8 Tests of a Schumpeterian Model of R & D and Market Structure

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8.1 Introduction

Schumpeter's (1950) ideas about the role of innovation in modern capitalist economies have inspired a substantial literature on the relationship between market structure and innovative activity. This literature has focused on Schumpeter's observation that seller concentration influences the appropriability of R & D. Unfortunately, as is apparent in the surveys of Kamien and Schwartz (1975) and Scherer (1980), it is unclear whether highly concentrated markets enhance the appropriability of the returns to R & D (e.g., Schumpeter 1950) or whether the opposite is true (Fellner 1951; Arrow 1962). In either case, industry concentration is viewed as an important determinant of R & D intensity.

With few exceptions (notably Phillips 1966, 1971), it was not until recently that economists turned their attention to the reciprocal influence of R & D on market structure. This new literature has emphasized Schumpeter's oft-cited notion of "creative destruction," where market structure is influenced by past and current innovative successes and failures. Specifically, innovation generates transient market power; this, in turn, is eroded by rival innovation and imitation. Thus, a truly Schumpeterian framework requires that both market structure and R & D be taken as endogenous variables. Seen in this perspective, the relation of R & D and market structure must be explained by an appeal to more fundamental factors that jointly determine concentration and R & D: the

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structure of demand; the richness of technological opportunities; and the technological and institutional conditions governing appropriability.

A number of recent theoretical papers have attempted to capture the essence of this Schumpeterian simultaneity. Among these contributions are Dasgupta and Stiglitz (1980a, 1980b), Futia (1980), Lee and Wilde (1980), Levin (1978), Loury (1979), and Nelson and Winter (1977, 1978, 1980).[1] The approach taken by Nelson and Winter is the most comprehensive in its representation of the relevant forces influencing market structure and R & D intensity. The price of this generality is high, since their models are analytically intractable and are open only to simulation. By contrast, many of the remaining models are stark and highly stylized; each omits aspects of technology and competition that are important for a broader understanding of the relationship between market structure and R & D. For example, none of the above models is truly dynamic; market structure is represented by the number of identical firms; only Futia explicitly recognizes R & D spillovers where firms benefit from the efforts of rivals; and finally, no attention is paid to other activities, such as advertising, that affect market structure.

The problems hampering theoretical treatments of the simultaneity issue have made rigorous tests of the Schumpeterian process extremely difficult. To date only Levin (1981) and Farber (1981) have explored the simultaneity issue in any detail. Only Levin has attempted to test for the presence of simultaneity among the relevant variables, but Levin's model (in which concentration, private and government, R & D, advertising, and price-cost margins are determined simultaneously) is specified in the loose, eclectic manner that is characteristic of most empirical work in industrial organization. Although the findings are encouraging, they can only be regarded as a preliminary test of the neo-Schumpeterian theories.

In this paper we provide a more exacting empirical test. Unfortunately, in our efforts to formulate precise hypotheses, we are forced to ignore several aspects of Schumpeterian dynamics. Nonetheless, we are able to incorporate several important features of reality which have heretofore been missing in formal models of the R & D process. We begin with what is perhaps the simplest of the theoretical models of R & D and market structure, the Dasgupta-Stiglitz (1980a) model of noncooperative oligopoly with free entry. We generalize this model by adding two significant features. First, we allow for spillovers in the knowledge generated by R & D. Hence, some fraction of the returns to each firm's R & D efforts are appropriated by its rivals. Although we are not able at this stage to

1. Although they do not discuss the simultaneous determination of R & D activity and market structure, the work of Pakes and Schankerman (this volume) on the determinants of R & D spending is akin to the papers cited here in clear identification of demand, technological opportunity, and appropriability as central exogenous variables.

incorporate a specific allocation of investment to imitative effort, as Nelson and Winter do, we believe that our characterization of R & D spillovers illuminates important aspects of the appropriability problem, as we explain below. Second, we include advertising expenditures among the decision variables of the firm. Like R & D, advertising is an instrument of competition, and in many industries it is of greater empirical consequence than R & D. By thus enriching the model, we hope to gain a more precise understanding of the role of both R & D and advertising in Schumpeterian competition.

An attractive feature of our approach is that the general model contains a family of nested models that can be tested using classical procedures. For example, by constraining the value of certain parameters (namely, the degree of R & D spillovers and the elasticity of demand with respect to advertising) the Dasgupta-Stiglitz model falls out as a special case of our own model. In addition, questions concerning the effects of imperfect appropriability of R & D returns can be reduced to considerations of the magnitudes or signs of certain parameters in the model.

We believe our approach to be an attractive one, but we must caution the reader at the outset that limitations of both theory and data still preclude a fully satisfactory treatment of the issues we explore here. The model remains quite stark, abstracting from at least four issues of undoubted importance. First, the model is one of a static industry equilibrium, which is hardly in the spirit of the Schumpeterian dynamic disequilibrium arguments. Second, we take no account of uncertainty, which even in the absence of risk aversion has important implications for the allocation of R & D effort. Third, to make the analysis tractable, we consider only symmetric industry equilibria, where all firms within an industry are identical. Fourth, we consider only cost-reducing R & D, neglecting the well-known fact that most industries devote a major share of their innovative efforts to developing new products and improving the quality of existing products. In future work, we plan to generalize our model to take account of dynamics, uncertainty, asymmetry, and product R & D.

Limitations of the data constrain our efforts as well. Our model is designed for testing on a cross section of industries, but R & D data are available for industries only at a highly aggregated level, requiring us to aggregate data on other variables up to this level. Even more serious are deficiencies in the operational measures of technological opportunity and appropriability. In this paper, we rely on relatively crude proxies. However, together with several colleagues, we have recently initiated work on the direct measurement of opportunity and appropriability conditions through a survey of R & D managers. When collected, these data should substantially improve the reliability of the empirical results obtainable with this or any related econometric model.

The remainder of the paper is organized as follows. Section 8.2 presents and analyzes the model. Section 8.3 develops the empirical specification. The data and the econometric techniques are discussed in section 8.4. In section 8.5 the econometric results are presented and interpreted, and section 8.6 indicates directions for future research.

8.2 A Model of R & D with Spillovers

We begin by considering a firm that seeks to maximize profit with the use of three instruments: output, R & D expenditures, and advertising expenditures. Following Dasgupta and Stiglitz, we assume that a firm's R & D expenditure serves to shift downward its unit cost function, which is independent of output, but we generalize their formulation to include the effect of industrywide R & D on cost. Thus, unit cost of firm i is

$$c_i = c(x_i, Z), \tag{1}$$

where x_i is the R & D expenditure of the ith firm, and Z is the sum of the R & D expenditures of all firms in the industry, including firm i.[2] It is further assumed that $c_1, c_2 < 0$, and $c_{11}, c_{22} > 0$; that is, there are positive but decreasing returns to both own R & D and to industrywide R & D.

This formulation emphasizes an important aspect of R & D technology neglected in most analytic models—external economies. An increase in the R & D expenditures of firm i not only reduces its own cost, but it also, through its "spillover" effect on Z, reduces the cost of all other firms in the industry. This characterization captures a central aspect of the appropriability issue; specifically, the cost function indicates the *technological* dimension of appropriability. To the extent that unit cost reduction is very elastic with respect to increments in the industrywide pool of R & D (holding own R & D constant), we infer that costless imitation is relatively easy, or that, technologically, the returns to R & D are relatively inappropriable. We shall indicate shortly how appropriability also has *structural* and *behavioral* dimensions.

Since our primary interest attaches to the analysis of R & D, we take a somewhat simpler approach with respect to advertising and its effect on demand. In particular, we assume that advertising shifts the industry demand curve. In principle, we could model advertising as altering the firm's own demand curve as well as spilling over to alter the demands facing all other firms. Such a characterization would reveal clearly the complete analogy between the roles of appropriability and R & D, since the appropriability of advertising also has technological, structural, and behavioral dimensions. Instead, we simply represent the industry inverse demand curve as:

2. Equation (1) can be generalized to include spillovers of R & D undertaken in other industries.

$$p = p(Q, A), \tag{2}$$

where $Q = \Sigma q_i$ represents industry output, and $A = \Sigma a_i$ represents total advertising expenditures of all firms in the industry. We further assume that $p_1 < 0$, $p_2 > 0$, and $p_{22} < 0$.

The problem facing the ith firm is, therefore,

$$\max_{q_i, x_i, a_i} \Pi_i = [p(Q,A) - c(x_i, Z)]q_i - x_i - a_i. \tag{3}$$

We assume that firms entertain Cournot conjectures regarding the output and advertising levels of all other firms. That is, we assume that the ith firm conjectures that $dQ/dq_i = 1$ and $dA/da_i = 1$. However, to bring clearly to the fore the full range of issues regarding the appropriability of R & D, we parameterize the conjectural variation with respect to R & D. That is, we let $dZ/dx_i = \theta_i$. Later, we shall explore several special cases by fixing θ_i.

We now write down the first-order conditions for the maximization of the ith firm's profit:

$$p\left(1 - \frac{s_i}{\epsilon}\right) = c, \tag{4}$$

$$-(c_1 + c_2\theta_i)q_i = 1, \text{ and} \tag{5}$$

$$p_2 q_i = 1, \tag{6}$$

where $\epsilon = p/Qp_1$, the price elasticity of demand,[3] and $s_i = q_i/Q$, the market share of the ith firm.

We assume free entry such that the maximized profits of all firms in the industry are greater than or equal to zero, while profits of all firms outside (potential entrants) are less than or equal to zero for all nonnegative levels of output. We further restrict our attention to *symmetric* equilibria, where all firms in the industry behave identically. This latter restriction is, of course, less than desirable in a model purporting to represent Schumpeterian competition, but we have found that consideration of asymmetric equilibria raises some extremely difficult analytical problems.

Dasgupta and Stiglitz have shown that, given certain restrictions on the parameters, symmetric free entry equilibria exist. Somewhat more complicated restrictions on the parameters are necessary in the present model, but a wide range of parameter values remain consistent with equilibrium. Dasgupta and Stiglitz have also derived conditions under which the profit of each firm in the industry is approximately equal to zero in a symmetric equilibrium. Of course, it is perfectly plausible that the

3. Dasgupta and Stiglitz (1980a) use the notation ϵ to represent the quantity elasticity of *inverse* demand. We find that intuition is facilitated by reverting to the more customary notation.

technology of R & D (or of advertising) would be such that equilibrium contains a very small number of firms earning nonnegligible profit, but the entry of one additional firm would result in negative profits for all.[4] In what follows, we assume that the zero-profit condition can be invoked. Thus, we close the model by noting that each firm earns zero profit in equilibrum:

$$[p(Q, A) - c(x_i, Z)]q_i = x_i + a_i. \tag{7}$$

Before proceeding, it is worth pointing out (in the manner of Dasgupta and Stiglitz) that conditions (4)–(7) may be used to illustrate that a market equilibrium involving cost-reducing and demand-shifting activities, such as R & D and advertising, will not result in a socially optimal allocation of resources. Conditions (4) and (7) indicate that prices must deviate from marginal cost to sustain R & D and advertising expenditures. Moreover, the left-hand sides of (5) and (6) show that the marginal private benefit of R & D and advertising depends on the firm's scale of output, whereas social optimality would require that the market output, Q, be substituted for q_i in these expressions.

We now proceed to analyze the market equilibrium in greater detail. First, note that in a symmetric equilibrium with n identical firms, $q_i = q$, $x_i = x$, $a_i = a$, $\theta_i = \theta$, and $s_i = 1/n$, for all firms. The zero-profit condition can then be summed over all firms by multiplying both sides of (7) by n to yield:

$$[p(Q, A) - c(x, Z)]Q = nx + na. \tag{8}$$

Dividing both sides by pQ, we have

$$\frac{p - c}{p} = R + S, \tag{9}$$

where the left-hand side is the Lerner index of monopoly power, R, is the ratio of industry R & D to sales, and S is the ratio of advertising to sales. Combining (9) and (4), we have

$$\frac{1}{n} = \epsilon(R + S), \tag{10}$$

where $1/n$ is the Herfindahl index of concentration. This striking result says that industry concentration is proportionate to the sum of R & D and advertising intensity, where the elasticity of demand is the factor of proportionality. Our result parallels that of Dasgupta and Stiglitz, who, by neglecting advertising ($S = 0$), arrive at $1/n = \epsilon R$.

We choose to treat (10) as a structural equation for concentration in the econometric work which follows. Since we derived (10) from the first-

4. The problem with the zero-profit condition arises from the requirement that n be integer valued.

order condition (4) and the zero-profit condition (7), we now use (5) and (6) to derive structural equations for R & D intensity and advertising intensity, respectively.

Multiplying both sides of (5) by $R = x/pq$ gives:

$$-(c_1 + c_2\theta)\frac{x}{p} = R. \tag{11}$$

Simple manipulation of (11) yields

$$-\left(\frac{c_1 x}{c} + \frac{c_2 Z\theta}{cn}\right)\frac{c}{p} = R. \tag{12}$$

But inspection of equation (9) reminds us that $c/p = 1 - (R + S)$. We also observe that $-(c_1 x/c)$ can be interpreted as the elasticity of unit cost with respect to x, holding Z constant, which we will denote as $\alpha = \alpha(x|Z)$, and that $-(c_2 Z/c)$ is the elasticity of unit cost with respect to Z, holding x constant, which we denote as $\gamma = \gamma(Z|x)$. It follows that (12) can be rewritten as:

$$\frac{R}{1-(R+S)} = \alpha + \frac{\gamma\theta}{n}. \tag{13}$$

The numerator of the left-hand side of (13) is the ratio of R & D to sales, while the denominator is the share of sales revenue that is devoted to neither R & D nor advertising. In zero-profit equilibrium this is just equivalent to the ratio of production cost to revenue. Thus, the left-hand side of (13) is simply the ratio of R & D to total production cost, a variant of the more familiar representation of R & D intensity, typically used in econometric work.

We can interpret (13) as a structural equation in which R & D intensity depends on two terms. The first, α, is the elasticity of unit cost with respect to own R & D, holding industrywide R & D constant. It seems reasonable to interpret α as a measure of technological opportunity, indicating the responsiveness of cost to own research effort. The second term, $\gamma\theta/n$, has three components, each of which represents one of the dimensions of appropriability mentioned previously. We noted that γ, the elasticity of unit cost with respect to industrywide R & D (holding own R & D constant), is a reasonable measure of the *technological* dimension of appropriability, since it represents the extent to which a firm benefits from an increase in the common pool of R & D effort. On the other hand, since a firm's own R & D effort augments the common pool, higher levels of γ are associated with greater R & D intensity as long as the conjectural variation, θ, is positive.

Appropriability has a *structural* dimension as well, which was emphasized by Schumpeter (1950) and later by Galbraith (1956). For any given technology of R & D and market size, a firm's appropriable benefits from augmenting the common pool of knowledge depend on its market share, which is $1/n$ in a symmetric equilibrium. On the conjecture that rivals do not respond ($\theta = 1$), a 1 percent increase in own R & D produces a $1/n$ percent increase in industrywide R & D. Thus, whereas a monopolist's costs fall by γ percent for a 1 percent increase in its contribution to the common pool, an oligopolist's costs fall only by γ/n percent. Through this mechanism, the intensity of R & D increases with the greater appropriability associated with a more concentrated market structure.

Finally, there is a *behavioral* dimension to appropriability, represented here by the conjectural variation parameter, θ. It is easy to show that the Cournot conjecture, $\theta = 1$, results in a Nash equilibrium when combined with our previous assumptions that firms have Cournot conjectures in output and advertising decisions. But some informal arguments concerning the disincentive effects of spillover in R & D implicity contain presumptions that $\theta < 1$. To the extent that firm j can costlessly borrow knowledge from firm i's R & D effort, it may choose to be a free rider and cut back on its own R & D. If the free-rider effect is sufficiently strong, θ may even be negative; that is, a one dollar increase in R & D expenditure by firm i may produce cutbacks in the R & D expenditures of the remaining firms that exceed one dollar in the aggregate. Such negative conjectural variations produce market equilibria that are not Nash equilibria, but the idea that free-rider effects are important in R & D is sufficiently well entrenched in the literature (e.g., Nelson 1959) to warrant testing for evidence of its presence.

In the empirical work that follows, we will examine several special cases of the model in which θ takes on prespecified values, as well as the case in which θ is free to vary. In particular, we will examine cases in which the value of θ is assumed to be 0, 1, and n, respectively. In the first case, the free-rider effect is such that rivals exactly offset a change in firm i's R & D, leaving industry R & D constant. The second is the Cournot-Nash case. In the third case, each firm behaves as if it expects its action to be matched by all others. This is the R & D analog of the Chamberlinian "constant market shares" conjecture. We shall test whether the data permit rejection of any of these three hypotheses about the value of θ.

Equations (10) and (13) represent structural equations for concentration and R & D intensity, respectively. We now derive a third equation for advertising intensity. Multiplying both sides of the first-order condition (6) by A/p and dividing both sides by q_i gives:

$$p_2 \frac{A}{p} = \frac{A}{pq_i}. \tag{14}$$

The left-hand side of (14) is the advertising elasticity of inverse demand, which we denote as η. Dividing both sides of (14) by n we have

$$\frac{\eta}{n} = S, \tag{15}$$

where S is the ratio of industry advertising to sales, A/pQ.

It is easily shown that this expression for advertising intensity is simply a generalization of the Dorfman-Steiner (1954) rule to the oligopoly case. Note that at any given price

$$\eta = \frac{\partial p}{\partial A}\frac{A}{p} = \frac{-\partial p}{\partial Q}\frac{Q}{p}\frac{\partial Q}{\partial A}\frac{A}{Q} = \frac{\phi}{\epsilon}, \tag{16}$$

where ϕ is the advertising elasticity of demand, and ϵ is the price elasticity of demand or, equivalently, the reciprocal of the inverse elasticity of demand. Thus, substituting (16) into (15), we have

$$S = \frac{\phi}{\epsilon n}, \tag{17}$$

which is, of course, identical to the familiar Dorfman-Steiner result when, in the monopoly case, $n = 1$.

To summarize, we have now derived three structural equations representing the simultaneous determination of industry structure, R & D, and advertising intensity:

$$\frac{1}{n} = \epsilon(R + S), \tag{10}$$

$$\frac{R}{1 - (R + S)} = \alpha + \frac{\gamma\phi}{n}, \text{ and} \tag{13}$$

$$S = \frac{\phi}{\epsilon n}. \tag{17}$$

These structural relations are reasonably general, although they do depend on the special assumptions of symmetry and of Cournot conjectures in advertising and output.[5] In addition, ϵ, ϕ, α, and γ need not be constant parameters. However, by specializing the cost and demand functions they become so, and it becomes possible both to solve for reduced form equations for n, R, and S and to operationalize the model for empirical work. Thus, we assume that both cost and inverse demand functions have constant elasticities, so that

$$C(x, Z) = \beta x \;\; {}^{\alpha} Z^{-\gamma}, \text{ and} \tag{18}$$

5. It is easy to see that the Dasgupta-Stiglitz model is a special case of our own—implicitly they asume $\gamma = \theta = 0$. Under these conditions, the model reduces to two structural equations for market structure and R & D: $1/n = \epsilon R$ and $R/(1 - R) = \alpha$. It is readily verified that these equations are equivalent to those contained in Dasgupta-Stiglitz (1980a).

$$(19) \qquad p(Q, A) = \sigma^{1/\epsilon} A^{\eta} Q^{-1/\epsilon}.$$

The inverse demand function (19), of course, corresponds to the demand function:

$$(20) \qquad Q(p, A) = \sigma A^{\phi} p^{-\epsilon}.$$

8.3 Empirical Specification

The model we have developed consists of three endogenous variables: the Herfindahl index of concentration (H $= 1/n$), research intensity, and advertising intensity. These three variables are jointly determined by the parameters of the cost and demand functions, which presumably differ across industries, and by the behavioral parameter, θ. We propose to test the model using cross-section data at the industry level to determine whether interindustry differences in opportunity, appropriability, and demand satisfactorily explain differences in concentration, R & D, and advertising. For the present we assume that θ is constant across all industries, except in the special case where $\theta = n$, and we test various hypotheses concerning its value.

Although the endogenous variables H, R, and S are directly observable (at least in principle), the exogenous parameters ϵ, ϕ, α, and γ are not. Since estimates of the price elasticity of demand exist for a wide range of industries, we treat ϵ_k as an observable exogenous variable for the kth industry. Next, to make the estimation problem tractable, we assume that α_k, the elasticity of unit cost with respect to own R & D in the kth industry, is a function of a vector of observables representing technological opportunity. Similarly, γ_k, the elasticity of unit cost with respect to industrywide R & D, is assumed to be a function of observables representing the degree of R & D spillovers (the technological dimension of appropriability). Finally, ϕ_k, the advertising elasticity of demand, is assumed to be a function of observable attributes of the industry's product. In the absence of any strong theoretical presumption, $\alpha_k(\cdot)$, $\gamma_k(\cdot)$, and $\phi_k(\cdot)$ are each assumed to be linear in parameters with an additive error term of mean zero. These errors are assumed to be uncorrelated with each other and uncorrelated with the error terms in the model's structural equations.

We can now write down a system of equations that can be estimated. Assuming that (10) is observed with multiplicative error and taking logarithms, we have

$$(21) \qquad \log \mathrm{H} = a_o + a_1(\log\epsilon) + a_2[\log(R + S)] + e_1.$$

The model makes very precise predictions about the signs and magnitudes of the coefficients of (21). Specifically, we will test the hypotheses, separately and jointly, that $a_o = 0$ and $a_1 = a_2 = 1$. It should be recalled that the Dasgupta-Stiglitz model is a special case of our own when $\phi = \gamma = 0$. We can compare estimates of (21) with estimates of

$$\log \mathrm{H} = a_o' + a_1' (\log \epsilon) + a_2' (\log R) + e_1', \tag{22}$$

to determine whether anything is gained by adding advertising to the model.

The second equation takes the general form:

$$\frac{R}{1-(R+S)} = \alpha(\cdot) + \theta \mathrm{H} \gamma(\cdot) + e_2, \tag{23}$$

where errors are contained in the $\alpha(\cdot)$ and $\gamma(\cdot)$ expressions as noted above. Substituting for $\alpha(\cdot)$ and $\gamma(\cdot)$, we have

$$\frac{R}{1-(R+S)} = \left[b_o + \left(\sum_{m=1}^{M} b_m \mathrm{OPP}_m\right) + u\right] + \theta \mathrm{H}\left[c_o + \left(\sum_{n=1}^{N} c_n \mathrm{APP}_n\right) + v\right] + e_2, \tag{24}$$

where OPP_m is an element in an M-dimensional vector of variables measuring technological opportunity, and APP_n is an element in an N-dimensional vector of variables measuring the technological conditions of appropriability. Before specifying these opportunity and appropriability measures, two general comments about (24) are in order.

First, the combined error term in equation (24), $e_2 + u + v\theta\mathrm{H}$, has undesirable properties, except in cases where θ is assumed to be either zero or n. In the general case, (24) implies that the concentration term, H, has a random coefficient equal to $\theta(c_o + v)$. We will discuss this problem in section 8.4.

Second, it will not be possible to identify θ from the parameters of (24), since θ multiplies each coefficient in $\gamma(\cdot)$. Nevertheless, it will be possible to test specific hypotheses about the value of θ. For example, the hypothesis that $\theta = 0$ implies that the coefficients of the last $N + 1$ terms of the estimated equation are jointly equal to zero. In fact, we cannot distinguish between the hypotheses that $\theta = 0$ and $\gamma = 0$, since the latter carries the same implication for the coefficients of (24). Rejection of this hypothesis, however, is equivalent to rejection of the Dasgupta-Stiglitz specification, in which $\gamma = 0$.

We will also be able to test whether $\theta = n$, the "constant R & D shares" conjecture, since $\theta\mathrm{H} = 1$ under this assumption. The specification resulting from this hypothesis is not nested in the empirical specification of the general model, since the elements in the APP vector now enter directly rather than interactively with H. We can, however, test the hypothesis $\theta = n$ against $\theta = 0$. Unfortunately, the hypothesis that conjectures are Cournot ($\theta = 1$) cannot be tested.

Given the available data, we have at best crude proxies for technological opportunity and appropriability. As noted in section 8.1, we are engaged in an effort to develop better measures through a survey of R & D managers. For the present, however, we follow and extend somewhat the approach of Levin (1981).

Opportunities for technical advance depend in part on the particular "science base" of an industry's technology. This suggests adopting the approach of Scherer (1965, 1967), who used dummy variables to classify industries as mechanical, chemical, electrical, or biological. We add metallurgical to this list as the excluded category in the regressions reported below. To represent the "closeness" of an industry's link to science, we use the share of basic research expenditures in total industry R & D. Life cycle models of industry evolution suggest that opportunities may increase in the early years of technological development, because technology is "cumulative" (e.g., Nelson 1981; Nelson and Winter 1982). Later, technological opportunities may be exhausted as industries reach maturity. This suggests that a variable representing industry age should be included among the opportunity measures in both linear and quadratic form. Finally, government policy may affect technological opportunity. It seems reasonable to hypothesize that government-funded R & D is complementary to private effort, thus increasing the elasticity of unit cost with respect to private R & D. Thus, to summarize, we postulate that $\alpha(\cdot)$ is:

$$\begin{aligned}(25)\quad \alpha = b_o &+ b_1(\text{ELEC}) + b_2(\text{CHEM}) + b_3(\text{BIO}) + b_4(\text{MECH})\\ &+ b_5(\text{BASIC}) + b_6(\text{AGE}) + b_7(\text{AGE}^2)\\ &+ b_8(\text{GOVRDS}) + u,\end{aligned}$$

where the first four variables are the technology base dummies described above, BASIC is the ratio of basic R & D to total industry R & D, AGE is industry age, and GOVRDS is the ratio of government-funded R & D to sales. Our expectation is that b_5, b_6, $b_8 > 0$, and $b_7 < 0$.[6] We do not have strong prior beliefs about the relative opportunity of each of the technology types, although we expect $b_1 > 0$ over the period covered by our data (1963–72).

6. There is an alternative expectation for the parameters b_6 and b_7 consistent with our discussion of the life cycle of technological opportunity. Our operational measure of industry age is based on the number of years since each four-digit industry first appeared in the Standard Industrial Classification (SIC), and it is entirely possible that the "early" years of the life cycle in which technological opportunity is growing typically occur before an industry is classified by the Bureau of Census. Under these circumstances, we would expect α to decline with age. Thus, we would not be surprised to find $b_6 < 0$. It is even possible that $b_7 > 0$ would be consistent with our expectations, provided the age at which opportunity is minimized is beyond the range of our observations.

The extent of interfirm spillovers of R & D depends both on legal-institutional features of the environment and on characteristics of the product or technology. For example, there are probably important interindustry differences in the effectiveness of patent protection. The inherent complexity of products and processes is also relevant to the ease of imitation. But these aspects of appropriability remain unmeasured. It is widely believed, however, that products, which can be examined directly by rivals, are more easily imitated than process innovations. Thus, the share of R & D expenditures devoted to new or improved products should be positively related to γ, the degree of spillovers. Fortunately, McGraw-Hill collects data of this sort, and recent work of Scherer (1981) presents alternative estimates derived from patent data.

Scherer's work also suggests another possible measure of appropriability. Industries differ widely in the extent to which they develop their own process technology or "borrow" it in the form of R & D embodied in capital goods and intermediate products. It seems reasonable to presume that interfirm R & D spillovers within the industry are positively associated with the share of process R & D that is "borrowed" rather than generated internally. This presumption rests on the idea that R & D within the industry spills over more readily if the participants are using a common process technology. If most process R & D is developed "in-house," it is more likely that firms have idiosyncratic technologies, and spillovers are less important. Thus, we take the ratio of borrowed R & D to total R & D "used" by an industry as another determinant of γ.

Finally, government funding of R & D frequently carries restrictions on appropriability, such as mandatory licensing. Thus, we expect government R & D to increase the extent of spillovers in an industry.

To summarize, we specify $\gamma(\cdot)$ as:

$$(26)\ \gamma = c_o + c_1(\text{PROD}) + c_2(\text{BORROW}) + c_3(\text{GOVRDS}) + \nu,$$

where PROD is the share of R & D devoted to new or improved products, BORROW is the ratio of R & D embodied in inputs to total R & D used (where R & D used by an industry is the sum of R & D embodied in inputs and its own process R & D), and GOVRDS is the ratio of government R & D to sales. We expect c_1, c_2, and $c_3 > 0$.

We now move to the third equation of the model, which we express in log-linear form:

$$(27)\qquad \log S = d_0 + d_1[\log\phi(\cdot)] - d_2\log\epsilon + d_3\log \text{H} + e_3.$$

This equation resembles the concentration equation (21), in that the model dictates the precise hypotheses that $d_0 = 0; d_1, d_2, d_3 = 1$. Here our problem is complicated because ϕ, the advertising elasticity of demand, cannot be observed directly. We assume, however, that ϕ is a function of product attributes that can be observed. Specifically, we assume that ϕ depends on whether the product in question is a consumer or producer's good, which we measure by the ratio of personal consumption expenditures to total industry sales. Moreover, in line with arguments advanced in the literature on advertising, we expect the responsiveness of demand to advertising to depend in part on whether the product is a durable one. Advertising is likely to have greater impact on the demand for nondurables, since other sources, such as retailers and other customers, tend to be relied on for information about long-lived products. We also add an interaction term, since the latter distinction is likely to be more pronounced for consumer goods.[7] Thus, we specify $\phi(\cdot)$ as:

$$(28)\quad \phi = \exp[g_0 + g_1(\mathrm{PCE}) + g_2(\mathrm{DUR}) + g_3(\mathrm{PCE^*DUR}) + w],$$

where PCE is the share of personal consumption expenditures in industry sales, and DUR is a dummy variable representing a durable good. We expect $g_1 > 0$, and g_2, $g_3 < 0$.

We choose an exponential form of $\phi(\cdot)$ for reasons of tractability, since substitution of (28) into (27) will now yield an equation that is linear in the parameters. Nonetheless, estimates of d_0 and d_1 cannot be recovered, since they appear only in combination with the coefficients of $\phi(\cdot)$. On the maintained hypothesis that $d_0 = 0$ and $d_1 = 1$, however, it is possible to identify these latter coefficients and to generate estimates of ϕ for each industry.

One additional issue requires discussion before the empirical specification is complete. It would be possible to treat government R & D as an exogenous policy instrument influencing opportunity and appropriability and, hence, private R & D. Yet there is considerable plausibility to the view that government R & D decisions are influenced by opportunity and appropriability conditions, even if not in quite the same way as private decisions are affected. In particular, the government may attempt to compensate for the inappropriability of R & D returns by allocating R & D funds to industries where spillovers are high and where concen-

7. Our argument abour durability is based on the insights of Porter (1974), which are employed in the subsequent work of Caves, Porter, and Spence (1980). Porter distinguishes between "convenience" goods, for which advertising is the principal form of selling effort, and "nonconvenience" goods, for which the buyer typically seeks information from other sources. In Porter's scheme, convenience goods are nondurable, purchased frequently, and sold at a low unit price. Operationally, at the highly aggregated level of our data, the classification of industries as producers of nondurables and durables is identical to the classification based on Porter's scheme.

Caves, Porter, and Spence claim that advertising intensity should be higher in convenience goods industries, but this conclusion does not strictly follow from their argument. Instead, they offer good reasons why the ratio of advertising to other forms of selling effort should be higher for convenience goods, but no reasons why the ratio of advertising to sales should be higher.

tration is low. This view receives support from the previous exploratory model of Levin (1981), where the hypothesis that GOVRDS is uncorrelated with the error term in the private R & D equation is decisively rejected in a test based on the work of Wu (1973), Hausman (1978), and Reiss (1981). Although a truly satisfactory model of government R & D allocation would give due weight to political forces, we observe that most of the variance of government differences in R & D expenditures across industries is explained by government procurement policy. Put simply, the government supports R & D in industries where it is a major customer; this holds especially for defense procurements. Therefore, we specify that the ratio of government R & D to sales is determined by:

$$\text{(29)} \qquad \text{GOVRDS} = h_0 + h_1(\text{DEFSHR}) + h_2(\text{GOVSHR}) + h_3\text{H} + \left(\sum_{M=1}^{M} h_{3+m}\text{OPP}_m\right) + \left(\sum_{n=1}^{N} h_{3+M+n}\text{APP}_n\right) + e_4,$$

where DEFSHR is the share of industry sales going to the federal government for defense purposes, and GOVSHR is the share of industry sales purchased by the federal government for other purposes.

8.4 The Data and Estimation Issues

Table 8.1 provides definitions, scalings, and the sources of the data used in this study. Table 8.2 furnishes sample statistics for these data. We have already discussed in some detail the difficulties involved in measuring opportunity and appropriability and the rationale behind our measures. Most of the remaining variables are conventional and require no further comment (for further reference, see Levin 1981). We will, however, comment briefly on the measurement of R & D expenditures, price elasticities of demand, and concentration before discussing estimation procedures.

The only definitionally consistent industry R & D expenditure data are those tabulated by the Bureau of the Census for the National Science Foundation (NSF). Unfortunately, they are only available for highly agregated NSF industry classifications. Our sample consists of the twenty basic manufacturing industries for which data are available since 1963. These industries are a composite of four-, three-, and two-digit SIC classifications (see table 8.2). Since industry data on such variables as concentration and the number of firms are only available for Census of Manufactures survey years (1963, 1967, and 1972), our sample consists of sixty observations.

On the demand side, we use the price elasticities calculated by Levin

Table 8.1 **Variable Definitions and Data Sources**

Variable	Definition (data sources in parentheses)
H	Herfindahl index of concentration (computed from COM)
R	Company-financed R & D expenditures divided by value of shipments (NSF, COM)[a]
S	Advertising expenditures divided by industry output (IO)
RDINT	Research intensity; $R/(1 - R - S)$
GOVRDS	Government-financed R & D expenditures divided by value of shipments (NSF, COM)[a]
ϵ	Price elasticity of demand (Almon, IO)
ELEC	Industry technology base predominantly electrical (scaled 0–1)
CHEM	Industry technology base predominantly chemical (scaled 0–1)
BIO	Industry technology base predominantly biological (scaled 0–1)
MECH	Industry technology base predominantly mechanical (scaled 0–1)
MET	Industry technology base predominantly metallurgical (scaled 0–1)
BASIC	Basic R & D expenditures divided by total R & D (NSF)
AGE	Years since industry first appeared in *Census of Manufactures* with substantially same definition as today (COM)
AGESQ	Square of AGE
PROD	Share of industry R & D expenditures devoted to new or improved products (McGraw-Hill)
BORROW	R & D embodied in inputs divided by total R & D "used," where latter is the sum of own expenditures on process R & D and R & D embodied in inputs (Scherer)
PCE	Personal consumption expenditures divided by industry sales (IO)
DUR	Dummy variable set equal to one for durable goods, zero otherwise
DEFSHR	Federal government purchases for national defense purposes divided by industry sales (IO)
GOVSHR	Federal government purchases for purposes other than national defense divided by industry sales (IO)

Key to Data Sources:

Code	*Source*
Almon	Almon, C., et al. 1974. *1985: Interindustry forecasts of the American economy*. Lexington, Mass.: Lexington Books.
COM	U.S. Bureau of the Census. 1963, 1967, 1972. *Census of manufactures*. Washington, D.C.: GPO.
IO	U.S. Department of Commerce, Bureau of Economic Analysis. 1963, 1967, 1972. *Input-output tables for the United States*. Washington, D.C.: GPO.
McGraw-Hill	McGraw-Hill. Economics Department. *Annual surveys of business plans for research and development*. Mimeo, annually.
NSF	National Science Foundation, *Research and development in industry*. Washington, D.C.: GPO, annually.
Scherer	Scherer, F. M. 1981. The structure of industrial technology flows. Northwestern University and FTC. Mimeo.

[a]R & D expenditure data were deflated by a salary index for chemists and engineers constructed from data in U.S. Bureau of Labor Statistics, *National Survey of Professional, Administrative, Technical, and Clerical Pay*. Washington, D.C.: GPO, annually. Industry-specific employment weights for chemists and engineers were taken from BLS Bulletin no. 1609, *Scientific and Technical Personnel in Industry, 1961–66*. Washington, D.C.: GPO, 1968. Value of shipment data were deflated by use of sectoral output price deflators made available on computer tape by the Bureau of Labor Statistics.

Table 8.2 **Sample Industries, Selected 1972 Data, and Sample Statistics**

		1972 Values of Selected Variables				
SIC (1967)	Industry	C4	H	*R*	*S*	GOVRDS
20	Food and kindred products	36	.062	.0023	.0193	.0000+
22, 23	Textile products and apparel	28	.044	.0011	.0060	.0000
24, 25	Lumber, wood products, and furniture	20	.030	.0016	.0057	.0000
26	Paper and allied products	31	.050	.0067	.0080	.0000+
281, 282	Industrial chemicals	45	.102	.0298	.0105	.0060
283	Drugs	29	.043	.0680	.1015	.0002
284–289	Other chemicals	37	.063	.0146	.0877	.0006
29	Petroleum refining and related industries	31	.047	.0158	.0115	.0005
30	Rubber and miscellaneous plastics products	31	.060	.0111	.0155	.0015
32	Stone, clay, glass, and concrete products	36	.071	.0075	.0075	.0001
331–332, 3391, 3399	Ferrous metals and products	41	.068	.0038	.0029	.0001
333–336, 3392	Nonferrous metals and products	49	.086	.0048	.0043	.0004
34	Fabricated metal products	29	.055	.0049	.0057	.0002
35	Machinery, except electrical	38	.066	.0245	.0044	.0053
366, 367	Communication equipment and electronic components	45	.092	.0963	.0022	.1104
361–365, 369	Other electrical equipment	53	.110	.0294	.0179	.0249
371	Motor vehicles and motor vehicle equipment	81	.251	.0263	.0103	.0043
372	Aircraft and parts	62	.129	.0559	.0021	.2385
381–382	Scientific and mechanical measuring instruments	36	.059	.0282	.0094	.0068
383–387	Optical, surgical, photographic, and other instruments	60	.123	.0519	.0268	.0142
Sample statistics:						
	Mean over all industries and years	39.6	.078	.0247	.0172	.0259
	Standard deviation	14.1	.045	.0237	.0253	.0656
	Minimum value	15	.025	.0006	.0010	.0000
	Maximum value	81	.251	.0963	.1015	.3654

(1981). These were computed using time-series estimates of constant elasticity demand functions made by Almon and his colleagues (1974). These estimates are available for fifty-six input-output sectors in which the predominant fraction of output goes to personal consumption. On the rather strong pair of assumptions that all output in the fifty-six consumer goods sectors goes to personal consumption and that all output of the remaining maufacturing industries finds its way into consumer goods industries, derived elasticities of demand were calculated for each of the input-output sectors in manufacturing. To the extent that some output of the fifty-six consumer goods industries is used as intermediate input or as investment goods and to the extent that some output of the remaining industries is consumed directly, the calculated elasticities will be biased in uncertain direction and magnitude. Nevertheless, the procedure produces no serious anomalies; the relative magnitudes of the elasticities across industries accord reasonably well with intuition.

The most difficult data problem we confront is to develop an operational analog of n, the number of firms. Obviously, the rather special assumption of symmetric firm size is not consistent with the observed heterogeneity of firm sizes. Our approach here is to instead view n as a numbers equivalent (see, for example, Hart 1971) and to regard (22) as an approximation to a world with heterogeneous firm sizes. Our practical problem is how to summarize the empirical size distribution of firms by a numbers equivalent. For this purpose we choose to treat n as the Herfindahl numbers equivalent.

To obtain an operational measure, we must therefore construct a Herfindahl index for each sample industry. Since the empirical size distributions of firms are available in an incomplete form (e.g., C4, C8, C20, C50, etc.), we chose to fit two distributions (the Pareto and the exponential) to the available data for each four-digit industry. Of the two distributions the exponential provided the more satisfactory approximation. Using the estimated parameters of these size distributions, we simulated the Herfindahl index for each four-digit industry and then used a weighted average of four-digit Herfindahl indexes to represent concentration at the more aggregated level of our sample. The resulting index values, which appear in table 8.2, are quite plausible. At the four-digit level, the correlation between the four-firm concentration ratio and our estimated Herfindahl index is .91.

We now turn to estimation problems. While estimation of the advertising and concentration equations involves straightforward application of nonlinear two-stage least-squares procedures, estimation of the R & D equation is not straightforward. As noted above, the problem arises because of the error in observing γ, which leads to a random coefficient on the concentration term, unless γ or $\theta = 0$, $\theta = n$, or $\sigma_v^2 = 0$. That is, the system (22), (24), and (27) will not require attention to the random coefficient problem in three cases. (1) when γ or $\theta = 0$, firms behave as Dasgupta-Stiglitz firms, and appropriability does not affect R & D intensity; (2) when $\theta = n$, concentration drops out of the R & D equation; and (3) if γ_k is measured without error, no randomness is in the concentration coefficient.

The third of these special cases is the least probable. Thus, if we wish to estimate the model without prespecifying θ, we must deal with the problem of random coefficients in a nonlinear simultaneous equations context. To date, only Kelejian (1974) has suggested a procedure for the linear simultaneous equations model with random coefficients, and for our model his specialized results are inapplicable.

Although we have not been able to find a fully efficient random coefficient estimator for our model, we are able to show that consistent estimates of the parameters in (24) can be obtained by nonlinear instrumental variables techniques. Details concerning the assumptions employed and a rigorous statement of this result are available from the authors on request.

The more serious problem arising from the random coefficient version of (24) is the possible inconsistency of conventional approximations to the asymptotic standard errors of the coefficients. This inconsistency results from the heteroscedastic disturbance term. Our approach to this problem is to apply a generalized least-squares (GLS) correction to our instrumental variables estimator. To do this we must estimate σ_ϵ^2 and σ_ν^2. We do so by an auxiliary regression technique that uses the squared residuals from the initial instrumental variables estimates (see Hildreth and Houck 1968).

8.5 The Results

Table 8.3 summarizes the full specification of our four-equation model, along with the expected signs and parameter restrictions derived from the analysis of section 8.3. All equations satisfy the conditions for identification of models involving nonlinearities in the endogenous variables. We estimated each equation over our twenty industry sample for the years 1963, 1967, and 1972. For each specification reported in this section we could not reject the hypothesis of homogeneity across time periods. We therefore limit discussion to the results obtained using the pooled sample.

Each equation was estimated using single equation instrumental variables techniques involving linear approximations to the reduced forms. For the private R & D equation we attempted the Hildreth-Houck GLS correction to take account of possible heteroscedasticity in the disturbance term. A decomposition of the residuals, however, revealed no evidence of heteroscedasticity. Furthermore, the GLS estimates and their standard errors were not much different from those obtained by the

Table 8.3 **Expected Signs and Magnitudes of Structural Coefficients**

Variable	LOG(H)	RDINT	LOG(S)	GOVRDS
LOG(ϵ)	+1.0		−1.0	
LOG($R+S$)	+1.0			
LOG(H)			+1.0	
ELEC		+		+
CHEM		?		?
BIO		?		?
MECH		?		?
BASIC		+		+
AGE		+?		+?
AGESQ		−?		−?
GOVRDS		+		
H		?		−
H*PROD		+		
H*BORROW		+		
H*GOVRDS		+		
PCE			+	
DUR			−	
PCE*DUR			−	
DEFSHR				+
GOVSHR				+
PROD				+
BORROW				+
CONSTANT	0.0	?	?	?

uncorrected instrumental variables procedure. For these reasons, we proceed as if $\sigma_v^2 = 0$, and we report the uncorrected parameter estimates and standard errors in table 8.5 below.

Overall the results are quite encouraging given the small sample size, the degree of aggregation, and the potential measurement errors in our data. The signs of virtually all coefficients in the private R & D equation are in agreement with our predictions in table 8.3. Further, the point estimates are remarkably robust to minor modifications in the specification, and many coefficients are significant at a size of .01. The results for the concentration, advertising, and government R & D equations are less encouraging than those of the company R & D equation. Here the specifications are quite sensitive to our implied restrictions. We now proceed to a more detailed discussion of the results.

8.5.1 The Concentration Equation

Table 8.4 reports the results of estimating two variants of the concentration equation (21). Clearly, the estimated coefficients fail to conform to our precise predictions about their magnitudes. In specifications (4-1), we decisively reject the hypothesis that the constant is equal to zero, and the strict hypotheses that $a_1 = a_2 = 1$ are also clearly rejected, separately

Table 8.4 **Parameter Estimates: Concentration Equation (asymptotic standard errors in parentheses)**

Variable	(4-1)	(4-2)
LOG(ϵ)	−0.064	0.040
	(0.039)	(0.056)
LOG($R + S$)	0.164***	0.704***
	(0.068)	(0.028)
CONSTANT	−2.146†††	—
	(0.262)	
Mean of dep. variable	−2.666	−2.666
Std. error	0.434	0.660

***Asymptotic t-ratio indicates significance at .01 level (one-tailed test).

†††Asymptotic t-ratio indicates significance at .01 level (two-tailed test).

and jointly. On the other hand, the term representing cost-reducing and demand-shifting activities [LOG (R + S)] is significantly greater than zero at the .01 level.

Matters improve substantially when we impose the restriction that the constant term equal zero. The price elasticity coefficient remains insignificantly different from zero and significantly below one, but it has the correct sign in (4-2). The coefficient on LOG($R + S$) jumps dramatically to a value not far from our prediction. We must nevertheless reject the hypothesis that $a_2 = 1$.

We also explored variants of equation (22) in which advertising is excluded from the model. These results were similar to those reported in table 8.4. The price elasticity coefficient was much too small, and it had the wrong sign when the constant was included. The coefficient of LOG(R) was below 0.2 when the constant was included, and it jumped to 0.57 when the zero restriction was imposed. These specifications are not nested in (4-1) and (4-2), so we did not test the restriction implicit in the Dasgupta-Stiglitz model that advertising has no effect on concentration.

The failure of (4-1) and (4-2) to conform precisely to theoretical expectations is hardly surprising, given our highly aggregated data and the potential for measurement error in the price elasticities. Moreover, it is likely that the concentration equation is particularly sensitive to our neglect of dynamics. A less stylized theory of Schumpeterian competition would surely model concentration as the outcome of a sequence of past and current investments in R & D and advertising, rather than as a contemporaneously determined variable.

8.5.2 The Company R & D Equation

The results for several variants of the company R & D equation (24) are presented in table 8.5. Note at the outset that the γ function reflecting

Table 8.5 **Parameter Estimates: R & D Equation (asymptotic standard errors in parentheses)**

	θ, γ Unrestricted		γ = Cons.	γ, θ = 0	θ = *n*
Variable	(5-1)	(5-2)	(5-3)	(5-4)	(5-5)
ELEC	−0.038	0.017*	0.033***	0.036***	0.029***
	(0.027)	(0.012)	(0.011)	(0.011)	(0.012)
CHEM	−0.006	−0.005	0.000	−0.001	−0.004
	(0.010)	(0.007)	(0.007)	(0.007)	(0.008)
BIO	0.064††	0.060†††	0.053††	0.043†	0.038†
	(0.031)	(0.022)	(0.023)	(0.022)	(0.022)
MECH	0.004	0.009	0.017†	0.021††	0.017†
	(0.014)	(0.010)	(0.010)	(0.009)	(0.010)
BASIC	0.101	0.259***	0.299***	0.349***	0.358***
	(0.153)	(0.100)	(0.104)	(0.098)	(0.098)
AGE/100	0.152	−0.106†	−0.155††	−0.147††	−0.121†
	(0.135)	(0.064)	(0.064)	(0.066)	(0.069)
AGESQ/100	−0.0016	0.0012†	0.0018††	0.0017††	0.0015†
	(0.0015)	(0.0007)	(0.0007)	(0.0007)	(0.0008)
GOVRDS	2.694***	0.078**	0.120***	0.121***	0.115***
	(1.005)	(0.043)	(0.042)	(0.043)	(0.043)
H	−0.750††	−0.362†	0.080	—	—
	(0.326)	(0.205)	(0.066)		
H*PROD	1.715***	0.742**	—	—	—
	(0.595)	(0.328)			
H*GOVRDS	−24.082†††	—	—	—	—
	(9.239)				
PROD	—	—	—	—	0.034
					(0.031)
CONSTANT	−0.054	0.009	0.020	0.021	0.008
	(0.033)	(0.016)	(0.016)	(0.017)	(0.030)
Mean of dep. variable	0.027	0.027	0.027	0.027	0.027
Std. error	0.022	0.016	0.017	0.017	0.017

*Asymptotic *t*-ratio indicates significance at .10 level (one-tailed test).

**Asymptotic *t*-ratio indicates significance at .05 level (one-tailed test).

***Asymptotic *t*-ratio indicates significance at .01 level (one-tailed test).

†Asymptotic *t*-ratio indicates significance at .10 level (two-tailed test).

††Asymptotic *t*-ratio indicates significance at .05 level (two-tailed test).

†††Asymptotic *t*-ratio indicates significance at .01 level (two-tailed test).

the technological dimension of spillovers is modeled by including only a constant term, PROD and GOVRDS, as arguments. Inclusion of both PROD and BORROW in the regressions produced less satisfactory results, probably because of their near collinearity. Since PROD had the more robust parameter estimates over a range of specifications, we report results for variants of (24) omitting BORROW.

The most general form of (24) is where the value of θ is arbitrary but constant across industries, as in (5-1) and (5-2). If R & D spillovers are assumed to be greater for products than for processes (i.e., PROD has a positive coefficient in the γ function), then the estimated coefficients imply that θ is greater than zero. Thus, firms appear to maintain positive conjectural variations with respect to R & D, although the free-rider effect could still be present if $0 < \theta < 1$.

A somewhat surprising result of (5-1) is that the coefficient on H*GOVRDS is negative, suggesting that government funding diminishes spillovers. Although this contradicts our earlier expectation, the result is plausible for several reasons. Most prominently, much government funding supports R & D for large-scale, capital-intensive defense systems which are not cheaply replicable despite mandatory licensing and technology transfer provisions.

Specification (5-2) omits H*GOVRDS on the hypothesis that another reason for its unexpected sign may be its near collinearity with the opportunity vector. Once again, GOVRDS is significantly positive, although its effect on the cost elasticity is relatively small. The magnitude of the coefficient indicates that on average a one dollar increase in government R & D spending leads to a seven cent increase in company R & D spending. Estimates for specifications (5-3) through (5-5) are about eleven cents; however, at the means (5-1) yields a predicted effect of seventy-four cents. The other opportunity variables in (5-2) come in strongly with the correct signs.

Specifications (5-3) and (5-4) represent two restricted versions of (5-1) and (5-2). In (5-3) we test the hypothesis that γ is a constant across all industries. The positive coefficient on the Herfindahl index indicates that θ is greater than zero under the implicit assumption that γ is greater than zero. In any case, Wald tests indicate that either (5-1) or (5-2) is to be preferred to (5-3).

Specification (5-4) corresponds to a Dasgupta-Stiglitz world with no R & D spillovers. Interestingly enough, this equation does quite well in that all the opportunity variables are of the correct sign and highly significant. Furthermore, the point estimates of the opportunity coefficients differ only slightly from those in (5-2). However, Wald tests on the hypothesis that either γ or θ equals zero lead to rejection of the Dasgupta-Stiglitz model in favor of (5-1) or (5-2). The χ^2 statistics are respectively $\chi^2(3) = 10.2$ and $\chi^2(2) = 6.8$.

The final specification we report is the "constant shares" case where θ equals n and thus varies across industries. Once again the results accord reasonably well with the previous versions of the company R & D equation. Interestingly, we cannot reject the Dasgupta-Stiglitz model in favor of the constant shares case, given the insignificance of the coefficient of PROD. Unfortunately, we are unable to test (5-5) against the other versions, since (5-5) is not nested in the θ, γ unrestricted cases.

Since it is widespread practice to treat concentration and government

R & D as exogenous variables in empirical models of the determination of company R & D, it is interesting to ask whether anything is gained by treating them as endogenous. We checked for the possibility of simultaneity bias using the test proposed by Wu (1973). For each specification in table 8.5, we decisively rejected the hypothesis that the regressors we take to be stochastic were in fact uncorrelated with the disturbances.

As further checks on the models (5-1)–(5-5), we have tested the plausibility of our parameterization of α and the reasonableness of the opportunity measures. Operationally this was done by excluding the opportunity measures from all five equations. The resulting Wald statistics, which are asymptotically distributed as χ^2 random variables with eight degrees of freedom, all exceeded the critical value at the .001 level. Thus, we decisively reject the α constant version of the model.

We also computed the implied cost function parameters in those instances where it was feasible to do so. Table 8.6 reports the estimated values of $\hat{\alpha}$ for each industry in 1972, derived from equation (5-4), and the estimated values of $\hat{\alpha} + \hat{\gamma}$, derived from equation (5-5). The results accord well with expectations. The implied elasticity of unit cost with respect to company R & D ranges from near zero in textiles, paper, and fabricated metal products to the 0.05–0.07 range in aircraft, drugs, and

Table 8.6 **Estimated Cost Elasticities and Actual R & D Intensity for Sample Industries, 1972**

Industry	$\hat{\alpha}$ (from eq. [5-4])	$\hat{\alpha} + \hat{\gamma}$ (from eq. [5-5])	R
Food and kindred products	.041	.038	.0023
Textiles products and apparel	.001	.001	.0011
Lumber, wood products, and furniture	.012	.016	.0016
Paper and allied products	−.001	−.002	.0067
Industrial chemicals	.035	.036	.0298
Drugs	.059	.061	.0680
Other chemicals	.012	.014	.0146
Petroleum refining and related industries	.020	.019	.0158
Rubber and miscellaneous plastic products	.003	.003	.0111
Stone, clay, glass, and concrete products	.013	.014	.0075
Ferrous metals and products	.004	.007	.0038
Nonferrous metals and products	.002	−.003	.0048
Fabricated metal products	−.001	.001	.0049
Machinery, except electrical	.021	.022	.0245
Communication equipment and electronic components	.066	.066	.0963
Other electrical equipment	.037	.039	.0294
Motor vehicles and motor vehicle equipment	.014	.009	.0263
Aricraft and parts	.049	.051	.0559
Scientific and mechanical measuring instruments	.020	.021	.0282
Optical, surgical, photographic, and other instruments	.030	.032	.0519

electronics. Table 8.6 also includes the 1972 values of R & D intensity for convenient reference.

Finally, before turning to the advertising equation, we shall interpret the coefficients on the industry age variables. The signs on the age and age-squared coefficients suggest that once an industry is defined by the Census, it already faces declining opportunities for R & D. The magnitudes of these coefficients imply that opportunities decline for forty to forty-five years after definition, at which point they increase again. Depending on the specification, the standard error for the estimate of this turning point is between five and six years.

8.5.3 The Advertising Equation

Estimation of the advertising equation yields results that are not entirely satisfactory. As table 8.7 reveals, in the theoretically preferred specification (7-1), the coefficient on the concentration term has the wrong sign; a result which corresponds to that reported in Levin (1981). Moreover, the price elasticity of demand has a coefficient smaller in absolute value than its expected magnitude. Indeed, the hypothesis that $d_2 = -1$ is decisively rejected at better than a .001 level. The determinants of ϕ, the advertising elasticity of demand, fare somewhat better. Both PCE and DUR have the expected signs, although the interaction term does not.

We have no prior expectation about the constant term, since it repre-

Table 8.7 **Parameter Estimates: Advertising Equation**

Variable	(7-1)	(7-2)
LOG(ϵ)	−0.012	0.191
	(0.091)	(0.096)
LOG(H)	−0.465	1.656***
	(0.455)	(0.125)
PCE	2.284***	2.949***
	(0.841)	(0.987)
DUR	−0.539*	1.173***
	(0.358)	(0.396)
PCE*DUR	2.373	−1.258
	(1.619)	(1.702)
CONSTANT	−6.308†††	—
	(1.317)	
Mean of dep. variable	−4.743	−4.743
Std. error	0.859	1.022

*Asymptotic t-ratio indicates significance at .10 level (one-tailed test).

***Asymptotic t-ratio indicates significance at .01 level (one-tailed test).

†††Asymptotic t-ratio indicates significance at .01 level (two-tailed test).

sents the sum of d_0, which is expected to be zero, and d_1g_0, which involves the constant in the ϕ function. If we constrain both d_0 and g_0 to be zero, however, the results improve markedly. The price elasticity coefficient reverses sign, but the remaining coefficients in (7-2) have the correct signs. The concentration term is now significantly different from zero, although the hypothesis that $d_3 = 1$ must be rejected at the .001 level. Each of the arguments of the ϕ function now has the predicted sign, and the hypothesis that $\phi(\cdot)$ is simply a constant across all industries can be rejected for both specifications (7-1) and (7-2). In the former case, the hypothesis that ϕ is a constant yields a test statistic that is $\chi^2(3) = 37.1$. In the latter case, the test that $\phi = 0$ is $\chi^2(3) = 104.4$.

The poor performance of the price elasticity variable in both this and the concentration equation calls attention to the very strong assumptions under which the elasticities were computed. Some further work is needed here; in future work we intend to employ alternative elasticity estimates.

8.5.4 The Government R & D Equation

As expected, the results in table 8.8 indicate that the allocation of government R & D expenditures is influenced most strongly by government defense procurement; the government supports R & D in those industries in which it is a major customer. Technological opportunity appears to offer little incentive to the government; of our opportunity measures only AGE and AGESQ are statistically significant at conventional levels. Interestingly, the signs of these coefficients are the reverse of those in most specifications of the private R & D equation. Given our expectation that the age profile proxies opportunity by first rising and then falling, we might tentatively note that the pattern of signs in tables 8.5 and 8.8 is consistent with the view that the government reacts to technological opportunity with a substantial lag relative to private industry.

The technological dimension of spillovers, here proxied by BORROW, appears to have some effect on government R & D; as expected, a higher degree of spillover increases the likelihood of government support. Again collinearity among the appropriability measures leads to better results when either PROD or BORROW is excluded. In this case, BORROW has the more plausible parameter estimate and a lower relative standard error. The structural dimension of appropriability, here represented by concentration, has the expected sign but falls well short of statistical significance. The remaining coefficients in the equation are almost completely insensitive to the exclusion of this variable, as shown in (8-2). This suggests that GOVRDS is not strictly endogenous, although its dependence on opportunity and appropriability conditions indicates that it is correlated with the error term in the private

Table 8.8 **Parameter Estimates: Government R & D Equation**

Variable	(8-1)	(8-2)
ELEC	0.010	0.009
	(0.016)	(0.014)
CHEM	−0.003	−0.003
	(0.011)	(0.010)
BIO	0.028	0.033
	(0.034)	(0.031)
MECH	0.010	0.008
	(0.014)	(0.012)
BASIC	0.012	0.015
	(0.159)	(0.141)
AGE/100	0.224††	0.220††
	(0.099)	(0.097)
AGESQ/100	−0.003††	−0.003††
	(0.001)	(0.001)
H	−0.038	—
	(0.099)	
BORROW	0.056**	0.053*
	(0.034)	(0.032)
DEFSHR	0.066***	0.066***
	(0.006)	(0.006)
GOVSHR	0.001	0.002
	(0.048)	(0.047)
CONSTANT	−0.072††	−0.071††
	(0.030)	(0.030)
Mean of dep. variable	0.026	0.026
Std. error	0.024	0.024

*Asymptotic t-ratio indicates significance at .10 level (one-tailed test).

**Asymptotic t-ratio indicates significance at .05 level (one-tailed test).

***Asymptotic t-ratio indicates significance at .01 level (one-tailed test).

††Asymptotic t-ratio indicates significance at .05 level (two-tailed test).

R & D equation. Thus, the use of instrumental variables for GOVRDS seems appropriate.

8.6 Conclusions

Given the deficiencies of the variables used to measure technological opportunity and appropriability conditions, as well as the highly aggregated nature of the data, the results reported in section 8.5 are quite encouraging. Although the statistical tests are not entirely consistent with our theoretical model, on the whole the findings support the Schumpeterian view that R & D investment and market structure are appropriately regarded as jointly determined outcomes of the competitive process. The private R & D equation performs especially well, yielding results that are quite robust and yet sufficiently precise to reject decisively the hypotheses that opportunity and appropriability conditions do not matter. Indeed, the private R & D results are substantially better than those obtained in the looser, more inclusive, specification in the earlier work of Levin (1981). The parameters of the concentration equation fail to conform to the precise predictions of our model, but the results nevertheless suggest a strong and significant connection between cost-reducing and demand-shifting activities and market concentration.

We do not wish to make exaggerated claims for our highly stylized theoretical model, which abstracts from obviously important features of Schumpeterian competition, such as dynamics and the heterogeneity of firms. But we believe that the model does place proper emphasis on demand, technological opportunity, and appropriability as the central forces determining the allocation of R & D and the evolution of market structure. In particular, we believe our treatment of R & D spillovers, which distinguishes clearly the technological, structural, and behavioral dimensions of appropriability, exemplifies how useful insights may be gained from relatively stark and stylized models. Moreover, our model brings to the foreground a thread linking much of the theoretical literature of the "new industrial organization": the endogeneity of market structure. Indeed, the recognition that market structure is endogenous is an element common to the literatures on Schumpeterian competition, monopolistic competition, strategic entry deterrence, and contestability. As these theoretical literatures continue to revise our understanding of structure-conduct-performance relationships, we will undoubtedly see more empirical work of the type represented here.

It is well to keep in mind, however, both the strengths and weaknesses of empirical work based on highly stylized analytic models. On the one hand, such models have the virtue of simplicity, of clear and precise hypotheses. On the other hand, important features of reality are brushed aside. To this extent our insights are only partial truths.

The present paper exemplifies this dilemma. We have tested a simple model which captures much that is important. But a model of Schumpeterian competition without dynamics, without transient monopoly, without innovators and imitators, is, at best, only part of the story. Much remains to be done.

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Comment Pankaj Tandon

This is an interesting paper, since it seeks to initiate the difficult task of building bridges between recent theoretical work on R & D and the empirical work on this subject, of which we have seen many fine examples at this conference. I welcome this bridge-building activity, but believe, as the authors do, that much remains to be done. I will therefore concentrate my remarks on the general modeling approach and on some of the problems that need special attention.

The authors are obviously aware of many of the modeling problems involved here, and they have commented on several. I will reemphasize only one—the question of timing. When one considers timing, it is probable—as the authors point out—that the effect of technological change on market structure is a long-term effect, one that cannot be easily captured in tests that span only ten years. Seen in this light, it is not surprising that the concentration equation fails to be convincing. On the other hand, the influence of market structure on R & D investment decisions is more likely to be captured in a short panel. As a short-run approximation, it is probably reasonable to assume a fixed market structure. Thus, the relative success of the R & D intensity equation was also to be expected.

Let me comment on what the authors mention as the two major contributions of their approach. The first relates to the inclusion of advertising as another variable influencing and being influenced by market structure. Though the authors comment on the similarity between advertising and R & D as instruments of competition, they treat them in quite an asymmetric manner in their model. Specifically, the way advertising is included is to model the aggregate industry demand curve as depending on the aggregate level of advertising in the industry. Thus, if there are n firms in the industry, any firm doing advertising gets in effect only $1/n$th of the increase in demand. Clearly this does not really capture the *competitive* characteristics of advertising; rather, advertising acquires the characteristics of a public good—with a serious attendant free-rider problem. The corresponding treatment for R & D would be to say that a firm's unit cost is a function only of Z (aggregate industry R & D). This doesn't seem reasonable. Likewise, I don't find the treatment of advertising convincing. The results from the advertising equation are not satisfactory in any case and might be better explained by a story that concentrated on the role of advertising in product differentiation. I don't know if I'm just revealing my bias as someone primarily interested in R & D, but I think I'd be happier with advertising left out of the model. Another

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reason for this is that it is far from clear to me that R & D and advertising are jointly determined. In a model with uncertain R & D outcomes, advertising may be *sequentially* determined, conditioned on the results of R & D.

Since the primary interest of this group is R & D, let me move on to the second, more interesting point, namely, the model of R & D spillovers. This is surely welcome. The public goods aspect of R & D has received insufficient attention in the theoretical and empirical literature, yet it is one of the things that makes R & D particularly interesting and distinct from traditional investment. I am, however, a little uncomfortable with the way spillovers have been modeled here. The authors have taken the unit cost of production to be a function of the firm's own R & D and of aggregate industry R & D. I have two problems with this. First, as is clearly evidenced by Professor Scherer's work on interindustry technology flows, spillovers are also important *across* industries. This will be of special importance when, as the authors promise us, more disaggregated data at the four-digit level are used. Further, such cross-industry externalities may be quite important in determining market structure in user industries. Two obvious cxamples spring to mind. The development of small, powerful computers will surely be important, although it is not clear whether the major influence will be to increase or decrease concentration. It seems that minimum efficient scale may be significantly reduced in many industries. On the other hand, small computers may combine with the second example, improved telecommunications capabilities, to considerably ease the control problem in large corporations. This would clearly tend to increase concentration. Some attention must be paid to these interindustry externalities.

The second problem with the spillover analysis concerns the logical consistency of the model. All firms in an industry are assumed to face the same technological opportunities. We then concentrate on symmetric equilibria. In the absence of uncertainty, the only logical interpretation of such an equilibrium is that every firm has discovered the same things. But then, why should the R & D of other firms be of any value to me, since I already know what they know? (In fact, this logic would say that the only permissible spillovers would be interindustry!) I grant that a model with asymmetric information and uncertainty—even with symmetry—is going to be analytically much less tractable, and it is not obvious that the estimable equations would be structurally different, but I do worry about the logical anomaly.

The spillovers were nevertheless an interesting addition to the model, particularly because of a side product that was generated. Including Z in the cost function enabled the authors to begin to model different behavioral hypotheses about firms, specifically: What are firms' conjectures about the response of their rivals to their own R & D? Unfortunately, the authors are not able to get clear answers on this, mainly because the conjectural parameter θ appears multiplicatively with the appropriability parameter γ. I have two suggestions. First, Z could be measured excluding the firm's own R & D. This seems conceptually preferable anyway, although I grant that at this level of aggregation it may not appear important. However, the interpretation of θ will be quite different and, in particular, its sign will matter. Now $\theta = 0$ will correspond to the Cournot conjecture, θ will be negative for free-rider situations, and θ will be positive for what might be called Schumpeterian conjectures. Under the assumption that γ is positive, it will be possible to run tests on the sign of θ. In the present version, θ is always positive, and it is not possible to find its magnitude distinctly from γ. Of course, equation (13) would have to be modified—the n in the denominator would have to be replaced by $(n - 1)$—and perhaps other things would change in the model. The second suggestion is that perhaps a model that pays more explicit attention to product differentiation may be more successful and desirable. In other words, we might get more directly at the conjectural hypotheses by thinking about the firm's demand or price being influenced by other firms' costs.

A specific comment here: In regression (5-4), the R & D equation for the Dasgupta-Stiglitz case, the authors do not tell us if the left-hand side was modified to be $R/(1 - R)$. Advertising surely ought to be excluded if the equation is to represent the Dasgupta-Stiglitz model.

I have a couple of other brief comments. We have not seen the conditions that ensure the existence of symmetric equilibria, but we can easily guess the parameters that must appear there. Since it is well known that R & D causes nonconvexities, it is of some interest to make sure that the existence conditions are being satisfied. It would be useful if the authors provided that information. Further, since α, the elasticity of unit cost with respect to R & D, is estimable in their model, it would be useful to report it and to compare it with the many other estimates of this parameter or its variants that exist in the literature.

One noticeable feature of this paper is how distinct it is methodologically from other papers presented at this conference. I think it may be useful for the authors in their bridge-building activity to look again at the work of Pakes and Schankerman (this volume) on the determinants of research intensity. This is perhaps the clearest exposition of the traditional approach, and it might be productive to attempt to modify this approach with an endogenous market structure.

Finally, let me say what I think is most attractive about this line of work. The significant way in which the endogenous market structure approach differs from the traditional approach is that the new approach introduces a zero-profit condition. This corresponds to what Scherer, in the context of the optimal patent literature, has called the Lebensraum effect. I think that it is entirely possible that this Lebensraum effect actually is the dominant consideration in R & D allocations, especially because of the serious possibility of nonconvexities. Consideration of the Lebensraum effect might also have implications for patent policy or antitrust. For example, some very crude Harberger-type calculations that I have done indicate that in industries where technological opportunity is high, the optimal market structure may be quite concentrated, precisely because of the Lebensraum effect. The trade-off between static and dynamic efficiency is very explicit in Schumpeter's work, and the approach of Levin and Reiss is a first step toward the integration of this trade-off into empirical work on R & D.