^G = A_1 L_{(t-\theta)}^a C^b_{(t-\theta)} \tag{2}$$

where

$\dot{K}_t^G$ = the gross-increment in own-produced knowledge at t

A_1 = a constant, which may be both firm and time specific

$L_{t-\theta}$ = research labor services at $t - \theta$

$C_{t-\theta}$ = research capital services at $t - \theta$

θ = the *mean* lag between the time research is undertaken and its embodiment in the traditional production processes of the firm

Equation (2) states that knowledge is produced by research labor and research capital and that the form of the production function is Cobb-Douglas.[2] Since the development of either a new technique or new product requires the use of research resources over an extended period of time, one would expect a distributed lag relationship to connect the deployment of research resources and the resultant increases in the firm's productivity.[3] Since our data cannot sustain an investigation of this distributed lag, we use the simplification of a mean lag which applies to all units of research resources equally. It should also be noted that we assume the parameters a and b to be the same for all firms in a given industry. These, plus the firm-specific constant A_1, are indices of what Scherer (1965) calls the "technological opportunity" of the industry. Variation in A_1, a and b reflects differences in the cost of producing new industrial knowledge, or in Rosenberg's terms (1969), differences in the "supply side" determinants of the rate of technical progress.

Assuming geometric decay of knowledge at the rate of δ_1 and taking the growth rates of research capital and research labor to be constant both during and prior to the period of analysis (as required by our data), the net increment to knowledge $\dot{K}_t^n$ is:[4]

$$\dot{K}_t^N = Ae^{(a\hat{L}+b\hat{C})t} - \delta_1 K_t \qquad (3)$$

where $A = A_1 L_0 C_0 e^{-(a\hat{L}+b\hat{C})\theta}$, and a hat denotes a rate of growth. Solving this differential equation and noting that $\lim_{t\to-\infty} K_t = 0$, the stock of productive knowledge becomes:

$$K_t = \frac{A_1 L_{t-\theta}^a C_{t-\theta}^b}{\delta_1 + a\hat{L} + b\hat{C}} \qquad (4)$$

This concludes the specification of the production relationships. However, the next section will require expressions for the reduction in unit costs attributable to an increase in research labor and research capital. Assuming that the firm is a cost minimizer facing fixed input prices, the unit cost function associated with (1) can be expressed as

$$Z = \frac{h(w,p_H)}{K} \qquad (5)$$

where Z represents unit costs, and w and p_H denote the (fixed) wage and rental rates for traditional labor and capital services, respectively. Substituting (4) into (5) and differentiating the cost function at time $t+\theta$ with respect to research labor and research capital services at time t, we obtain

$$-\frac{\partial Z_{t+\theta}}{\partial L_t} = \frac{aZ_{t+\theta}}{L_t} \tag{6a}$$

and

$$-\frac{\partial Z_{t+\theta}}{\partial C_t} = \frac{bZ_{t+\theta}}{C_t} \tag{6b}$$

2. Private Rates of Return to Research Resources and Optimal Research Input Intensities

In the American economy the bulk of industrial research is performed by firms. If these firms are motivated by potential profits, the level of their research effort will be determined by the expected net income generated by investment in research resources. As a result, the large observed intra-industry variance in research intensity should be attributable to the variance in the expected private returns to research. The objective factors which could cause differences in the expected net income generated by the use of research resources are: 1) variation in the costs of research inputs; 2) differences in the productivity of research resources in generating usable industrial knowledge; and 3) differences in the ability to derive monetary benefits from a given unit of produced knowledge.

Variation in costs of research inputs will be incorporated into the model and discussed in the next section. In connection with the productivity of research resources, the basic model assumes that all firms in a given "industry" produce a single homogeneous output subject to the same production conditions (as specified in the previous section), and the model is tested separately on each "industry" in our data set. Consequently, differences in the expected returns from research beyond those caused by differences in the cost of research inputs will be associated with differences in the ability to derive monetary benefits from a given unit of produced knowledge. However, the industries in the data set are defined quite broadly, so there could be some intraindustry differences in the output elasticity of research resources. At this stage, we do not separate these supply side differences from those in the ability to capture the monetary benefits from knowledge. We return to this problem in the concluding remarks.

The difficulty in specifying a mechanism which determines the stream of private benefits that accrue to new industrial knowledge is a result of the fact (stressed by Arrow, 1962) that knowledge has no, or a very small, cost of reproduction. Hence, the realized social rate of return to an innovation will vary directly with the number of units of output in which is it embodied. However, the fact that knowledge has no cost of reproduction also has implications for the characteristics of the private returns accruing to the producers of an innovation. Since any economic unit aware of the information embodied in the innovation can exploit it, the private benefits from the production of industrial knowledge must be a result of quasi-rents, or temporary monopolies, accruing to the producer of the innovation.[5] The strength of these monopolies, that is, the abilities of firms to appropriate the benefits from the knowledge which they have developed, will determine the private return to research resources and therefore the research intensity of firms. In short, the private return to the development of a new cost-reducing technique will depend on the number of units of output embodying this new knowledge and the fraction of the cost reduction attributable to the innovation which is appropriated by the innovating firm.

We begin by reviewing the "maximum appropriability environment," first described by Arrow (1962) and subsequently adapted to determine the rate of return to research resources by Nordhaus (1969b). Consider a constant cost industry in competitive equilibrium and an innovation which reduces the cost of production for the firms in the industry and only for such firms. The maximum appropriability environment is based on the assumption that the innovator patents the innovation costlessly and leases the cost-reducing technique to all firms in the industry (including itself), subject to the condition that the final product must sell at a uniform price to consuming units. The lease can be defined in terms of a royalty per unit of output produced with the innovation, ρ_0. The lessor acts as a monopolist and sets the initial royalty so as to maximize profits subject to the constraint that the royalty plus the new cost of production $(\rho_0 + Z_1)$ is less than or equal to the pre-innovation cost of production $(Z_0 = P_0)$. In virtually all cases the profit-maximizing royalty at the date of introduction will be $\rho_0 = Z_0 - Z_1 = \Delta Z$.[6]

Since the maximum appropriability environment assumes that the lessor will capture the direct potential benefits from all firms in the industry, the revenue collected in the first year of the innovation in that appropriability environment is the shaded region in Figure 1, or $\rho_0 Q_0^I = \Delta Z Q_0^I$ where Q_0^I denotes the industry output in the year the innovation is introduced. Arrow does not consider the entire stream of revenues accruing to an innovation, nor does he allow for the possibility of less than full appropriability. We now extend Arrow's discussion to allow for non-maximal, firm specific appropriability environments and for the calculation of the entire revenue stream accruing to the innovation.

Let $k_{i\tau}$ be the fraction of industry output from which firm i receives royalties on its innovation of age τ, $\rho_{i\tau}$ be the royalty per unit of output, and $B_{i\tau}$ be total revenues accruing to the innovation in year τ. Then

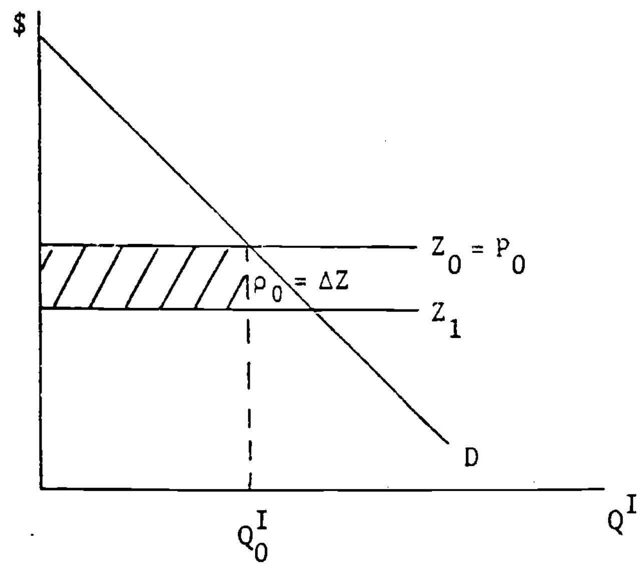
$$B_{i0} = \rho_{i0} k_i Q_0^I = \Delta Z k_{i0} Q_0^I \tag{7}$$

and the discounted value of the stream of revenues generated by the innovation (Π) is

$$\Pi = \int_0^\infty B_{i\tau} e^{-r\tau} d\tau = \int_0^\infty \rho_{i\tau} k_{i\tau} Q_\tau^I e^{-r\tau} d\tau \tag{8}$$

where r is the discount rate.

Figure 1



The specification of non-maximal, firm-specific appropriability environments is based on the following two assumptions:

1. It is easier, or less costly, for a firm to capture the benefits of the knowledge it produces through embodiment in its own output (internal appropriation) than through embodiment in the output of other firms.

2. The revenues accruing to an innovation decline with the age of the innovation.

Internal appropriation is less costly because of the difficulties involved in establishing a market for information. First, prospective purchasers do not know the value of the information before it is purchased, and the information cannot be secured in divisible quantities. Second, the purchaser of the information may resell it, or "reshape" and sell it, thereby undermining the original seller's monopoly position. As a result, the information is not likely to be sold to all potential users and the innovator will not be able to capture the full benefits of the information from those firms which do purchase it.[7] By contrast, internal appropriation of the information is not subject to these marketing constraints, at least not to the same degree.

There are three factors which may cause revenues accruing to the innovation to decline over time. First, new techniques will be developed which either displace or partly substitute for the original innovation. Second, the use of the information in any productive way will reveal and spread it, in part by inspection of the resultant output and the mobility of personnel among firms. This will tend to erode the monopoly power of the innovator, thereby reducing either the unit royalty which can be charged or the part of industry output from which royalties accrue, or both. Third, the accumulation (by a single firm or group of collusive firms) of small innovations over time is equivalent (in terms of cost reduction) to a large innovation. This will eventually violate the Arrow royalty condition, which in turn reduces the unit royalty that accrues to at least one of the innovations.

In order to maintain a specification which is both as general as possible and consistent with the preceding two assumptions, we let

$$\rho_{i\tau}k_{i\tau} = (\rho_{i0}e^{-\delta\tau})e^{\overline{k}+k_i}\frac{Q_{i\tau}}{Q_\tau^I} = \Delta Z e^{\overline{k}+k_i-\delta\tau}\frac{Q_{i\tau}}{Q_\tau^I} \tag{9}$$

where $\sum_{i=1}^{n} k_i = 0$ by construction (n is the number of firms in the industry) and $Q_{i\tau}$ denotes the expected output of firm i at time τ. Revenues in period τ become

$$B_{i\tau} = \rho_{i\tau} k_{i\tau} Q_\tau^I = (\Delta Z e^{-\delta\tau}) e^{\overline{k}+k_i} Q_{i\tau} \tag{10}$$

We will interpret the parameters in the following manner: δ is the rate of decay in the unit royalty, $e^{\overline{k}+k_i}$ is the proportion of firm i's share of industry output from which the firm receives this royalty, and $e^{\overline{k}}$ is the (geometric) mean of this proportion over all firms in the industry. However, it is impossible to distinguish empirically between a rate of decay in the proportion $e^{\overline{k}+k_i}$ and δ, or between a firm specific component in the rate of decay and e^{k_i}. Since appropriable revenues alone suffice to determine the private benefits from an innovation, it is immaterial whether the firm specific component applies to the royalty (the price side of revenues) or to the number of units from which the firm receives these royalties (the quantity side of revenues). Hence, these relationships may be interpreted as saying that the revenues generated by a given innovation of age τ depend upon: 1) the importance of the innovation ΔZ; 2) the age of the innovation τ (through the rate of obsolescence of the *private* returns from knowledge δ); 3) a firm-specific structural parameter e^{k_i} which determines the extent to which the firm can monopolize the information produced by its research resources; and

4) the expected output of the innovating firm $Q_{i\tau}$, because of the relative ease of internal appropriation.[8]

To obtain the present value of revenues generated by the employment of the marginal unit of research labor at time t (Π_ℓ), substitute (6a), (7), and (9) into (8). Setting the price of output equal to one (as it implicitly is in our data) and recalling from (6a) that the cost reduction does not occur until θ years after the employment of the unit of research labor, we have

$$\Pi_\ell = \int_\theta^\infty \frac{a}{L_0} e^{\overline{k}+k_i-(\delta+r)\tau} Q_{0i} e^{g_i^*\tau} d\tau$$

where g_i^* is the expected rate of growth of output of firm i. Equating Π_ℓ to the wage rate for research labor (w_r), taking a first order Taylor's expansion of $\log(\delta+r-g^*)$ around $\log(\delta+r)$ and rearranging terms, we can express the optimal research labor intensity as:[9]

$$\log\left(\frac{w_r L}{Q}\right) = \log \beta_0 + \alpha g^* + k_i \tag{11a}$$

where

$$\beta_0 = (a/\delta + r)e^{-(\delta+r)\theta+\overline{k}}$$

and

$$\alpha = \frac{1}{\delta+r} + \theta$$

An analogous procedure for determining the optimal research capital intensity yields:

$$\log\left(\frac{P_c C}{Q}\right) = \log \beta_1 + \alpha g^* + k_i \qquad (11b)$$

where

$$\beta_1 = (b/\delta + r)e^{-(\delta+r)\theta+\overline{k}}$$

and P_c is the price of research capital services.

Several features of equations (11a) and (11b) are worth noting. First, since the returns from both research labor and research capital are derived from the returns to industrial knowledge, any factor which affects the returns to knowledge will influence the optimal intensities of both the research variables. It is this important fact which permits econometric identification of the relative importance of the unobserved structural parameter (k_i) in determining the research intensities of firms.

Second, equations (11a) and (11b) indicate that the firm's employment of research resources will vary directly with its expected market size and its "appropriability base," and inversely with the rate of obsolescence and the rate of discount. The importance of expected market size in determining the optimal level of research resources follows directly from the fact that knowledge has no cost of reproduction.[10] Schmookler (1966) demonstrated the empirical importance of this point at an inter-industry level, while Griliches (1958) has shown the dominant influence of expected market size in determining the relative social rates of return to hybrid seed innovations.

The structural parameter (k_i) reflects the extent to which a firm can capture the benefits from the cost-reducing innovations it develops. This will be determined jointly by the market structure of the industry (e.g., similarity of firms in terms of market power, production processes employed, research orientation, ease of imitation), the abilities of the entrepreneur or manager of the firm, and the general institutional setting in which the firm operates--factors associated with the Schumpeterian tradition.

Third, for a given value of initial revenues accruing to an innovation, the higher is the rate of obsolescence (δ), the smaller the total value of private benefits from the innovation and therefore the less intense will be the research effort. Moreover, since research produces a stock (knowledge) whose benefits accrue over the future, the optimal research intensity will vary inversely with the rate of discount.[11] Finally, the longer the gestation lag (θ), the larger is the influence of the future in determining the returns to R&D, and hence the more important the effect of expected growth on the optimal R & D intensity.[12]

The model presented here posits a set of firms which produce knowledge from research resources, and produce output by combining this knowledge with traditional factors of production. The price of output is determined by the cost of traditional factors plus quasi-rents generated by temporary monopoly power over the information produced by the research resources. It is important to realize that there will be no private benefits from the employment of research resources without some degree of monopoly power. *The unique characteristics of knowledge as a commodity imply that the private rate of return to research resources must be determined jointly by the parameters of the production function for knowledge and the ability of the firm to internalize the benefits from the knowledge it produces.* This point seems to be incompletely understood in the literature.

3. Structure and Identification of the Three Equation Model

The basic structural form of the model consists of factor demand equations for research labor, research capital and traditional labor. By adding the relevant stochastic terms, this section converts the model into an estimable form. Actually, two stochastic specifications are investigated. The first specification, which imposes a fairly stringent set of assumptions on the properties of the errors, produces a simple three equation model and a transparent identification scheme. The second specification relaxes the more stringent assumptions on the errors, and enables both a more complete set of tests of the model and an investigation of the intertemporal stability of the appropriability parameter. The cost of this generality, however, is a more complicated six equation model. In this section we describe the three equation model. The empirical results for this model and a summary of the additional information in the six-equation model are presented in the next section.

Letting asterisks denote the optimal levels of each variable and adding the factor demand equation for traditional labor to (11a) and (11b), the structural form of the model is written as:

$$\log w_r + \log L^* - \log Q^* = \log \beta_0 + \alpha g^* + k_i \tag{12a}$$

$$\log P_c + \log C^* - \log Q^* = \log \beta_1 + \alpha g^* + k_i \tag{12b}$$

$$\log w + \log N^* - \log Q^* = \log \beta_2 \tag{12c}$$

It is assumed that a firm's expected growth rate equals its *average* past growth rate plus a component which reflects common expectational changes in the trend of industry demand.[13] That is:

$$g_i^* = \Delta g + \overline{g}_i \quad \text{for} \quad i = 1 \ . \ . \ . \ n \tag{13}$$

where $\overline{g}_i$ is the average past growth rate of firm i, and Δg is the commonly held, expected difference between the average past and future growth rates.

The variable in (12) denoted by Q^* is expected output, i.e., the value of output upon which input decisions are made. We follow Mundlak and Hoch (1965) in assuming "partial transmission" of the error in output to the input decision-making process. Letting the superscript ° denote the observed value of a variable, we have:

$$Q^\circ = \gamma_0 K N^{\gamma_1} H^{\gamma_2} e^{\eta_q + \nu_q}$$

and

$$Q^\circ = E[Q^\circ | \eta_q] = \gamma_0 K N^{\gamma_1} N^{\gamma_2} e^{\eta_q}$$

where

$$E(\nu_q) = E(\eta_q) = 0 \quad \text{and} \quad E[\nu_q^2] = \sigma_q^2 \tag{14}$$

In the context of the "simultaneity" literature, the partial transmission assumption is quite general, encompassing both the full transmission assumption of Marschak and Andrews (1944) and the zero transmission assumption of Zellner et al. (1966) as special cases. [14]

The disturbance η_q should be interpreted as resulting from firm specific differences in management and technology, and the effect of transitory factors which *are known before* input decisions are made. The term ν_q, on the other hand, results from transitory factors which *are not known* before input decisions are made, such as machine breakdowns, and from measurement error.

The observed level of each factor of production differs from its optimal level by an error which has two components, a decision component resulting from an inoptimal choice of factor levels and a pure measurement component. Letting ε_j be the sum of the two errors for factor j we have:

$$C^{\circ} = C^{*}e^{\varepsilon_c}$$

$$L^{\circ} = L^{*}e^{\varepsilon_\ell} \tag{15}$$

$$N^{\circ} = N^{*}e^{\varepsilon_n}$$

where $E(\varepsilon_j) = 0$ and $V(\varepsilon_j) = \sigma_j^2$ for $j = c,\ell,n$.

What remains is to specify the covariance structure of the various error components, and it is in this specification that the three and six equation models differ.

It is quite common to assume that ν_q is independent of the errors in the various factors.[15] That is,

$$E(\nu_q\varepsilon_j) = 0 \quad \text{for} \quad j = c,\ell,n \tag{16}$$

The reasoning is twofold. First, since there are independent measures of each variable, there is no reason to expect any correlation between their respective measurement errors. Second, the non-measurement component of ν_q is due to acts of nature such as weather conditions and machine performance (see Zellner et al. [1966]), whereas the decision component of the factor errors occurs before the realization of ν_q and is due to human (management) error. Assumption (16) is accepted *a priori* in the three equation model but is subjected to a test in the six equation model described below.

The three equation model also assumes a zero covariance among the errors in the various factors. That is:

$$E(\varepsilon_p\varepsilon_j) = 0 \quad \text{for} \quad p \neq j \quad \text{and} \quad p,j = c,\ell,n \tag{17}$$

Since the underlying assumptions of behavioral models which result in the error structure in (17) are not very persuasive, the six equation model will allow for free correlation among the factor errors. The advantage of the three equation model based on (17) is its simplicity and, as the six equation results will demonstrate, the bias due to the simplification in (17) is minimal. [16]

For the remainder of the analysis it will prove convenient to redefine all variables as deviations from their sample means, but for simplicity we leave the notation unchanged. With this understanding, substitution of (13), (14) and (15) into (12) yields the following system of equations in observed or manifest dependent variables:

$$\log w_r + \log L^\circ - \log Q^\circ = \alpha\bar{g} + k_i + \varepsilon_c - \nu_q \tag{18a}$$

$$\log p_c + \log C^\circ - \log Q^\circ = \alpha\bar{g} + k_i + \varepsilon_\ell - \nu_q \tag{18b}$$

$$\log w + \log N^\circ - \log Q^\circ = \varepsilon_n - \nu_q \tag{18c}$$

System (18a) - (18c) forms a set of factor share equations for research labor and capital, and traditional labor with the structure of the stochastic terms incorporated.

Assuming that the appropriability parameter, k_i, is uncorrelated with the various error components and with $\bar{g}$, [17] a maximum likelihood estimation technique provides consistent and asymptotically efficient estimates of α and of the variance-covariance matrix of disturbance Ω^*, where

$$\Omega^* = \begin{bmatrix} \sigma_k^2 + \sigma_c^2 + \sigma_q^2 & & \\ \sigma_k^2 + \sigma_q^2 & \sigma_k^2 + \sigma_\ell^2 + \sigma_q^2 & \\ \sigma_q^2 & \sigma_q^2 & \sigma_q^2 + \sigma_n^2 \end{bmatrix} \tag{19}$$

The identification of the various components from (19) is straightforward. Any factor which affects the returns to the production of knowledge will affect the optimal intensities of both research resources. Consequently, the covariance between the disturbances in the two research intensity equations will capture σ_k^2. However, this covariance also picks up any measurement or expectational error in output (ν_q). Since the traditional labor intensity equation will also contain the error in output, σ_q^2 can be identified by the covariance between the research intensity and the traditional labor demand equations. Finally, the variances of the errors in the research resource variables are calculated as the residual portion of the research intensity equations. It is also clear from (19) that if

$\sigma_{\ell c} \neq 0$, then the estimate of σ_k^2 will be biased upwards or downwards according as $\sigma_{\ell c} \gtrless 0$. However, the consistency of the estimated α is unaffected by any correlation among the factor errors.

Let us return to the variance in research intensity. The research expenditures of a firm are calculated as the sum of the firm's expenditures on research labor and research capital. That is:

$$R^{\circ} = w_r L^{\circ} + P_c C^{\circ} \tag{20}$$

Since we define research capital to include all R&D expenditures other than payments to scientists and engineers, (20) is an identity. Analogously, we define the optimal level of research expenditures as the sum of the optimal levels of expenditures on research capital and research labor:

$$R^{*} = w_r L^{*} + P_c C^{*} \tag{21}$$

Substituting (12a) and (12b) into (21), and using (20), (21) and the error components in (15), the observed research intensity can be expressed in terms of the structural parameters of the model as:

$$\log R^{\circ} - \log Q^{\circ} = \alpha\overline{g} + k_i + \varepsilon_r - \nu_q \tag{22}$$

where

$$\varepsilon_r = \psi\varepsilon_\ell + (1 - \psi)\varepsilon_c$$

and

$$\psi = a/(a+b)$$

Equation (22) is definitionally equal to a linear combination of (18a) and (18b). Hence, any two linearly independent combination of these three equations contain all the information available in the data. The form of the data made it easier to estimate an equation for research expenditures than for research capital. Therefore, the system of factor share equations which will be estimated is:

$$\log R^{\circ} - \log Q^{\circ} = \alpha\bar{g} + k_i + \psi\varepsilon_{\ell} + (1-\psi)\varepsilon_c + \nu_q \qquad (23a)$$

$$\log w_r + \log L^{\circ} - \log Q^{\circ} = k_i + (1-\psi)(\varepsilon_{\ell} - \varepsilon_c) \qquad (23b)$$

$$\log w + \log N^{\circ} - \log Q^{\circ} = \varepsilon_n - \nu_q \qquad (23c)$$

which has the following variance-covariance matrix of disturbances:

$$\Omega = \begin{bmatrix} \sigma_k^2+\psi^2\sigma_{\ell}^2+(1-\psi)^2\sigma_c^2+\sigma_q^2 & & \\ \psi(1-\psi)\sigma_{\ell}^2-(1-\psi)^2\sigma_c^2 & (1-\psi)^2(\sigma_{\ell}^2+\sigma_c^2) & \\ \sigma_q^2 & 0 & \sigma_q^2+\sigma_n^2 \end{bmatrix} \qquad (24)$$

where ψ may be consistently estimated by the antilog of the constant term in (23b). Of course, all the comments that applied to (18) and (19) apply equally to (23) and (24).

The parameters from (23) and (24) [or from (18) and (19)] permit a decomposition of the variance in research intensity into three components: 1) variance due to differences in the expected growth rate of the internal appropriability base of the firm $(\alpha^2\sigma_{\bar{g}}^2)$; 2) variance caused by differences in the appropriability parameter

(σ_k^2) which determines the private benefits accruing to a cost-reducing innovation, given the internal appropriability base of the firm; and 3) variance caused by measurement and decision errors in research resources and in expected output.

In addition (24) allows for one formal and one informal test of the underlying model. The system can be estimated with and without the imposition of a zero covariance term between the disturbances from equations (23b) and (23c). Under the null hypothesis that the assumptions of the model are true against the alternative that $\sigma_{\ell n} \neq 0$ and/or $\sigma_{cn} \neq 0$, the ratio of the constrained to the unconstrained log likelihood ratio will distribute asymptotically as χ_1^2.[18] Also, of course, there are non-negativity restrictions on all the estimated variances. Since these restrictions are equivalent to a ranking of the elements of the covariance matrix, and as such are not guaranteed by our estimating procedure, the non-negativity conditions constitute an informal test of the model.

4. Empirical Results

This section begins with a brief description of the scope and the sources of the data, and then presents and interprets the empirical results.[19] The data were gathered jointly by the National Science

Foundation and the Bureau of the Census. They contain individual company information on R&D expenditures, the number of scientists and engineers, total employment and sales--all based on the 1957-1965 annual NSF-Census R&D Surveys--and a variety of other company economic indicators based on a match with the 1958 and 1968 Census of Manufacturers and Enterprise Statistics. The data include observations on one level year value and a corresponding growth rate for most variables.

The sample used here consists of 433 large (1000+ employees) firms which account for 48 percent of all R&D performed in American industry in 1963, and 78 percent of all R&D excluding Aircraft and Missiles.[20] The firms are broken down into four broad industry groups --Chemicals and Petroleum, Electrical and Communications Equipment, Fabricated Metal Products and Machinery, and Motor Vehicles and other Transport Equipment--and the analysis is performed on each of these industries separately.

The data contain two measures of $\bar{g}$, the average past growth rate in value added. The first is a nine-year (logarithmic) average of the past growth rate in sales $(\bar{g}_1)$, while the second is calculated as the difference between the logarithms of value added in 1963 and 1957 divided by 6 $(\bar{g}_2)$. Both $\bar{g}_1$ and $\bar{g}_2$ differ from $\bar{g}$ by pure measurement error, but $\bar{g}_1$ contains an additional error due to the discrepancy between the true past growth rates in value added and sales. The information in both these measures can be incorporated in the analysis by letting:

$$\bar{g}_1 = \bar{g} + \nu_1 \qquad (25)$$

$$\bar{g}_2 = \bar{g} + \nu_2$$

where

$$E(\nu_j) = E(\nu_j \bar{g}) = E(\nu_1 \nu_2) = 0$$

and

$$V(\nu_j) = \sigma^2_{\nu_j} \quad \text{for} \quad j = 1,2$$

That is, the observed measures of $\bar{g}_1$ and $\bar{g}_2$ are both subject to classical measurement error and the two measurement errors are assumed to be uncorrelated.[21]

Equations (23), (24) and (25) fully specify the form of the model to be estimated. Before presenting the empirical results, however, exogenous information is used to derive a plausible range for α. There are two reasons for our special interest in α. Recall that $\alpha = [1/(r+\delta] + \theta$ where r, δ and θ are the discount rate, the decay rate in appropriable revenues accruing to the innovation, and the mean lag between the outlay of research resources and the beginning of the associated revenue stream. The parameters δ and θ

are key parameters in calculating the private rate of return to knowledge producing activities. Second, a comparison of exogenous information on the value of α with the direct estimates here will provide an informal test of the assumptions of the model (see fn. 17). The estimates of δ and θ are taken from Pakes and Schankerman (1978). The approximate ranges for δ and θ are 0.18 - 0.36 and 1.2 - 2.5 (years), respectively. Based on a discount factor of 0.10, these estimates provide a fairly narrow a priori range for the coefficient α of between 3.3 and 6.1, which in turn will be compared to the actual estimates obtained here.

All models were estimated using a full information maximum likelihood technique developed by Jöreskog (1973b).[22] The empirical results for the three equation model are presented in Table 1.1. The χ_1^2 value in line 8 tests the zero covariance constraint described earlier. None of the four industries had a test statistic with a surprising value. Treating the χ_1^2 deviate for the various industries as drawings from independent χ^2 distributions, and summing over industries, results in the more powerful $(\chi_4^2)/4$ test statistic. The observed value of $(\chi_4^2)/4$ was .744, while the one and five percent critical values of a $(\chi_4^2)/4$ deviate are 3.33 and 2.37, respectively. Also note that twenty-four free parameters with *a priori* non-negativity

TABLE 1

ESTIMATES OF THE THREE EQUATION MODEL[a]

	Chemicals and petroleum	Metal products and machinery	Electrical and communi-cations equipment	Motor vehicles and transport equipment
1. α	3.94	2.16	5.64	5.58
s.e.	2.26	1.30	2.40	3.40
2. σ_k^2	0.98	0.74	1.60	0.89
3. σ_ℓ^2	+0.00	0.24	0.07	0.04
4. σ_c^2	0.59	1.12	0.63	2.41
5. σ_q^2	+0.00	0.06	0.03	-0.04*
6. σ_n^2	0.06	0.02	0.04	0.11
7. $\sigma^2\sigma_{\bar{g}}^2/\sigma_{\log R/Q}^2$ [b]	0.03	0.02	0.03	0.04
8. χ_1^2	1.83	0.06	0.79	0.31
9. n	110	187	102	34

[a] Asterisks denote error variances which violate *a priori* non-negativity constraints.

[b] $\sigma_{\bar{g}}^2 = \mathrm{cov}(\bar{g}_1\bar{g}_2)$.

constraints were estimated. Of these, only one was negative and this one (σ_q^2 in the fourth industry) was less than one standard deviation from zero.

All of the estimated α coefficients are of the right sign and statistically significant. Moreover, three of the four point estimates of α lie in the interval predicted by the prior information summarized earlier, and the single exception is less than one standard deviation from that interval. To derive a summary measure of α we tested the null hypothesis that the differences between the various estimates of α are simply a result of random differences in the estimators. The hypothesis is strongly accepted. The value of α for the combined sample is 3.85 with a standard error of 0.76.[23] On the whole, then, the data and the exogenous information provide mutually consistent information on the magnitude of the parameters which determine α.

The most notable result of Table 1 concerns the effect of the firm's past growth rate. Though this variable is neither statistically nor economically insignificant in determining the firm's R & D intensity,[24] differences in growth rates account for only a relatively minor portion of the intra-industry variance in R & D intensity. In fact, line 7 of Table 1 indicates that differences in growth rates account for only two to four percent of this variance.

As noted, the intra-industry coefficient of variation in R & D intensity is about seven times as large as that of traditional factors of production. There are two possible explanations. First, the fact that knowledge has no cost of reproduction implies that, unlike other factors of production, research intensity will differ both because of variance in expected growth rates and because of differences in the extent to which firms can appropriate the benefits of the knowledge they produce. Second, the variance in the available measures of R&D intensity may reflect a larger "error in variable" than the variance of other factors of production.

The assumption that differences in expected growth rates could be approximated by differences in average past growth results in reasonable values of α, but the variance in growth rates is too small to account for a major portion of the observed intraindustry variance in R&D intensity. Hence, it is evident that a pure demand inducement mechanism does not do well in explaining the *intraindustry* variance in R&D intensity. The next obvious question is what portion of that variance is due to error (σ_r^2) and what part is explained by the variance in the ability to appropriate the benefits from knowledge

(σ_k^2). Since the estimates of both σ_r^2 and σ_k^2 in the three equation model are biased if there is any correlation among the factor errors, we now briefly describe and present a summary of the results of estimating the six equation model which allows for free correlation among these errors.[25]

The six equation model is constructed by adding the factor demand equations for research capital, research labor, and traditional labor in year $t-1$ to those same equations for year t. Each error component is assumed to be generated by a separate stationary stochastic process. The model allows for a $\chi^2_{20}/20$ test of the stationarity assumptions (T_1), a $\chi^2_8/8$ test of the assumption of no correlation between the transitory portion of the output error and the factor errors (T_2), and a $\chi^2_8/8$ test of the intertemporal stability of the coefficients of the observed independent variables (T_3). T_1, T_2, and T_3 test for consistency between the data and the assumptions used to identify the model. In addition, the six equation model investigates two aspects of the intertemporal stability of the appropriability paremeter. Let

$$k_t = \lambda k_{t-1} + \mu_t$$

where

$$E[k_{t-1}\mu_t] \;=\; E[\mu_t] \;=\; 0$$

and

$$E[\mu_t^2] \;=\; \sigma^2_{\mu_t}$$

Then the model permits a test of the assumption that the variance in the appropriability parameter is constant over time $(\sigma^2_{k_t} = \sigma^2_{k_{t-1}})$, and produces a measure of the correlation coefficient between the values of the appropriability parameter for a given firm in two different years $(\lambda^2\sigma^2_{k-1}/\sigma^2_{k_t}$ or, if $\sigma^2_{k_t} = \sigma^2_{k_{t-1}}$, $\lambda^2)$.

The observed values of the test statistics for T_1, T_2 and T_3 were 1.49, 0.04, and 0.33, respectively. None of these values is surprising. It should be noted that the observed value of T_2 indicates strong acceptance of the assumption of a zero covariance between the transitory error in output and the factor errors in this sample. The difference between the sum of squared residuals in the model using all three test constraints and in the totally unconstrained model can be used to produce a $\chi^2_{36}/36$ test of the validity of the model as a whole. The observed value of the $\chi^2_{36}/36$ deviate was 0.91 which is less than its expected value under the null hypothesis that all the constraints are satisfied. The $\chi^2_4/4$ statistic which tested the hypothesis $\sigma^2_{k_t} = \sigma^2_{k_{t-1}}$ on the combined sample of four industries had a value of 1.61. While this indicates acceptance of the hypothesis at the five percent level, a sample with more than two time periods would be required to determine more conclusively whether the variance in the appropriability parameter is in fact constant over time.

Table 2 summarizes the basic decomposition of the variance in R&D intensity from the six equation model. Note first that the estimates of the growth coefficient (α) are only slightly different from the estimates from the three equation model. Since both models estimate α consistently, this result was expected. Line 2 provides the estimates of the total error variance in research expenditures from the three equation model ($\sigma_r^{2\,TEM}$), while lines 3 and 4 present the estimates of $\sigma_{\ell c}$ and the error variance in research expenditures from the six equation model (σ_r^2). Recall that the estimates of $\sigma_r^{2\,TEM}$ are biased upward or downward as $\sigma_{\ell c} \gtrless 0$. Accordingly, the large negative values of $\sigma_{\ell c}$ in the second and fourth industries account for the fact that $\sigma_r^{2\,TEM}$ is about twice as large as σ_r^2 in these two industries.

Line 5 provides estimates of the fraction of the variance in research expenditures that is attributable to errors in research resources $\sigma_r^2/\sigma_{\log R}^2$. The average and the coefficient of variation of this fraction across the four industries are 0.09 and 0.24, respectively. While these estimates of $\sigma_r^2/\sigma_{\log R}^2$ provide only an upper bound to the ratio of measurement error variance to total variance in research expenditures, they do suggest the possibility of a rather large "errors in variable" bias in micro analyses using research expenditures as an independent variable. Auxiliary calculations reinforce this interpretation.[26]

TABLE 2

SUMMARY OF RESULTS OF THE SIX EQUATION MODEL

	Chemicals and petroleum	Metal products and machinery	Electrical and communi-cations equipment	Motor vehicles and transport equipment
1. α	4.10	2.62	5.13	3.49
2. $\sigma_r^{2\,TEM}$	0.23	0.47	0.31	1.18
3. $\sigma_{\ell c}$	0.06	- 0.23	0.02	- 0.47
4. σ_r^2	0.33	0.20	0.37	0.58
5. $\sigma_r^2/\sigma_{\log R}^2$	0.12	0.07	0.08	0.09
6. $(\sigma_r^2 + \sigma_q^2)/\sigma_{\log R/Q}^2$	0.23	0.28	0.21	0.40
7. $\alpha^2\sigma_{\bar{g}}^2/\sigma_{\log R^*/Q^*}^2$ a/	0.04	0.04	0.06	0.03
8. $\sigma_k^2/\sigma_{\log R^*/Q^*}^2$ b/	0.96	0.96	0.94	0.97
9. λ^2	1.00	0.99	0.99	0.99
10. n	110	187	102	34

a/ $\sigma_{\bar{g}}^2 = \mathrm{cov}(g_1 g_2)$.

b/ $\sigma_{\log R^*/Q^*}^2 = \sigma_{\log R/Q}^2 - \sigma_r^2 - \sigma_q^2$.

We now consider the basic decomposition of the variance in research intensity. Lines 6 to 8 present the relevant information. Line 6 lists the portion of the variance in research intensity attributable to errors. One minus this value is the fraction of the variance in research intensity accounted for by the structural form of the model. The average and the coefficient of variation of this fraction over the four industries in the sample are 0.72 and 0.12, respectively. That is, 72 percent of the intraindustry variance in research intensity is accounted for by the structural form of the model and, as line 8 indicates, over 95 percent of this is accounted for by differences in k.

One further point is worth noting. Not only do differences in the appropriability parameter account for a large majority of the intra-industry variance in R & D intensity, but the relative value of k associated with any given firm seems to be stable over time. That is, the autoregressive parameter (λ) connecting the values of k_t and k_{t-1} is essentially unity in all four industries.

Concluding Remarks

This paper explores the factors which underlie the demand for research by profit-oriented firms. The intra-industry coefficient of variation of research intensity is much larger than those of traditional factors. This important empirical fact is consistent with the theoretical argument that knowledge possesses unique economic characteristics, and that the demand for research depends both on the parameters of the production function for knowledge and on the ability of the firm to appropriate the benefits from the knowledge it generates. We propose a systematic framework for decomposing the observed intra-industry variance in research intensity into three components: 1) demand inducement, measured by growth rates of output; 2) a firm-specific structural parameter; and 3) errors in the observed variables.

There are three principal empirical findings from this decomposition. First, about 25 percent of the variance in research intensity is due to errors in the variables and most of it is concentrated in the measure of research capital. The noise to total variance ratio in research expenditures ($\sigma_r^2/\sigma_{\log R}^2$) is about ten percent and should be considered in microeconomic studies using research resources as an independent variable. Estimated coefficients of observed research expenditures are likely to be substantially biased downward since the bias depends on the error-variance relative to that part of the variance in the research variables which is not correlated with the rest of the regressors.

Second, about 75 percent of the intra-industry variance is related to the structural parameters of the model, but very little of this structural variance is accounted for by differences in growth rates. This result is somewhat surprising. Schmookler (1966) and others demonstrated the role of demand inducement in determining the inter-industry pattern of the level of research, and Pakes (1979) confirms its influence on the inter-industry distribution of research intensity. We are left with a striking contrast between the role of demand inducement at the intra-industry and inter-industry levels of aggregation, but to explore it is beyond the scope of this paper.

By far the greatest part of the intra-industry variance is related to differences in the firm-specific parameter k. This parameter is structural in the sense that it is consistent between the research labor and capital demand equations and does not appear in the traditional factor demand equations. Moreover, the value of k associated with any given firm seems to be quite stable over time. If there are no intra-industry differences in the elasticities of the knowledge production function (technological opportunity), the variance in k is due entirely to interfirm differences in appropriability. The industry groups used here are quite broadly defined and there is probably some variance in research elasticities, part of which will be captured in σ_k^2. A definitive breakdown of σ_k^2 into appropriability and technological opportunity components remains for future research.

The more general, and we believe more important, implication of this inquiry is one which does not depend on the specific interpretation given to σ_k^2. Both the theoretical and empirical analysis indicate that it is not reasonable to treat the demand for research in a manner analogous to the demand for traditional factors of production, including capital. This conclusion is reinforced by evidence in Nadiri (1978), in which a generalized set of factor demand equations is estimated on micro panel data. The $F(113,904)$ test statistic for the presence of firm-specific effects in the research demand equation is 121.3, which should be compared both to the five percent critical level of 1.08 and to the value in the traditional capital demand equation of 18.6. These results also hold when the sample is stratified by size of the firm. The general conclusion we draw from all this evidence is that substantially richer models are required to provide insight into the structure of incentives driving the demand for research and thereby to explain the distribution of research-related growth across firms.

Notes

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[1]The problems alluded to are of two types. First, errors in R & D variables make more complicated input relationships difficult to estimate (Griliches and Ringstaad, 1971). Second, a lack of good price and quantity indices on the separate outputs that a firm produces precludes the use of multiproduct production functions.

[2]Two points are in order. First, "research capital" refers to an aggregate of all research resources other than research labor. Second, in this paper the firm-specific constant captures the effects of "learning by doing" and of other firms' research as inputs in the production process of the firm in question.

[3]Griliches (1973, 1975) has discussed the various lags connecting research resources and productivity. One of the few attempts to analyze the lag structure empirically is Evenson's study (1968) of aggregate data for American agriculture.

[4] Since knowledge is a produced capital input, we must make some approximation with respect to the employment of research resources in the pre-sample period. The data we use are for 1963 and contain 1957-1963 average growth rates. Using the fact that research resources in American industry grew at a fairly constant rate between the end of World War II and the mid-1960s, a specification analysis indicated that the constant growth rate assumption was the best approximation for our sample.

[5] This is a well known result which has been discussed by Arrow (1962), Machlup (1962), and Nordhaus (1969a, 1969b). Patent laws are in fact a device for strengthening these monopolies by bestowing institutionally created property rights on the producers of information. See Bowman (1973).

[6] If P_1 is the profit maximizing price for a monopolist with constant unit cost Z_1, the "Arrow royalty" described in the text will yield maximum profits if and only if $P_1 > P_0$. If the industry demand is price inelastic over the relevant range, the Arrow royalty will be optimal regardless of the magnitude of the cost reduction due to the innovation. If the industry demand is price elastic, the condition $P_1 > P_0$ can be written $\Delta Z/Z_0 < |\eta(P_1)^{-1}|$, where η denotes the price elasticity of industry demand. It is apparent from this inequality that the Arrow royalty will be optimal for all but the most major

innovations and will certainly be optimal for the cost reduction resulting from the employment of the marginal research resource.

[7]As Arrow (1962, p. 615) remarks: "In the absence of special legal protection, the owner cannot simply sell information on the open market. Any one purchaser can destroy the monopoly, since he can reproduce the information at little or no cost. Thus, the only effective monopoly would be the use of information by the original possessor. . . . With suitable legal measures, information may become an appropriable commodity. Then the monopoly power can indeed be exerted. However, no amount of legal protection can make a thoroughly appropriable commodity of something so intangible as information."

[8]Since the appropriability base is allowed to vary among firms, the specific decomposition used here is immaterial. However, any assumption on the statistical properties of the appropriability parameter will be restrictive. The decomposition chosen here has two advantages. First, it permits an indirect test of the only econometrically relevant assumption on the properties of k (see fn. 17.) Second, since royalty payments, which are about three percent of research expenditures (Wilson, 1975, Chapter 3), are included in our measure of output, one would want to make the firm's output a direct determinant of the returns to its research.

[9] Since only the moment matrix of the variables was available, we were limited to linear combinations of the original variables and forced to use Taylor approximations. The ratio of the approximation error to the true value is just over two percent, and if g is distributed symmetrically, this will not affect the estimate of α.

[10] This should be distinguished from the role of market size in models of the demand for traditional capital. The level of investment in traditional capital is related to the expected growth of output (accelerator models), whereas in our model the level of investment in the stock of R & D depends on the expected level of output.

[11] Lucas (1967) tested this point on aggregate data for American industry and obtained coefficients of the expected sign and magnitude.

[12] This does not mean, however, that an increase in θ raises the optimal R & D intensity since θ affects both β_0 and β_1.

[13] This formulation is not too unreasonable and has the advantage of producing a simple econometric model which is directly estimable with the available data. The data did allow us to experiment with more sophisticated expectations formulae which

permit the firm to take into account both its own and the industry's past growth performance in formulating expectations on its own future growth rate. The results are similar to those reported here. Pakes (1978) uses a general rational expectations formulation on a different data set and obtains similar results.

[14]The special cases are $\nu_q = 0$ and $\eta_q = 0$, respectively. We have investigated a more general model which assumes differential transmission to different factor demand equations, but again the results did not differ significantly from those presented here. Note also that K picks up the effect of all research expenditures that have already gestated and are still productive. Also, we have ignored the difference between $E(e^{\nu_q})$ and 1.

[15]See Mundlak (1963), Mundlak and Hoch (1965), and Zellner et al. (1966).

[16]Two points should be noted in connection with (17). First, any error in the assessment of revenues (e.g., differential monopoly power or a difference between the expected and the actual price of output) will be captured in σ_q^2 and will not bias the three equation results. Second, the assumption $E(\varepsilon_\ell \varepsilon_c) = 0$ is more troublesome than the assumptions $E(\varepsilon_\ell \varepsilon_n) = E(\varepsilon_c \varepsilon_n) = 0$ for two reasons. First, there is a test of the latter two assumptions embodied in the three equation results. In addition, since research resources affect

output only after a gestation lag, if there is a production function constraint which connects the values of different contemporaneous factor decision errors, it will cause a non zero correlation between ε_ℓ and ε_c, but not between either ε_ℓ or ε_c and ε_n.

[17] Since k_i is a structural parameter, the assumption that k_i is orthogonal to the error components is roughly analogous to the classic regression assumption of independence of the errors and the regressors. The assumption $E(k\bar{g}) = 0$, however, requires additional comment. There is no reason to expect k to be correlated with $\bar{g}$, but we can do better than rely on our intuition. If $E(k\bar{g}) \neq 0$, the estimates of α derived from the models which rely on zero correlation should differ from estimates based on other techniques. An assortment of exogenous information on the components of α (described in the next section) yields estimates of α which are very similar to those obtained from our models, and this may be interpreted as an indirect test of the assumption $E(k\bar{g}) = 0$. We might add, however, that if $E(k\bar{g}) \neq 0$, we can reinterpret α and k such that the estimate of σ_k^2 becomes that portion of the underlying variance in appropriability that is orthogonal to the variance in $\bar{g}$.

[18] Actually, the null hypothesis of the χ_1^2 test is $\sigma_{\ell n} - \sigma_{cn} = 0$. However, under the alternative that $\sigma_{\ell n} - \sigma_{cn} \neq 0$, the event $\sigma_{\ell n} = \sigma_{cn}$ will occur only on a set of measure zero. Accordingly, we neglect this possibility.

[19]Griliches (forthcoming) provides a more complete description of this data base.

[20]The original sample consists of 883 firms. We discarded the data for the "aircraft & missiles" and the "all others" industries. The first was dropped because it is dominated by government financed R & D (74 percent versus 20 percent in the other industries). Our market-inducement model has limited applicability, unless it were known that privately and government financed R & D are close substitutes and the supply of the latter is very elastic. Moreover, there were only 31 firms and there were inconsistencies in the data. The "all others" category was discarded on the grounds that it contains both intra-industry and inter-industry variance in R & D intensity.

[21]Actually, since value added is a component of sales, part of ν_1 is likely to be transferred to ν_2 and there will be some correlation between these errors. We show below, however, that the maximum possible bias caused by this correlation is minimal and certainly does not warrant discarding the information in one of the growth rate measures.

[22]The models presented here are a special case of a more general class of structural equation models described by Jöreskog (1973a) and Wiley (1973).

[23]It can be shown that if any of the measurement error in value-added is transferred to sales, the estimates of α reported above are biased downwards. However, even under the polar assumption that all the measurement error in value-added is transferred to sales, the estimate of α becomes only 4.15 with a standard error of 1.01. Therefore, the unbiased point estimate lies between 3.85 and 4.15.

[24]The elasticity of R & D intensity with respect to past growth rates, evaluated at the sample mean of the growth rate, is about 0.25.

[25]For the details of the six-equation model and its empirical results, see Pakes (1978) or Schankerman (1979).

[26]Unfortunately, we cannot decompose the estimate of σ_r^2 into a decision and a measurement component, but two pieces of evidence suggest that the bulk of σ_r^2 consists of measurement error. First, almost all of the errors in research expenditures are due to errors in research capital. Since reported research includes all (rather than only the capitalized portion) of research capital expenditures, we (and all other investigators in this area) have a measure of gross investment in research capital rather than the desired measure of research capital services. On this account we would expect a large measurement error component in research capital. Second, preliminary

application of the three equation model to industry averages of all variables indicates that the error variance in research expenditures in these aggregate variables approaches zero. The averaging procedure would tend to cancel out the part of the error variance caused by measurement error and by random, inoptimal choice of factor levels, but it would not eliminate that part caused by a misspecification in the structural form of the model.

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