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COST-REDUCING AND DEMAND-CREATING R&D WITH SPILLOVERS

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Abstract: This paper analyzes R&D policies when the returns to cost-reducing and demand-creating R&D are imperfectly appropriable and market structure is endogenous. Previous characterizations of appropriability are generalized to permit the possibility that own and rival R&D are imperfect substitutes. We also describe how equilibrium expenditures on process and product R&D, as well as equilibrium market structure, depend on technological opportunities and spillovers. In contrast to previous work, diminished appropriability does not necessarily reduce R&D expenditures. For example, under some conditions, an increase in the extent of process (product) spillovers will lead to an increase in product (process) R&D. We estimate several variants of the model using manufacturing line of business data and data from a survey of R&D executives.

1. Introduction

In many industrial organization models, underlying demand and cost conditions determine the equilibrium number and size of firms ("market structure") as well as equilibrium values of decision variables such as price, output, and capacity. When firms invest in research and development (R&D), however, both demand and cost conditions are subject to change.[2] In most models of cost-reducing R&D, a specification of underlying opportunities for technical change replaces the static production

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[2] Major contributions to this literature are surveyed by Dasgupta (1986) and Baldwin and Scott (1987). Among the models that have focused upon the relationship between cost-reducing R&D and market structure are: Dasgupta and Stiglitz (1980), Flaherty (1980), Lee and Wilde (1980), Levin (1978), Levin and Reiss (1984), Loury (1979), Nelson and Winter (1982), Reinganum (1982), and Spence (1984).

function as a determinant of R&D and market structure. Several of these cost-reduction models (notably Reinganum (1982), Levin and Reiss (1984), and Spence (1984)) have also examined how appropriability problems affect private incentives to perform R&D. Spence, in particular, finds that an increase in spillovers (a decrease in "appropriability") diminishes the incentives of individual firms to invest in process R&D.

This paper extends these models of R&D and market structure in two directions. First, we derive and estimate a model in which firms perform not only cost-reducing process R&D, but also demand-creating product R&D. By allowing technological opportunities and the degree of appropriability to differ between process and product R&D, we can examine the effect of spillovers on both the amount and composition of R&D. Second, we generalize previous characterizations of R&D spillovers to permit the possibility that own and rival R&D may be imperfect substitutes. We thus consider how variations in the degree of substitution between own and rival R&D may affect private incentives to undertake R&D.

Although our model is a static, non-stochastic parable for what is undoubtedly a dynamic, stochastic process, we believe that it yields a number of important insights about the relationships among R&D spillovers, technological opportunities, and market structure. We explore these relationships through comparative statics that show how spillovers affect R&D spending and market concentration. The importance of these effects is assessed by estimating the parameters of the model using cross-section R&D data on U.S. manufacturing lines of business. These data are drawn from several sources, including the FTC Line of Business Program, the Census of Manufactures, and a survey of R&D executives by Levin, Klevorick, Nelson, and Winter (1987). The survey data provide more detailed measures of the extent of technological opportunities and spillovers than have heretofore been available. Our estimates suggest that there is significant interindustry variation in the extent and productivity of spillovers. The estimates also help explain certain anomalies, such as why industries with high spillovers, continue to spend large amounts on R&D.

2. A Model of Cost Reduction and Demand Creation with Spillovers

2.1. Process R&D and Costs

We assume that firms incur fixed costs (f) and constant marginal costs (C) when producing output (q), and that process R&D affects only marginal costs. In addition, we assume that there are three types of process R&D expenditures that affect a firm's marginal costs: the firm's own investments in process R&D, process R&D done by competitors, and R&D done by firms outside the industry.[3] The effects of own process R&D and intraindustry spillovers are embodied in the i th firm's unit variable cost function as

$$C_i = C(x_i, X_i) \tag{1}$$

where x_i is the quantity of process R&D done by firm i, and X_i is the pool of industry knowledge available to firm i. A discussion of spillovers from outside the industry is deferred until the empirical section. We model the stock of industry knowledge available to firm i as

$$X_i \;=\; x_i + \omega_x \sum_{j \neq i}^{N} x_j \;=\; x_i + \omega_x \bar{X}_i \tag{2}$$

where ω_x is a scalar parameter representing the *extent* of process R&D spillovers and N is the equilibrium number of firms in the industry. Equation (2) implicitly assumes that own and rival R&D are perfect substitutes in the pool of industry knowledge available to firm i, with one unit of own R&D being as valuable as $1/\omega_x$ units of any rival's R&D. The assumption that the R&D of all other firms is equally

[3] The empirical significance of R&D spillovers from outside the industry (especially from materials suppliers and equipment suppliers) has been documented by Schmookler (1966), Scherer (1984), Bernstein and Nadiri (1988), and others.

valued is somewhat restrictive; it is made here because it greatly simplifies the model and the empirical specifications that follow.

Several special cases of the cost function (1) have been used in previous work. When unit costs depend only on the pool of industry R&D (i.e. $C = C(X_i)$), we obtain a process R&D specification identical to that in Spence (1984). Alternatively, if ω_x is set to zero, then unit costs depend only on own process R&D and we obtain the specification used in Dasgupta and Stiglitz (1980). We include separately own R&D and the pool consisting of own and rival R&D in equation (1) to emphasize that own R&D contributes to a firm's idiosyncratic capabilities as well as to an industry pool of knowledge. This particular specification also emphasizes that idiosyncratic knowledge is not a perfect substitute for shared industry knowledge. Levin and Reiss (1984) modelled this possibility with a variant of equation (1) in which the degree of substitution between own and rival R&D was constrained by setting ω_x equal to one. In the empirical section, we will test the cost specification in (1) against the nested Dasgupta and Stiglitz, Spence, and Levin and Reiss specifications. '

Finally, to clarify the relationship between own and rival R&D, we compute the elasticity of unit costs with respect to each type of process R&D:

$$\epsilon_x = -\frac{x_i}{C}\frac{\partial C}{\partial x_i} = -x_i\frac{C_x}{C} - x_i\frac{C_X}{C} = \alpha_x + \gamma_x\frac{x_i}{X_i}, \tag{3}$$

$$\epsilon_{\bar{X}} = -\frac{\bar{X}_i}{C}\frac{\partial C}{\partial \bar{X}_i} = \omega_x\gamma_x\frac{\bar{X}_i}{X_i} \tag{4}$$

where the subscripts on C denote first partial derivative arguments. Equation (3) defines two different elasticities: α_x, the elasticity of cost with respect to own R&D assuming no spillover effects, and γ_x, the elasticity of cost with respect to the industry pool of R&D. When a firm is a monopolist, we obtain the proprietary total cost elasticity: $\alpha_x + \gamma_x$. When the firm is an oligopolist, the second term in (3) includes a nonproprietary productivity effect. This effect allows for the possible dilution (at the margin) of own R&D by a rival's R&D. Assuming, for example, that α_x and γ_x are positive constants, equation (3) implies that increased R&D competition by rivals (i.e. a higher $\bar{X}_i$) lowers the marginal productivity of own R&D, even though increasing rival R&D lowers own costs.

The elasticity defined in equation (4) is a unit-free measure of the R&D externality effect. It suggests that there is an important distinction between the *extent* to which usable knowledge spills over to rival firms (as measured by ω_x) and the *productivity* of that shared knowledge (as measured by γ_x). This distinction between the extent of spillovers and their productivity is often blurred in discussions of the economic consequences of technological spillovers. To see how the distinction may be useful, consider two technologically similar industries that spend different amounts on R&D. This difference might be attributed to the usual appropriability problem: the industries simply differ in the extent to which firms have access to the knowledge generated by a rival's R&D. (For example, the industries might differ in the strength of patent protection or the ease by which products can be reverse engineered.) Alternatively, both industries may have the same extent of R&D spillovers, but they may differ according to the usefulness of acquired R&D in lowering costs.

2.2. Product R&D and Demand

On the demand side, we depart from previous studies by explicitly modelling product R&D, which we assume affects a firm's demand schedule in much the same way that process R&D affects costs.[4] Our specific formulation of how product R&D affects demand draws upon earlier models of product differentiation by Spence (1976), Dixit and Stiglitz (1977), and Koenker and Perry (1981). We assume that there is

[4] In this model there is a sharp distinction between process and product R&D expenditures. We assume that process R&D affects only costs and that product R&D affects only demand. This distinction is made largely for conceptual convenience. It enables us to label the R&D tradeoffs a firm faces in choosing between demand-creating (e.g. introducing better or new products) and cost-reducing investment activities. As a practical matter, however, it should be noted that the correspondence between product and process R&D and demand-creating and cost-reducing R&D is not so clear, especially because the design and development of improved products often requires accompanying process improvements.

an aggregate utility function representing consumer preferences of the form,

$$U(Q) = U\left(G_1 q_1 + G_2 q_2 + \ldots + G_N q_N\right) \tag{5}$$

where

$$G_i = G_i(y_i, Y_i), \tag{6}$$

Q is an industry output index, q_i is an observable measure of each firm's output, y_i is the product R&D done by the i th firm, and Y_i is a weighted sum of industry product R&D. The industry pool of product R&D is analogous to the knowledge pool of process R&D. Specifically,

$$Y_i = y_i + \omega_y \sum_{j \neq i}^{N} y_j = y_i + \omega_y \bar{Y}_i. \tag{7}$$

The output weights, the G_i, are to be interpreted as the perceived quality or attractiveness of the ith firm's product. As before, we restrict our attention to the case where there are no spillovers from outside the industry.

The output weights in (6) allow R&D expenditures to affect each firm's demand curve. Note that own product R&D influences demand both directly by altering the perceived quality of the product and indirectly via its effect on the quality of other firms' products.[5] The implied inverse demands for these goods are obtained by setting price equal to the partial derivative of the consumer benefit function,

$$P_i = \frac{\partial U}{\partial Q}\, G_i(y_i, Y_i) = P(Q)\, G_i, \tag{8}$$

where P is a suitably defined industry price index.

Spillovers in product R&D introduce substitution effects that are similar to those present in process R&D. Defining the elasticities of G as in equations (3) and

[5] If advertising also shifts demand by changing actual or perceived quality, then one can extend this model to include advertising in the output weights.

(4) gives

$$\epsilon_y = \frac{y_i}{G}\frac{\partial G}{\partial y_i} = \alpha_y + \gamma_y \frac{y_i}{Y_i}, \tag{9}$$

$$\epsilon_Y = \frac{\bar{Y}_i}{G}\frac{\partial G}{\partial \bar{Y}_i} = \omega_y \gamma_y \frac{\bar{Y}_i}{Y_i}. \tag{10}$$

These elasticities of product quality with respect to product R&D have interpretations that are similar to those given above for the elasticities of cost with respect to process R&D. Notice, however, that γ_y need not be positive because increases in rival R&D may reduce the perceived attractiveness of a firm's product.[6]

3. Equilibrium

If firms face constant unit costs for process and product R&D inputs, then the profit maximization problem for a firm is:

$$\max_{\{q_i, x_i, y_i\}} \left(P_i(q_i, Q, y_i, Y_i) - C_i(x_i, X_i) \right) q_i - x_i - y_i - f_i. \tag{11}$$

We assume that firms have Cournot-Nash conjectures regarding the output and R&D decisions of other firms.[7] In addition, we assume that each firm confronts the same decision problem and that we can restrict attention to symmetric equilibria. Although these latter two assumptions obviously preclude an explanation of intraindustry variations in R&D strategies, more general models cannot be identified with the data available. Thus, we focus on explaining interindustry differences in process and product R&D.

[6] In a purely technological sense, the spillover of a rival's product R&D should enhance the quality of one's own product. However, the output weights, the G's, reflect both tastes as well as technological attributes. Thus, the hedonic benefits derived from a product may decrease in response to a rival's product innovation.

[7] In our 1984 paper, we used the somewhat more general approach of parameterizing the conjectural variation with respect to process R&D. This additional generality has little empirical payoff, as our data and empirical specifications do not permit us to identify these conjectures.

The three first-order conditions and the free-entry, zero-profit condition that characterize any potential equilibrium are:

$$P\left[1-\frac{1}{\epsilon N}\right]=C \tag{12}$$

$$-\left[\frac{\partial C}{\partial x}+\frac{\partial C}{\partial X}\right]\ q=1 \tag{13}$$

$$\left[\frac{\partial P}{\partial y}+\frac{\partial P}{\partial Y}\right]\ q=1 \tag{14}$$

$$[P-C]\ q=x+y+f. \tag{15}$$

In equation (12), ϵ is the price elasticity of demand $(-PdQ/dPQ)$. Equations (12) through (13) have familiar marginal cost equal to marginal revenue interpretations. Equation (15) is the zero profit condition. The right hand side of this expression contains the fixed or quasi-fixed costs that prevent unlimited entry.

To characterize the equilibrium values of the endogenous variables, we manipulate equations (12) and (15) to obtain an equation explaining market concentration. Aggregating equation (15) across all firms, dividing through by industry sales, and making use of equation (12) yields

$$H=\frac{1}{N}=\epsilon\,(R+D+F), \tag{16}$$

where H is the Herfindahl index of concentration and R and D are, respectively, the industry process and product R & D-to-sales ratios. The variable F is the ratio of other industry fixed costs to industry sales. Nested within equation (16) is the proportionality result derived by Dasgupta and Stiglitz (1980) for process R & D, $1/N=\epsilon\,R$.

Next, we transform first-order condition (14) into an equation explaining the industry product R&D-to-sales ratio (D). Multiplying both sides of equation (14) by y/P, and dividing through by q, gives

$$D=\alpha_y\left[1-\frac{H}{\epsilon}\right]+\gamma_y\left[\frac{1}{1+\omega_y(N-1)}-\frac{H}{\epsilon}\right]. \tag{17}$$

In this expression, α_y is the elasticity of product quality with respect to product R&D. The second term contains the appropriability parameters. If product R&D is interpreted as advertising, and there are no spillovers, then this expression can be simplified to the familiar Dorfman and Steiner (1954) condition for the advertising-to-sales ratio.

Finally, we can derive an equation for process R&D expenditures. The derivation of this equation is similar to that of equation (17). Multiplying equation (13) through by x/P gives

$$R = -\left(\frac{1}{P}\right)\left[x\frac{\partial C}{\partial x} + x\frac{\partial C}{\partial X}\right]. \tag{18}$$

Converting this expression into one involving elasticities of the unit cost function

$$\frac{R}{1-(R+D+F)} = \alpha_x + \frac{\gamma_x}{1+\omega_x(N-1)}. \tag{19}$$

Equation (19) is similar to the process R&D equation estimated in Levin and Reiss (1984). The left-hand side is the ratio of process R&D to total variable production costs. The right hand side "explains" the ratio of R&D to costs in terms of elasticities of the unit cost function and the parameter representing the extent of spillovers.

It is important to note the similarities between the structures of the process and product R&D equations. The first term in each expression (the α) is an elasticity of cost or price, holding spillover effects constant. We take this term to represent the *technological opportunities* that firms face in engaging in cost-reducing or demand-creating research holding spillover effects from the pool of industry R&D constant. The second term in each of these R&D equations reflects two aspects of appropriability: the extent and the productivity of spillovers. The next section examines how R&D spending varies with changes in these underlying technological opportunity and appropriability conditions.

4. Comparative Statics

For expositional clarity and to facilitate the empirical work that follows, the comparative statics are based on simplified demand and cost functions. In particular, we use the following constant elasticity specifications

$$C_i = A_c\,[x_i]^{-\alpha_x}[X_i]^{-\gamma_x} \tag{20}$$

$$P_i = A_p \left[\sum_{j=1}^{N} G_j q_j\right]^{-\frac{1}{\epsilon}} G_i, \tag{21}$$

$$G_i = A_g\,[y_i]^{\alpha_y}[Y_i]^{\gamma_y} \tag{22}$$

where the A's represent unknown positive constants. We also assume for simplicity that $F = 0$. The system to be analyzed can then be represented as three equations in three unknowns: H, R, and D:[8]

$$H = \epsilon\,(R + D) \tag{23}$$

$$D = \alpha_y\left(1 - \frac{H}{\epsilon}\right) + \gamma_y\left(\frac{1}{1+\omega_y(N-1)} - \frac{H}{\epsilon}\right) \tag{24}$$

$$\frac{R}{1-(R+D)} = \alpha_x + \frac{\gamma_x}{1+\omega_x(N-1)}. \tag{25}$$

The reduced form parameters of interest are those representing spillovers ($\gamma_x, \gamma_y, \omega_x$, and ω_y), R&D opportunities (α_x and α_y), and the price elasticity of demand (ϵ).

In the special case in which all R&D is directed toward cost-reduction, the system simplifies to two equations. The comparative statics of this system are straightforward. Concentration and process R&D intensity rise with increases in technological opportunities and the elasticity of demand. They also rise with increases in the productivity of spillovers, but fall with increases in the extent of

[8] We conduct the comparative statics on the R&D-to-sales variables (as opposed to the absolute quantities of R&D) because our estimating equations are based upon these variables. One could also consider performing comparative statics on the equations that determine output, the number of firms, and the absolute quantities of process and product R&D. The R&D-to-sales variables, however, avoid difficult estimation issues raised by the use of R&D price deflators. See Griliches (1979).

spillovers. Only the latter effect is identified by Spence (1984), because in his model own and rival R&D are perfect substitutes. When proprietary and non-proprietary R&D are imperfect substitutes, an increase in spillover productivity, a form of diminished appropriability, causes R&D intensity to rise because own R&D is enhanced by increases in industry knowledge.[9]

In the more general model in which R&D may be directed toward both cost reduction and demand creation, it is impossible to sign unambiguously the comparative statics of the complete system for all feasible values of the technological opportunity and appropriability parameters. When the Jacobian of the system is positive, as it is when evaluated using the empirical estimates reported in this paper, increases in the extent of process and product spillovers decrease concentration and the ratio of total R&D to sales. Increases in the productivity of spillovers have the opposite effect; they tend to increase own R&D spending and decrease the number of firms. Under certain circumstances, such as when the extent of spillovers is near zero, an increase in the extent of process (product) spillovers may induce sufficient substitution so as to increase the intensity of product (process) R&D.[10]

5. The Empirical Specifications

An ideal approach to measuring interindustry differences in technological opportunity and appropriability would be to derive a dynamic analog of the present model and to test its implications using panel data on R&D spending. Unfortunately, the only R&D data available over a reasonable period of time are the highly aggregated NSF data used in our 1984 paper. Here instead we use cross-section line of business data collected by the Federal Trade Commission (FTC). These data have the

[9] Cohen and Levinthal (1989) develop a model where R&D investment is necessary to acquire external knowledge. They observe that increases in the extent of spillovers may also increase R&D.

[10] Levin and Reiss (1986) contains a more complete discussion of these comparative statics.

advantage of matching more closely the markets modelled in the theory. They do not, however, allow us to study the dynamics of R&D spending.

To keep our empirical specifications tractable, we retain the constant elasticity specifications used in the comparative statics. We account for differences in R&D spending patterns across industries by allowing these elasticities to vary with exogenous measures of technological opportunity and appropriability. The following subsections describe the empirical model, the data, and our estimation techniques.

5.1. The Concentration Equation

The concentration equation is the most straightforward of the structural equations to convert to an empirical specification. Taking the natural logarithm of both sides of equation (16) and assuming that the unobserved errors are additive, yields

$$lnH_i = \beta_0 + \beta_1 ln\epsilon_i + \beta_2 ln(R_i + D_i + F_i) + \psi_{1i}. \tag{26}$$

In this equation, i indexes lines of business in our sample and ψ_{1i} is an additive error. The theoretical model predicts that the intercept (β_0) should be zero and the two slope coefficients (β_1 and β_2) should be unity.

The concentration equation contains three theoretical constructs that are not directly observable: the Herfindahl index, fixed costs, and the price elasticity of demand. In the empirical work that follows, we employ the approximations to these variables developed in Levin and Reiss (1984). The Herfindahl index was calculated from estimated distributions of market shares that were obtained by fitting truncated exponential size distributions to Census of Manufactures concentration data. Where necessary, the Herfindahl indices were aggregated using sales data to match FTC line of business industry categories. The price elasticities of demand were obtained using Levin's (1981) procedure for transforming consumer demand elasticities reported by Almon et al. (1974) into derived demand elasticities. The measurement of fixed costs is subject to the idiosyncrasies of accounting conventions. (See for example Fisher (1987)). We therefore estimated the model both with and without a proxy for fixed costs. Our proxy for fixed costs is all assignable and nonassignable depreciation and amortization as reported in the Line of Business data for 1976. Our R&D data are also drawn from this source.

The concentration equation derived above may be incomplete if it omits important fixed and quasi-fixed expenditures that affect entry. One important variable omitted from the model is advertising. The concentration equation (26) is easily amended to take into account advertising expenditures, provided one assumes that advertising affects demand in the same way that product R&D does. Specifically, the concentration equation becomes

$$lnH_i = \beta_0 + \beta_1 ln\epsilon_i + \beta_2 ln(R_i + D_i + A_i + F_i) + \psi_{1i}$$

where A_i is the industry advertising-to-sales ratio. The advertising data used to estimate this specification also are taken from the 1976 Line of Business data.

5.2. The R&D Equations

Our theoretical model distinguishes between process and product R&D. In practice, firms do not make this distinction when they report how much R&D they perform. This led us to consider two approaches to estimating the parameters of the R&D equations. The first combines the process and product R&D equations. Adding both equations together so that the dependent variable is total R&D spending as a fraction of total production costs gives

$$\begin{aligned}\frac{R+D}{1-(R+D+A+F)} = \alpha_x + \alpha_y + \frac{\gamma_x}{1+\omega_x(N-1)} \\ + \frac{\gamma_y}{1-\frac{H}{\epsilon}}\left(\frac{1}{1+\omega_y(N-1)} - \frac{H}{\epsilon}\right).\end{aligned} \tag{27}$$

This equation does not require us to distinguish between process and product R&D in the data, but it has the disadvantage of combining many nonlinear and possibly collinear terms.

An alternative is to allocate total R&D spending between product and process R&D on the basis of patent information. Scherer (1984) classified a large sample of patents according to whether they protected process or product innovations. We used his tabulations to estimate how much of total R&D spending was for process and product R&D. By dividing total R&D into process and product R&D, we are able to estimate separately the process

$$\frac{R}{1-(R+D+A+F)} = \alpha_x + \frac{\gamma_x}{1+\omega_x(N-1)} \tag{28}$$

and product

$$\frac{D}{1-(R+D+A+F)} = \alpha_y + \frac{\gamma_y}{1-\frac{H}{\epsilon}}\left(\frac{1}{1+\omega_y(N-1)} - \frac{H}{\epsilon}\right) \tag{29}$$

R&D equations. We employ this approach because it reduces the computational burden associated with the nonlinearities in (27). On the other hand, if the weights used to assign process and product R&D are imperfect, then this procedure is likely to bias or otherwise affect the coefficient estimates.

To estimate (28) and (29), we need to specify how the α, γ, and ω parameters depend on line of business characteristics. We do not have a precise theory that tells us how we should measure technological opportunity or spillover productivity across industries. We do, however, have detailed survey data from R&D executives on differences in opportunity and appropriability conditions across different lines of business. These survey data have the advantage that they explicitly distinguish between the conditions that affect product and process R&D. Other advantages and disadvantages of these data are described in detail in Levin et al. (1987).[11]

To account for interindustry differences in technological opportunity, we used survey measures of the extent to which upstream suppliers and downstream users

[11] Two disadvantages are particularly important here. The respondents were asked to give answers to questions on an inherently subjective scale, and the survey questions do not adequately distinguish between the productivity of own and industry R&D. This latter limitation limits our ability to identify convincingly differences between α and γ. See also the discussion in Levin et al. (1987).

contribute to technical progress in a line of business. We expect that the contributions of upstream materials suppliers (MATER) and equipment suppliers (EQUIP) might affect a line of business' investment in process R&D, but the effect might be positive or negative. Upstream contributions in the quality of materials or production equipment, for example, may diminish the opportunities for complementary investments downstream, or they may reveal new opportunities for investments downstream. Similarly, we expect the contributions of downstream users (USERS) to affect the opportunities for investment in product R&D, although the net effect is once again ambiguous.

The variables MATER, EQUIP, and USERS were originally recorded on a seven-point Likert scale. We experimented by using actual industry mean responses, alternative scalings of the responses, and categorical summaries of the responses to the survey. Here we report the results obtained when the responses to each of these survey questions were recoded to a zero-one variable. The variables are set to one when the respondents in a line of business reported that suppliers or users were "important" contributors to technical progress. Importance was defined relative to the average response on each question. It is either all responses greater than or equal to four or responses greater than or equal to six.

We experimented with other measures of technological opportunity derived from the survey, such as one representing the contributions of science to an industry's technology, but, in general, the survey variables did not account for much interindustry variation in α_x or α_y, the elasticities of unit cost and product quality with respect to process and product R&D respectively. Thus, we rely upon coarser categorical summaries to capture broad industry differences in the nature of technological opportunities. In the process R&D equation, we distinguish technologies by the zero-one variables: CHEM, equal to one when the process technology is chemical in nature, and ASSEMBLY, equal to one when the process technology involves the assembly of components. In the product R&D equation, we again distinguish chemical industries; we also employ the dummy variable METAL, which is equal to one for industries that produce primary and fabricated metal products. We expect that these latter industries will have relatively few opportunities for performing product R&D.

Technological opportunities may also depend on industry-specific factors that cannot easily be captured in survey data or technology variables. We found that dummy variables for the cement (CEMENT) and the semiconductor (SEMI) industry improved the results for both the process and product R&D equations. In addition to these categorical variables, we included in both R&D equations measures of the energy intensity of the product (ENERGY). This variable is the fraction of all material costs that were energy-related in 1977. We expect that more energy-intensive industries are likely to have greater opportunities for lowering production costs and fewer opportunities for product improvements. In the product R&D equation, we also included a measure of the extent to which the product is a consumer good, PCESHR. This variable is defined as the ratio of personal consumption to total domestic consumption.

The survey contained only a few measures that might serve to represent the productivity of spillovers (γ). We experimented with WITHIN, a measure of the importance of the contribution of firms within a line of business to the line of business' technological progress, and GOVLAB, a measure of the importance of the contribution of government research laboratories to technological progress within the industry. Neither of these variables, nor a measure of technological maturity (AGE) that we used in our earlier paper, appeared to explain variations in the productivity of the industry pool of R&D. We therefore report the results with a constant spillover productivity parameter that differs only by whether the industry is an electronics industry. The variable representing the communications equipment, semiconductors, and computer electronics industries is ELECTRON.

To measure the extent of spillovers (ω), we used data on the effectiveness of chanisms for protecting the competitive advantages of process and product .tions. These mechanisms, which are used to appropriate the returns to in- on, are: patents to prevent duplication, patents to secure royalties, secrecy, me, moving quickly down the learning curve, and superior sales or service ef-[2] As reported in Levin et al. (1987), there is a significant correlation among sponses to these questions; this led us to reduce the responses to fewer dimen- ısing principal components analysis. Separate principal component analyses ned on the industry mean responses to the questions concerning product and s R&D appropriability yielded two readily interpretable components. In each is, the two components explained more than 60 percent of the overall variance questions analyzed. The results of the principal components analyses and rdized principal component scores are presented in Table 1. For both process oduct R&D, the first principal component (PC1 and PD1) loads positively on chanisms of appropriation. Thus, PC1 and PD1 can be interpreted as repre- g the strength of appropriability conditions in general; they therefore should atively related to the extent of spillover parameters, ω_x and ω_y. The second pal components (PC2 and PD2) distinguish between the relative effectiveness ent and non-patent means of appropriation. Among our selected industries, miconductor industry rates highest in overall appropriability, although it is vest in the relative effectiveness of process patents. Nuts, bolts and screws owest in overall appropriability, while the drug industry ranks highest in the veness of patents.

The Sample

1 of 130 manufacturing lines of business responded to the R&D survey. We ed several of these because the survey responses were incomplete or R&D data

Ve also experimented with responses to a set of survey questions that focus ability of firms to learn from their rivals. Results with those variables are ally comparable to those presented here.

were unavailable, leaving us with a final sample of 116. Table 2 provides descriptive statistics on the sample. Appendix A contains a summary of our variable names and definitions.

6. The Empirical Specifications and Results

6.1. The Concentration Equation

Linear instrumental variables estimates of the concentration equation are presented in Table 3. As in Levin and Reiss (1984), reasonable results could be obtained only by imposing the restriction that $\beta_0 = 0$. Three different specifications are reported in Table 3, each of which treats the price elasticity of demand as an exogenous regressor. The specifications in the table differ according to which fixed and quasi fixed costs are assumed to affect entry and the long run number of firms. In each specification, the price elasticity of demand has the correct sign, but we cannot reject the null hypothesis that it is equal to zero.[13] The coefficients on the cost variables have the right sign and are fairly precisely estimated. Only in the second specification, however, are we able to accept the null hypothesis that $\beta_2 = 1$.

Our rejection of the model explaining concentration is not too surprising given that the Herfindahl indicies and the price elasticities are estimated quantities. We explored the possibility that measurement errors in the price elasticity estimates biased the coefficients downward, thereby affecting the results. The results in Table 3 do not change much when the price elasticity is treated as a stochastic regressor.[14] Moreover, corrections for apparent heteroskedaticity do not significantly alter the above conclusions. A test of the equation's overidentifying restrictions, however uniformly rejects the specification of each equation at a 2.5 percent significance

[13] The standard errors employ White's (1980) suggested correction for heteroskedasticity.

[14] Wu-Hausman tests do not reject the null hypothesis that the price elasticities are uncorrelated with the error term.

level.[15]

6.2. The Process R&D Equation

Estimates of several process R&D equations are reported in Table 4. The first column of the table is based on Dasgupta and Stiglitz's (1980) no-spillovers model of process R&D (i.e. $\gamma = \omega = 0$). This simple model explains 46 percent of the variance in the dependent variable. The implied process R&D elasticity (α_x) is positive and significant for almost every line of business. On average, the estimates imply that firms lower their costs by .45 % for every doubling in their own process R&D. The estimates also suggest, however, that the total cost elasticity varies across industries in several important ways. First, there are significant industry effects. Chemical processing industries have greater technological opportunities than the average industry in our sample, and the semiconductor industry has an even higher own R&D elasticity.[16] On the other hand, industries specializing in assembly appear to have fewer technological opportunities on average. Second, the contributions of upstream suppliers as reflected in MATER and EQUIP tend to reduce a firm's process R&D elasticity, although the coefficients are imprecisely estimated. Finally, lines of business with energy-intensive technologies have significantly increased opportunities for process improvements. Greater opportunities do not exist, however, in energy-intensive industries in which material suppliers make important contributions to technological change.

The second column in Table 4 reports coefficient estimates of a model in which spillovers are complete ($\omega_x = 1$), as in Levin and Reiss (1984). The intercept term in γ indicates that a doubling in the industry pool of process R&D lowers the average firm's costs by 2.3 percent. This effect is imprecisely estimated, and we cannot

[15] For a discussion of this test see section 5 of Hausman (1983).

[16] Chesher and Jewitt (1987) have shown that White's procedure is sensitive to extreme leverage points in the design matrix. The dummy variable SEMI takes on a value of one at an extreme point. For this variable, we report the (smaller) t-statistic associated with the uncorrected standard errors.

reject the null hypothesis that spillovers are unproductive ($\gamma_0 = 0$). Process R&D spillovers do appear to be important in electronics industries, with a doubling in the pool of industry R&D leading to a 5.1 % decrease in costs.

The third column reports a more general specification where the extent of spillovers ω is treated as a constant parameter. This specification has nested within it the previous two specifications. We can therefore test the hypothesis that own and rival R&D are perfect substitutes by testing whether α is zero. (Recall that, if α is zero, own R&D only enters through its contribution to the pool of industry R&D.) A likelihood ratio test rejects that $\alpha = 0$ at the 5 % level. The extent of spillovers parameter (ω) is insignificant, however, implying that we cannot reject the Dasgupta-Stiglitz model with no process R&D spillovers.[17]

In evaluating the effect of the pool of industry process R&D on costs, it is important to separate the productivity effect, as measured by γ, and the extent of spillovers, as measured by ω. Statistical tests of whether non-proprietary process R&D is productive (i.e. $\gamma = 0$) are complicated by the presence of ω. Under the null hypothesis that spillovers are unproductive, ω is a meaningless nuisance parameter. Its presence in the model under the alternative, however, affects the validity of standard asymptotic arguments. The inference problems that arise in this situation have been discussed by Davies (1977; 1987). We adopted his method for testing whether $\gamma = 0$.[18] This test statistic rejects the hypothesis that spillovers are unproductive at the 10% level. Even though this test provides modest support that process R&D spillovers are productive, an overall goodness of fit test rejects the null hypothesis that the specification in the third column is a significant improvement over the Dasgupta-Stiglitz model.

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[17] If the extent of spillovers parameter were truly zero then we could not separately identify γ asymptotically. Put another way, although we can test nondegenerate null hypotheses such as $\omega = 1$, it is more problematic to test degenerate null hypotheses such as $\omega = 0$.

[18] Specifically we employ the joint significance test procedure outlined in Davies (1987).

The final column in Table 4 reports a specification where the extent of spillovers parameter is allowed to vary with the principal component scores for appropriability.[19] The qualitative conclusions on most of the variables are preserved. The mean process R&D spillover estimate is still greater than 20 percent. Although PC1 has the expected sign, we cannot reject the hypothesis that ω is constant across industries. The test of the overidentifying restrictions at a 2.5 percent significance level indicates that there is no model misspecification.

6.3. The Product R&D Equation

Table 5 contains product R&D specifications that parallel the process R&D specifications in Table 4. The estimates in the first column indicate that there are significant industry differences in the elasticity of product quality with respect to product R&D. Chemicals, cement, and semiconductors have relatively high elasticities with respect to own product R&D. Lines of business that produce metal products and those that are energy-intensive have fewer opportunities for product quality improvement. Downstream technological contributions have a positive, but insignificant effect on technological opportunities. Finally, the negative coefficient on PCESHR indicates that consumer products industries face lower product R&D elasticities than do other industries.

The second column in Table 5 reports estimates of a model in which spillovers are complete ($\omega = 1$). As in the case of process R&D, the electronics industries appear to have significantly higher spillover productivities. The third column in Table 5 estimates the extent of spillover parameter under the assumption that it does not vary across industries. The estimate of the extent of spillovers (.12) is lower for products than for processes. In both cases, we cannot reject the hypothesis that ω is equal to zero. We can, however, decisively reject the null that α is equal to zero. A test of whether product spillovers are unproductive cannot reject the null

[19] The standard errors in this specification have not been adjusted for the sampling variability in the principal component estimates.

in the average industry or in electronics. For reasons given in Davies (1987), this test is likely to have low power against the alternative that the extent of spillovers is small. Indeed, it is possible to reject the perfect spillovers model in column 2.

The final column in Table 5 includes the principal component scores as covariates in ω_y. We still cannot reject homogeneity across industries in the extent of spillovers. There are at least two reasons for this result. First, the principal component scores are imperfect measures of appropriability. Second, the nonlinearities in the specification make it difficult to precisely estimate the spillover parameters, especially because the endogenous variable (the Herfindahl index) enters the specification in a nonlinear way. The test of the overidentifying restrictions also casts doubt on this specification.

6.4. Parameter Values for Selected Industries

Table 6 presents estimates of the elasticities of unit cost and product quality with respect to own and rival R&D for selected lines of business. (The actual elasticity estimates are the figures in the table divided by 100.) These estimates were generated using the specifications in the last columns of Tables 4 and 5. The own process R&D elasticities are estimated with reasonable precision, but the elasticities with respect to rival R&D are very imprecise. The elasticity of unit costs with respect to own process R&D is quite low on average; but in the semiconductor industry it is an order of magnitude larger than the average, indicating that a doubling of process R&D would lower unit costs by 3.45 percent. It is also relatively high in industries with chemically-based or electronic technologies (e.g. aircraft, drugs, and organic chemicals). By contrast, own process R&D elasticities are quite low for food product and machinery industries.

The elasticity of product quality with respect to own R&D is much higher than the cost elasticity in most industries. The electronic and chemical industries, as well as oil field machinery and aircraft, appear to have significantly more productive own R&D than food, metal products, and, somewhat anomalously, the plastics products industries.

The results for the productivity of rival process and product R&D are less encouraging. In general, there is not enough variation in the conditions affecting appropriability to distinguish among industries. Despite the modest interindustry variation, rival process R&D appears to be of greatest importance in electronics industries. Rival product R&D is also productive in communications equipment, but not nearly as much as own product R&D.

7. Conclusion

This paper modelled the tradeoffs firms face in choosing between imperfectly appropriable cost-reducing and demand-creating R&D. In the theoretical section, we showed that process and product R&D may be substitutes or complements, depending upon the relative magnitudes of parameters reflecting process and product spillovers, and technological opportunity. Our empirical results support the view that differences in technological opportunity affect the resources committed to both process and product R&D. We also find that proprietary and nonproprietary product R&D are imperfect substitutes, but we fail to capture with great precision interindustry differences in both the extent and productivity of spillovers.

The analysis of the paper leaves some important questions unresolved. Our distinction between the extent of spillovers and their productivity helps understand why certain industries, such as the electronics industries, can have high spillovers and yet also perform large amounts of R&D. A more complete model, however, would make appropriability conditions endogenous – not only because firms partially control how much of their R&D effort is proprietary or non-proprietary, but also because technological change itself affects the underlying conditions that determine the extent of spillovers and their productivity. Empirical work by Jaffe (1985) on the technological proximity of firms appears to confirm that firms link their internal R&D activities to enhance intrafirm spillovers. Our use of survey data to explain interindustry differences in opportunities and appropriability is a step forward, but the survey data do not adequately distinguish between factors determining the productivity of R&D spillovers and the extent to which knowledge spills over. Finally, although our static model provides some insights about relationships of R&D and market structure, it is but a small step toward understanding the more complete dynamic process where market structure evolves through time.

Appendix A: The Data and Variable Definitions (Sources in Parentheses)

H	1972 Herfindahl index of concentration. (COM)
C	Company-financed R&D expenditures in 1976. (FTC)
S	Total line of business sales and transfers in 1976. (FTC)
ϕ	Percentage of industry patents that are process related. (Scherer)
$R = \phi\frac{C}{S}$	Fraction of sales spent on process R&D. (FTC)
$D = (1-\phi)\frac{C}{S}$	Fraction of sales spent on product R&D. (FTC)
A	Fraction of sales spent on advertising and other selling expenses in 1976. (FTC)
F	Fraction of sales spent on assignable and nonassignable general overhead in 1976. (FTC)
PELAS	Price elasticity of demand. (See text. Almon, IO)
WITHIN	A survey measure of the extent to which this industry produces usable knowledge internally. (Survey: Question III.E.1.)
MATER	Equal to one if materials suppliers contribute significantly to technological progress (Survey: Question III.E.2.)
EQUIP	Equal to one if manufacturing equipment suppliers contribute significantly to technological progress. (Survey: Question III.E.3.)
USERS	Equal to one if users of the product contribute significantly to technological progress. (Survey: Question III.E.5.)
GOVLAB	Equal to one if government laboratories contribute significantly to technological progress. (Survey: Question III.E.7.)
PROCPAT	A survey measure of the effectiveness of process patents. (Survey: Question I.A.1.)

PRODPAT	A survey measure of the effectiveness of product patents. (Survey: Question I.B.1.)
FUTURE	Equal to one if opportunities for developing a new process are likely to be better in the future. (Survey: Question IV.F).
CHEM	Equal to one if the technology or product is largely chemical.
METAL	Equal to one if the industry is largely a metal processing industry.
HOMPRD	Equal to one if the product is homogeneous.
SEMI	Equal to one for the semiconductor industry.
ELECTRON	Equal to one for electronics industries.
CEMENT	Equal to one for the cement industry.
ENERGY	The fraction of input materials costs that are energy related in 1977. (COM)
PCESHR	Personal consumption expenditures divided by output. (IO)
DEFSHR	Federal defense expenditures divided by output. (IO)
AGE	Number of years between 1977 and the year in which the industry was first listed in the Standard Industrial Classifications Index.
PC1	First principal component measuring the extent of process spillovers. (See text.)
PC2	Second principal component measuring the extent of process spillovers. (See text.)
PD1	First principal component measuring the extent of product spillovers. (See text.)
PD2	Second principal component measuring the extent of product spillovers. (See text.)

Data Sources

Almon	Almon, C. et al. (1974).
COM	U.S. Bureau of the Census. *1972 Census of Manufacturers*. Washington D.C.: GPO.
FTC	Federal Trade Commission, *Annual Line of Business Reports, 1976*. Washington, D.C.: FTC.
IO	U.S. Department of Commerce, Bureau of Economic Analysis, *1972 Input-Output Tables for the United States*. Washington, D.C.: GPO.
Scherer	Scherer (1984).
Survey	Levin et al. (1987).

Table 1. Principal Component Analysis

Process Appropriability

Survey Question	First Principal Coefficient	Second Principal Coefficient
Patents Preventing Duplication	.323	.625
Patents for Royalties	.388	.559
Secrecy	.382	-.234
Lead Time	.562	-.325
Learning Curve Advantage	.464	-.361
Sales and Service	.262	.078

Product Appropriability

Survey Question	First Principal Coefficient	Second Principal Coefficient
Patents Preventing Duplication	.420	-.425
Patents for Royalties	.393	-.499
Secrecy	.401	-.167
Lead Time	.539	.266
Learning Curve Advantage	.406	.430
Sales and Service	.230	.536

Selected Principal Component Scores

Industry	PC1	PC2	PD1	PD2
Frozen Foods	.13	-.49	-.56	1.66
Grain Mill Products	-.74	-.58	-.96	1.26
Nuts, Bolts and Screws	-1.94	-.44	-1.52	-.91
Oil Field Machinery	.52	-.07	.77	-.23
Organic Chemicals	-.14	.79	.31	-1.06
Plastic Products	.21	-.19	.44	-.54
Drugs	.32	1.67	.81	-1.97
Semiconductors	1.10	-.96	.86	1.09
Communications Equipment	.07	-.33	.40	.38
Aircraft	.76	-.60	.58	.27

These questions correspond to the Yale Survey questions I.A.1 - I.A.6 and I.B.1 - I.B.6. A higher score on each question meant the mechanism was more effective in protecting the returns to R&D.

Table 2. Descriptive Statistics

	Mean	Standard Deviation	Minimum	Maximum
PROCESS PATENTS (in %)	31.22	29.59	.00	100.00
PROCESS R&D/SALES (in %)	.40	.53	.00	3.03
PRODUCT R&D/SALES (in %)	1.43	1.57	.00	8.00
A (in %)	8.07	6.07	.12	30.88
F (in %)	7.40	3.48	2.18	20.46
H	.08	.06	.01	.31
PELAS	1.89	1.51	1.00	9.21
ENERGY	.06	.07	.01	.55
PCESHR	.18	.30	.00	1.00
Dummy Variables:				
CHEM	.12	.33	.00	1.00
ELECTRON	.03	.16	.00	1.00
SEMI	.01	.09	.00	1.00
METAL	.14	.35	.00	1.00
MATER	.12	.33	.00	1.00
EQUIP	.14	.35	.00	1.00
USERS	.04	.20	.00	1.00
ASSEMBLY	.19	.39	.00	1.00
Other Survey Variables:				
PC1	.14	1.45	-4.93	5.35
PC2	.04	1.20	-2.87	2.74
PD1	.11	1.27	-3.10	4.74
PD2	.03	1.23	-4.99	3.34
SAMPLE SIZE	116			

Table 3. Herfindahl Equation Estimates

Dependent Variable: LN H

β_1	ln PELAS	.082 (.52)	.216 (1.00)	.154 (.72)
β_2	ln (R + D)	.605 (27.86)		
β_2	ln (R + D + A)		1.062 (22.27)	
β_2	ln (R + D + A + F)			1.418 (21.93)
RSE	Regression Standard Error	.758	1.014	1.044
χ^2	Overidentification Test	47.74	43.32	38.16
N = 116				

All specifications were estimated using instrumental variables. Asymptotic t-statistics are in parentheses below the coefficient estimates. The asymptotic standard errors employ the heteroskedasticity correction suggested by White (1982). The instruments include: a constant term, lnPELAS, CHEM, ELECTRON, SEMI, WITHIN, MATER, USERS, EQUIP, AGE, AGESQ, DEFSHR, PCESHR, PROCPAT, PRODPAT, ENERGY, METAL, ASSEMBLY, FUTURE, CEMENT, and HOMPRD. The chi-squared statistic for misspecification is the sample size times the R^2 obtained by regressing the model's residuals on the instruments (see Hausman (1983)).

Table 4. Process R&D Equation Estimates

		Specification			
Coefficient	**Variable**	$\omega = 0$	$\omega = 1$	$\omega = \omega_0$	
α_{x0}	CONSTANT	.31	.11	.03	.06
		(4.51)	(.84)	(.06)	(.14)
α_{x1}	ASSEMBLY	-.27	-.23	-.24	-.27
		(-4.36)	(-3.95)	(-3.98)	(-3.22)
α_{x2}	CHEM	.42	.44	.43	.43
		(1.92)	(2.11)	(2.07)	(2.06)
α_{x3}	CEMENT	-1.78	-1.54	-1.49	-1.45
		(-3.88)	(-2.91)	(-2.62)	(-2.26)
α_{x4}	SEMI	3.02	2.70	2.72	2.66
		(6.67)	(4.75)	(4.82)	(4.34)
α_{x5}	ENERGY	2.76	2.53	2.47	2.45
		(3.05)	(2.52)	(2.34)	(2.29)
α_{x6}	MATER	-.07	-.06	-.06	.00
		(-.80)	(-.74)	(-.68)	(.01)
α_{x7}	MATER*ENERGY	-2.41	-2.30	-2.34	-4.05
		(-2.56)	(-2.27)	(-2.30)	(-.91)
α_{x8}	EQUIP	-.04	-.03	-.03	-.11
		(-.60)	(-.48)	(-.54)	(-.84)
γ_{x0}	CONSTANT		2.36	1.00	1.02
			(1.48)	(.60)	(.45)
γ_{x1}	ELECTRON		2.74	.67	.62
			(2.82)	(.25)	(.22)
ω_{x0}	CONSTANT		1.00	.21	.26
				(.20)	(.18)
ω_{x1}	PC1				-.05
					(-.18)
ω_{x2}	PC2				.02
					(.14)
RSE	Regression Std. Error	.450	.436	.435	.441
χ^2	Overidentification Test	23.99	22.82	22.96	20.40

There are 116 observations. The mean of the dependent variable is .45 with a standard deviation of .59. Asymptotic t-statistics are in parentheses below the coefficient estimates. The specification in the first column was estimated using ordinary least squares. The other equations were estimated using instrumental variables. The instrumental variables include those in Table 3, except lnPELAS, and also MATER*ENERGY, GOVLAB, PC1, and PC2. All standard errors are corrected for heteroskedasticity except those for SEMI. (See text.) The chi-squared statistic is the sample size times the R^2 obtained by regressing the model's residuals on the instruments (see Hausman (1983)).

Table 5. Product R&D Equation Estimates

		Specification			
Coefficient	**Variable**	$\omega = 0$	$\omega = 1$	$\omega = \omega_0$	
α_{y0}	CONSTANT	2.46	1.90	1.07	-1.06
		(7.58)	(8.00)	(.66)	(-.19)
α_{y1}	METAL	-.99	-.84	-.73	-.79
		(-2.77)	(-2.87)	(-2.42)	(-2.60)
α_{y2}	CHEM	1.36	1.26	1.23	1.04
		(1.83)	(2.26)	(2.07)	(2.14)
α_{y3}	PCESHR	-1.37	-1.23	-1.43	-1.39
		(-2.42)	(-2.86)	(-3.01)	(-3.10)
α_{y4}	CEMENT	3.89	3.18	4.16	4.27
		(3.77)	(3.35)	(3.28)	(3.23)
α_{y5}	SEMI	1.46	-4.16	-4.44	-3.97
		(.79)	(-2.49)	(-2.43)	(-2.45)
α_{y6}	ENERGY	-11.48	-9.22	-10.67	-10.05
		(-5.07)	(-4.88)	(-4.65)	(-4.52)
α_{y7}	USERS	.74	.73	.42	.36
		(.58)	(.72)	(.45)	(.42)
α_{y8}	USERS*ENERGY	-2.18	-2.07	-.26	-3.24
		(-.36)	(-.43)	(-.05)	(-.74)
γ_{y0}	CONSTANT		5.23	3.09	3.85
			(1.16)	(1.43)	(.68)
γ_{y1}	ELECTRON		99.10	11.92	5.78
			(5.43)	(.56)	(3.09)
ω_{y0}	CONSTANT		1.00	.120	.011
				(.35)	(.40)
ω_{y1}	PD1				-.003
					(-.49)
ω_{y2}	PD2				.004
					(0.54)
RSE	Regression Std. Error	1.834	1.280	1.282	1.237
χ^2	Overidentification Test	56.82	37.76	36.17	34.46

There are 116 observations. The mean of the dependent variable is 1.43, with a standard deviation of 1.57. Asymptotic t-statistics are in parentheses below the coefficient estimates. All equations were estimated using instrumental variables. The instrumental variables include those in Table 3 and USERS*ENERGY, GOVLAB, PD1, and PD2. All standard errors are corrected for heteroskedasticity except those for SEMI. (See text.) The chi-squared statistic is the sample size times the R^2 obtained by regressing the model's residuals on the instruments (see Hausman (1983)).

Table 6. R&D Elasticity Estimates (x 100)

Industry	ϵ_x $\alpha_x + \gamma_x \frac{x}{X}$	$\epsilon_{\tilde{X}}$ $\gamma_x \omega_x \frac{\tilde{X}}{X}$	ϵ_y $\alpha_y + \gamma_y \frac{y}{Y}$	$\epsilon_{\tilde{Y}}$ $\gamma_y \omega_y \frac{\tilde{Y}}{Y}$
Frozen Foods	.25 (1.36)	.83 (.31)	.32 (.91)	.93 (1.20)
Grain Mill Products	.31 (3.24)	.82 (.31)	1.41 (7.13)	.76 (1.08)
Nuts, Bolts and Screws	.22 (.79)	.98 (.41)	.53 (0.49)	1.68 (.97)
Oil Field Machinery	.01 (.13)	.87 (.33)	2.15 (2.37)	.63 (.59)
Organic Chemicals	1.02 (7.75)	.81 (.30)	2.22 (6.18)	.32 (.44)
Plastic Products	.20 (.75)	.98 (.41)	-.02 (-.02)	1.63 (1.33)
Drugs	.76 (5.47)	.88 (.34)	2.40 (4.26)	.17 (.15)
Semiconductors	3.45 (7.82)	1.02 (.20)	3.24 (2.62)	.94 (.42)
Communications Equipment	.56 (1.95)	1.20 (.23)	7.35 (8.29)	1.02 (.41)
Aircraft	.50 (4.15)	.65 (.24)	2.22 (6.33)	.30 (.60)
Sample Mean	.45	.77	1.54	.59
Sample Std. Dev.	.43	.17	1.12	.47

Figures in this table are based on the estimates in the fourth columns of Tables 4 and 5. Asymptotic t-statistics are reported in parentheses. To obtain the elasticity estimate, divide each number by 100.

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