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TECHNOLOGICAL OPPORTUNITY AND SPILLOVERS OF R&D: EVIDENCE FROM FIRM'S PATENTS, PROFITS AND MARKET VALUE

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ABSTRACT

This paper presents evidence that firms' patents, profits and market value are systematically related to the "technological position" of firms' research programs. Further, firms are seen to "move" in technology space in response to the pattern of contemporaneous profits at different positions. These movements tend to erode excess returns.

"Spillovers" of R&D are modelled by examining whether the R&D of neighboring firms in technology space has an observable impact on the firm's R&D success. Firms whose neighbors do much R&D produce more patents per dollar of their own R&D, with a positive interaction that gives high R&D firms the largest benefit from spillovers. In terms of profit and market value, however, their are both positive and negative effects of nearby firms' R&D. The net effect is positive for high R&D firms, but firms with R&D about one standard deviation below the mean are made worse off overall by the R&D of others.

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I. INTRODUCTION[1]

This paper presents quantitative estimates of the importance of two supply-side factors in determining the productivity of manufacturing R&D. These are "technological opportunity" and "spillovers" of R&D. The empirical approach is to develop variables relating to technological opportunity and spillovers based on the technological nature of firms' past research. The existence of technological opportunity and spillover effects is then inferred from the estimated effects of these constructed variables on the firm's patent applications, its accounting rate of return, and its market value. This estimation is carried out on a cross-section of 432 firms, using data for two time periods, one 1972-74 and the other 1978-80. All of the firms' decision variables are treated as endogenous, using as instruments the spillover and technological opportunity variables, as well as variables describing the industries that the firms are in.

By technological opportunity, I mean exogenous variations in the cost and difficulty of innovating in different technological areas. These variations may be due to intrinsic characteristics of the technology, or they may be due to the state of exogenous scientific knowledge at a point in time. Therefore, the pattern of technological opportunity may change over time, though I assume that it generally changes fairly slowly, requiring a number of years for significant changes to manifest themselves.

The other influence on the firms' R&D program that I examine is spillovers of R&D from other firms (Griliches (1979)). Since knowledge is inherently a public good, the existence of technologically related research efforts of other firms may allow a given firm to achieve results with less research effort than otherwise. If we could observe the pure technological output of the firm's research, this would be an unambiguously positive externality. Unfortunately, we can only observe various economic manifestations of the firm's R&D success. In this case, the positive technological externality is potentially confounded with a negative effect of others' research due to competition. It is not possible, with available data, to distinguish these two effects; I do, however, find evidence that both are present.

It should be emphasized that I do not model the strategic interaction of the firms doing R&D in similar areas, with or without spillovers. I assume throughout that firms hold Cournot conjectures about the effects of their actions on the other firms, and I do not in any way impose equilibrium on the actions of the different firms.

The spillover and technological opportunity phenomena have in common that their effect on a particular firm will depend on the technological nature of the firm's research. Jaffe (1985) develops a methodology for characterizing the "technological position" of the firm's research program and constructing variables related to spillovers and technological opportunity. This methodology is summarized in the next section of this paper. Section III develops the estimating equations. Section IV presents the main empirical results. Section V presents additional results examining the changes in the apparent pattern of technological opportunity between the two periods. Section VI contains concluding comments.

II. CHARACTERIZING THE TECHNOLOGICAL POSITION OF FIRMS

In order to look for the effects of technological opportunity and spillovers, we would like to identify the technological areas in which the firms are engaged in research. We could imagine, if there are K such areas that relate to manufacturing products or processes, that the "technological position" of a firm's research program could be characterized by a vector $F = (F_1 \ldots F_K)$ where F_k is the fraction of the firm's research budget devoted to area k.[2] This, unfortunately, is not observable, but data do exist that are closely related. The patents received by the firm are classified by the patent office into technology-based patent classes.

This classification system provides the basis for the search of "prior art" necessary before a new patent can issue. It is important to note that this system is <u>not</u> an alternative product or industry classification. It is technology based. There is surely some relationship between industries and patent classes, in the sense that firms in a given industry will, on average, patent more in some classes than in others. But the mapping from classes to industries is not unique in either direction. This is illustrated by an example given by Jacob Schmookler, who used these data extensively. He notes that in a patent subclass relating to "dispensing of solids" he found a patent for a toothpaste tube and one for a manure spreader (Schmookler (1966)).

The fact that the patent classification system is technology-based rather than product-based is often viewed as a limitation on the economic usefulness of these data. It probably is so if one is seeking a measure of innovation by industry, for use in, for example, a structure/performance study. For our purposes, however, it is a decided virtue.

Throughout this paper, I utilize the distribution of the firms' patents over patent classes to characterize the technological position of the firm. In the basic data, there are 328 patent classes (though the classification system actually contains thousands of subclasses). This information is available for the patents granted between 1969 and 1979 to about 1700 manufacturing firms in the R&D panel that has been assembled recently at the National Bureau of Economic Research. This dataset is a marriage of Compustat and Patent Office data that is documented in Cummins, et al (1984) and Bound, et al (1984). The companies in the dataset were granted about 260,000 patents over the period. The average firm has one or more patents in about 20 of the 328 classes. The classes themselves vary greatly in importance, from "Chemistry, carbon compounds" with 20,000 patents taken by 340 different firms to "Bee culture" which has one patent.[3] To make the distribution vectors empirically usable, the 328 classes were grouped into 49 categories. This grouping was essentially ad hoc, based on the names, with more aggregation of classes with few patents, and less aggregation of those that had many.

Firms' technological positions are, in the long run, a matter of choice for the firms. If technological opportunity affects profitability, then we would expect firms to move to the more profitable positions. I expect, however, that changes in the technological position of firms can be brought about only slowly. Expertise in various areas is not easily acquired, and good will and reputation in product markets represent sunk costs that make jumping from one place to another costly. In this study, reflecting the view that technological position is endogenous, but only over relatively long time periods, I construct two technological position vectors for the firm: one is based on all patents applied for up to 1972, and one is based on all patents applied for after 1972.[4] In the estimation, I treat each of these distributions as exogenous for the purpose of regressions involving cross-sections of firms at the end of each period. I then examine the changes in position between the two periods, and see if they can be explained as responses to the pattern of technological opportunity.

Thus the basic data characterizing the firm's technological position are two 49-element distribution vectors, one for the earlier period and one for the later. These vectors are used in two ways. First, they are utilized to construct a variable which will be used to infer the existence of spillovers. I assume that the existence of technological spillovers implies that a firm's R&D success is affected by the research activity of its neighbors in technology space. To make this notion operational requires significant additional structure. I assume that the total relevant activity of other firms can be summarized by a "potential spillover pool" that is simply a weighted sum of other firms' R&D, with weights proportional to the proximity of the firms in technology space.[5] To measure the proximity of firms i and j, I use the angular separation or uncentered correlation of the vectors F_i and F_j:

$$P_{ij} = \frac{F_i F_j'}{[(F_i F_i')(F_j F_j')]^{\frac{1}{2}}} \tag{1}$$

This proximity measure has the properties that it is unity for firms whose position vectors are identical, it is zero for firms whose vectors are orthogonal, and it is bounded between 0 and 1 for all other pairs. It is closer to unity the greater the degree of overlap of the two firms' research interests.[6]

The potential spillover pool S_i is constructed using the proximities defined in Eq. (1) as weights in a summation of all other firms' R&D:[7]

$$S_i = \sum_{j \neq i} P_{ij} R_j \tag{2}$$

This approach assumes that the conditions of appropriability are the same across all technological areas. Suppose, as in the formulation of Spence (1984), that imperfect appropriability means that a fraction θ of each firm's research "leaks out." If $\theta = 0$, then appropriability is perfect; if $\theta = 1$, R&D is a pure public good. For my formulation, it doesn't matter what θ is,[8] but I have assumed that it is the same for all firms. To the extent that this is untrue, S_i is poorly measured.

The 49-element technological position vectors were also utilized to assign the firms to "technological groups." A clustering algorithm was utilized to group the firms based on their technological position.[9] The idea is to identify those firms whose technological focus is sufficiently similar that they face the same state of technological opportunity. This clustering was carried out twice, yielding for each firm a technological cluster assignment for 1972 and one for 1978. These assignments can be used to construct dummy variables for the technological groups. These dummy variables will be used in the estimation below to allow for variations in technological opportunity.

Tables One and Two summarize these technological clusters. For later reference, the important thing to note is that almost a third of the firms changed clusters between the two periods. Despite this, the clusters themselves were fairly stable, as indicated by the high proximity between the center of each cluster in the early period, and its center in the later period. In Section V I will show that the moves that did occur can be related to the pattern of profitability across the groups.

III. MODELLING THE PRODUCTIVITY OF R&D

A. Overview

The general approach taken here is to assume that there exists a stable relationship between the investment by the firm in R&D and the production of new economically useful knowledge. This relationship is conditioned by the spillovers that the firm receives and the state of technological opportunity. We do not observe new knowledge, but we do

TABLE ONE: COMPARISON OF CLUSTERING RESULTS FOR FIRST AND SECOND PERIODS

	FIRST PERIOD		SECOND PERIOD		BETWEEN THE TWO PERIODS		
	NUMBER OF MEMBERS	AVERAGE PROXIMITY TO CLUSTER CENTER	NUMBER OF MEMBERS	AVERAGE PROXIMITY TO CLUSTER CENTER	FIRMS LEAVING CLUSTER	FIRMS JOINING CLUSTER	PROXIMITY BETWEEN FIRST AND SECOND CENTERS
ADHESIVES & COATINGS	30	.65	24	.68	13	7	.93
CHEMISTRY,CARBON	45	.81	39	.81	12	6	.99
CHEMISTRY,ELECTROCHEMISTRY	16	.78	13	.77	6	3	.97
CHEMISTRY,ORGANIC	21	.85	22	.90	3	4	.96
CLEANING AND ABRADING	16	.70	14	.68	9	7	.94
COMPOSITIONS	20	.81	20	.79	3	3	.99
CUTTING	24	.65	15	.67	14	5	.92
ELEC COMPUTERS & DATA PROC	21	.74	20	.72	5	4	.99
ELEC TRANSMISSION & SYSTEMS	34	.79	26	.79	15	7	.99
ELECTRONIC COMMUNICATION	28	.79	32	.73	8	12	.99
FLUID HANDLING	27	.74	24	.70	15	12	.99
FOOD	34	.85	29	.89	9	4	.99
MEASURING, TESTING & SIGNALING	31	.66	20	.65	18	7	.90
MEDICAL	13	.72	25	.65	3	15	.90
METALS AND METAL WORKING	33	.75	29	.75	15	11	.99
MISC CONSUMER GOODS	24	.72	29	.64	9	14	.95
POWER PLANTS (NON-ELECTRIC)	51	.70	29	.77	25	3	.96
RECEPTACLES & PACKAGES	24	.76	36	.66	6	18	.99
REFRIDGERATION & HEAT EXCHANGE	29	.71	37	.64	11	19	.97
STATIC STRUCTURES	27	.65	38	.62	11	22	.94
VEHICLES	25	.71	36	.66	5	16	.96
OVERALL	573	.75	557	.72	215	199	.96

Note: 16 firms included in the first period clustering had no patents in the second period, and hence were excluded. These firms are among the "leavers."

First period is 1965-72 and second period is 1973-78.

TABLE TWO: VARIABLE MEANS FOR TECHNOLOGICAL CLUSTERS

CLUSTER	FIRST PERIOD MEMBERS (1972 DATA)				SECOND PERIOD MEMBERS (1978 DATA)			
	NUMBER OF FIRMS	SALES	R&D	PATENTS	NUMBER OF FIRMS	SALES	R&D	PATENTS
ADHESIVES & COATINGS	30	369	3.2	6.7	24	384	3.0	4.7
CHEMISTRY,CARBON	45	1064	28.2	66.8	39	1257	33.2	62.1
CHEMISTRY,ELECTROCHEMISTRY	16	708	44.8	89.3	13	1389	60.7	60.4
CHEMISTRY,ORGANIC	21	565	26.3	45.7	22	807	39.7	61.0
CLEANING AND ABRADING	16	506	7.9	19.2	14	423	7.7	11.7
COMPOSITIONS	20	3326	25.6	86.6	20	3960	32.2	81.1
CUTTING	24	131	2.2	6.2	15	183	2.7	6.9
ELEC COMPUTERS & DATA PROC	21	997	61.5	63.7	20	2122	87.1	63.9
ELEC TRANSMISSION & SYSTEMS	34	640	18.9	57.2	26	1039	30.5	72.0
ELECTRONIC COMMUNICATION	28	923	24.1	53.9	32	1077	27.7	43.7
FLUID HANDLING	27	613	12.2	40.0	24	925	19.3	36.8
FOOD	34	883	5.4	7.6	29	1070	7.2	4.5
MEASURING, TESTING & SIGNALING	31	380	7.3	14.2	20	721	23.5	19.4
MEDICAL	13	323	8.9	17.1	25	770	17.2	21.0
METALS AND METAL WORKING	33	964	12.4	21.5	29	1004	10.6	11.3
MISC CONSUMER GOODS	24	335	4.6	11.9	29	340	5.8	9.6
POWER PLANTS (NON-ELECTRIC)	51	1758	56.7	48.5	29	3895	106.0	49.2
RECEPTACLES & PACKAGES	24	352	3.6	11.8	36	444	3.0	7.0
REFRIDGERATION & HEAT EXCHANGE	29	367	5.2	13.3	37	420	4.8	11.7
STATIC STRUCTURES	27	199	1.1	2.7	38	183	1.8	4.7
VEHICLES	25	440	10.3	15.8	36	647	13.6	19.1
ALL FIRMS	573	801	19.0	34.0	557	1035	24.2	30.1

Note: Sales is in billions of 1972 dollars
R&D is in millions of 1972 dollars

observe several of its consequences. On average, if R&D is a sensible activity for the firm, the new knowledge should lead eventually to the generation of profits. This profit stream should be reflected in the firm's market value. Along the way, the new knowledge may also generate patent applications. In this section I develop estimating equations that relate the firm's patent applications, its profits and its market value to its R&D, its other attributes, the spillover and technological opportunity variables, and industry variables.

A long-recognized problem in this sort of estimation is the likelihood that firms differ in ways that we do not observe, such as their management skill. These unobservables are likely to enter positively in the error terms of equations that measure, in any sense, the firm's productivity. They will also influence the investment decisions of optimizing firms, introducing correlation between the error terms and some of the right-hand side variables in the productivity equations. The classic solution to this problem if a panel of firms is observed over time is to assume that the unobservables are unchanging over time for a given firm. This limits their contamination to the cross-sectional dimension of the data, implying that consistent estimates of structural parameters can be derived from the variance "within" firms over time. This leads to the so-called "fixed effects" estimator.

This approach has a serious drawback, which is that the bulk of the variance in firm data is usually in the cross-sectional dimension. Thus, the fixed-effects approach discards most of the information in the data. An alternative is to view the problem as a standard one of endogenous right-hand side variables, and to develop equations for the endogenous variables as a function of other variables that can be assumed to be exogenous. In this paper, the firm's R&D, its capital stock and its market share are treated as endogenous; it is assumed that in the reduced form of the system they depend on industry variables such as the industry's size, growth rate and R&D intensity.[10] The key assumption implicit in this approach is that the unobserved firm characteristics do not significantly affect these industry variables.

In order to emphasize the exploitation of the cross-sectional information in the data, I will focus on steady-state relationships. This is not because dynamics are uninteresting. They have been the focus of much previous work.[11]

B. The Patent Equation

I begin by assuming that the new knowledge produced by the firm in any period is related to its R&D in that period according to a modified Cobb-Douglas technology of the form:[12]

$$k_i = \beta_1 r_i + \beta_2 r_i s_i + \gamma_1 s_i + \sum_{c=1}^{21} \delta_{1c} D_{ic} + \epsilon_{1i} \qquad (3)$$

where k_i is the new knowledge generated by firm i, r_i is its R&D spending, and s_i is the potential "spillover pool" whose construction is described above. All variables are expressed in logs.[13] The D_{ic}'s are a set of dummy variables for the technological clusters discussed in the previous section; if technological opportunity is important, the δ_{1c}'s will differ across c. ϵ_{1i} is a random disturbance, assumed to be distributed independently but not necessarily identically across i.[14] It includes unobserved firm-specific attributes that may be correlated with r_i. Eq. (3) implies that the R&D of other firms may increase the knowledge output of the firm directly, and also may increase the elasticity with respect to own R&D. If β_2 and γ_1 are both zero, then Eq. (3) is a standard "knowledge production function" (Griliches (1979)).

Knowledge is not observed, but I assume that a fraction of it is patented according to:

$$P_i = \exp[\sum_{c=1}^{21} \alpha_c D_{ic}][\exp(\nu_i)]K_i \tag{4}$$

Thus, the ratio P_i/K_i (the "propensity to patent") for any firm i depends on its technological position, but also contains a firm-specific component. I will again assume ν_i is independent across firms. Note that I rule out by assumption a dependence of the propensity to patent on the potential spillover pool; allowing such a dependence would effectively preclude identification of the spillover effect.

Taking logs in Eq. (4) and substituting into Eq. (3) yields an equation relating patents to R&D and the pool:[15]

$$p_i = \beta_1 r_i + \beta_2 r_i s_i + \gamma_1 s_i + \sum_{c=1}^{21} (\delta_{1c} - \alpha_c) D_{ic} + \epsilon_{1'i} \tag{5}$$

Because we have to allow for the dependence of the propensity to patent on technological position, the technological cluster dummies in the patent equation cannot be related solely to technological opportunity. As will be discussed below, this hinders somewhat our ability to draw conclusions about technological opportunity.

C. The Profit or Rate of Return Equation

In modelling the profits of the firm, I want to allow for the existence of unobserved firm-specific entreprenuerial skill, as well as possible effects of market power. The modelling approach is simply to treat market power and the unobserved firm attributes (as well as the R&D of other firms) as intangible assets that augment the productivity of the firm's R&D and capital stocks. One way to do this is to postulate a modified restricted profit function in log-log form:[16]

$$\pi_i = \beta_3 m_i + \beta_4 \underline{r}_i + \beta_5 s_i \underline{r}_i + \beta_6 c_i + \gamma_5 s_i + \gamma_6 c4_i^I + \sum_{c=1}^{21} \delta_{2c} D_{ic} + \epsilon_{2i} \tag{6}$$

where π_i is the gross operating income of firm i, m_i is its market share, and $\underline{r}_i$ is the stock of accumulated R&D investments, distinct from the annual flow used in the patent equation. c_i is the capital stock, $c4^I$ is the four-firm concentration ratio in the firm's industry, and the other variables are as before. Note that I could have started by writing Eq. (6) in terms of the unobserved knowledge stock, and then substituted from the knowledge production function as above. In this case, however, no insight is gained by doing so.

If $\beta_3=\gamma_6=0$, then Eq. (6) would be the restricted profit function derived from the production function:

$$Q_i = L_i^{b_0} C_i^{b_1} \underline{R}_i^{(b_2 + b_3 s_i)} S_i^{b_4} \exp\left(\sum_{c=1}^{21} \delta_{2c} D_{ic}\right) \exp(\epsilon_{2i}) \tag{7}$$

by solving out labor through its optimal choice. This would be valid under the assumption that input and output markets are competitive, and that all firms face the same prices or else prices are independent of the exogenous variables and can be absorbed in ϵ_2. Adding market share and concentration as in (6) has the following interpretation. If output markets are not competitive, then the effect on the firm's revenues can be seperated into a component that depends on the firm's own market share, and a component that depends on the overall structure of competition in the industry. Further, these effects enter in a simple multiplicative way.[17]

As written, Eq. (6) is meaningful only for single product firms, for which the market share and concentration ratio variables are well-defined. In practice, most firms are in many industries. Data are typically unavailable, however, on the breakdown by line-of-business of the firms' capital and R&D. This precludes any attempt at finding the "correct" aggregation scheme within the firm. I simply specify relationships among the firm-level variables. For market share, concentration and other industry variables, I utilize the sales-weighted average across 4-digit SIC's within the firm.

Eq. (6) can be converted into an expression for the (log of the) rate of return on the firm's capital stock by subtracting c_i from both sides. This yields:

$$\pi_i - c_i = \beta_3 m_i + \beta_4 \underline{r}_i + \beta_5 s_i \underline{r}_i + (\beta_6 - 1)c_i + \gamma_5 s_i + \gamma_6 c4_i + \sum_{c=1}^{21} \delta_{2c} D_{ic} + \epsilon_{2i} \qquad (8)$$

D. Development of the Market Value Equation

Much attention has been focused in recent years on the conceptual problems with using accounting rates of return to measure economic profits (Fisher and McGowan(1983)). Salinger (1984) argues that the stock market provides a better indicator, because it is free of accounting biases and it captures long-run effects. There are, however, also conceptual difficulties with the use of market values. I view accounting profits and market value as multiple noisy indicators of the phenomena of interest.[18]

There are two approaches that one can take to the firm's value. If constant returns to scale prevails in the long run and if all the firm's assets, including market power, spillovers and unobserved firm skills, are traded on competitive markets, then the value of the firm has to be equal to the sum of the replacement costs of each of these assets. Thus one approach is simply to value the firm as a linear function of the various assets (Griliches(1981), Salinger (1984)). The alternative is to evaluate explicitly the present value of the flow of expected net revenues. In practice, each of these approaches has problems.

If some of the firm's assets are not traded in competitive markets, or if there are long-run increasing returns, then the linear relationship breaks down. I believe that the phenomema of interest here suggest both of these complications are likely to be present. Though it could be argued that market power is essentially tradeable,[19] and top executives can be bought and sold, the firm's unobserved assets include the organizational capital of the firm and its brand-name loyalty, which probably cannot be,[20] and spillovers of R&D are non-tradeable by definition. Further, spillovers of R&D, market power and the unobserved firm skills all may have attributes of public goods within the firm, creating increasing returns.

On the other hand, to correctly evaluate the expected flow of net revenues, we should solve for the optimal investment stream. To do this with the number of assets involved here requires heroic simplification. Given these difficulties, Jaffe (1985) contains estimates of two forms of a market value equation, each of which is an approximation to one of the two approaches. They yield similar results, so I report only one set here.

The approach is related to that of Griliches (1981) and Salinger (1984). The firm's market value is assumed to be a linear function of a weighted sum of the firm's conventional and R&D capital stocks:

$$V_i = \hat{q}[C_i + (\beta_7 + \beta_8 s_i)\underline{R}_i] \qquad (9)$$

That is, the relative value of a dollar of R&D and a dollar of capital depends on the spillover pool; for the firm with the mean pool, the relative value is β_7, which may or may not be unity. The package of capital and R&D is valued at a price $\hat{q}$. This price is itself assumed to depend on the firm's market power, its unobserved attributes, and its technological cluster:

$$\hat{q}_i = \bar{q}\, M_i^{\beta_9} S_i^{\gamma_7} (C4_i^I)^{\gamma_8} \exp\left(\sum_{c=1}^{21} \delta_{3c} D_{ic}\right) \exp(\epsilon_{3i}) \qquad (10)$$

Thus market power, spillovers and technological opportunity are assumed to augment value multiplicatively rather than additively.[21] This implies that a given degree of market power can be spread over any amount of capital. Compare two firms who have identical shares of identically concentrated industries, but one is twice as big as the other, because its industry is twice as big. It seems plausible that the market value of the larger firm should be twice that of the smaller, as implied by (9) and (10). On the alternative that the value is the sum of the value of the capital and the value of the market power, the larger firm's value would be less than twice that of the smaller.

If we now substitute (10) into (9), divide through by C_i, take logs, and use the approximation $\log(1 + x) \approx x$, we get:

$$v_i - c_i = \log\bar{q} + \beta_7 (R/C)_i + \beta_8 s_i (R/C)_i + \beta_9 m_i + \gamma_7 s_i + \gamma_8 c4_I + \sum_{c=1}^{21} \delta_{3c} D_{ic} + \epsilon_{3i} \qquad (11)$$

The dependent variable in Eq. (11) is just the log of Tobin's q, which can be thought of as the long-run analogue of the log of the rate of return in the profit equation.

IV. EMPIRICAL RESULTS

A. Data and Estimation Issues

The model is estimated on two cross-sections of 432 firms from the NBER R&D panel, one centered on 1973 and one centered on 1979. Each cross-section is an average of three years in order to smooth out transient effects and approximate long-run values. Instead of simply estimating the 3 equations on the pooled cross sections, I estimate a 6-equation system consisting of each equation for each year on the 432 firm cross-section. This allows for an arbitrary pattern of serial correlation and heteroskedasticity across time.

The market share variable is taken from the PICA database at the Harvard Business School (Shesko (1981)) and is available only for 1972. I use the 1972 share in the 1978 equation as a proxy. All other firm variables are evaluated as averages for the years 1972-74 and 1978-80. The capital stock variable is a measure of the inflation-adjusted total net capital stock of the firm (including an allowance for inventories and unconsolidated subsidiaries). The market value measure is the value of common stock plus estimates of the value of preferred stock and debt.[22] Gross accounting profit is operating income plus R&D expense. The technological cluster dummies for the 1972 equations are based on the first period clustering, and those for the 1978 equations are based on the second.

The profit and value equation derivations refer to the stock of accumulated R&D. This is not something reported by the firm. Stocks must be constructed from reported R&D flows, making assumptions about the rate of obsolescence and R&D investments before the firms began reporting the annual R&D spending. Griliches and Mairesse (1984) experimented with several formulations; they found that results were relatively insensitive to the rate of obsolescence. They chose 15% per year, and that was utilized here as well. The R&D stock used is the mean of the non-missing values for the three years, 1972-74 or 1978-80.

Four spillover pool variables were constructed, because the patent equation depends on the annual R&D flow while the other equations relate to the stocks. A pool of stocks and a pool of flows were constructed for each cross-section using the weighted summation procedure described in Section II. Those for 1972 use as weights proximities based on the first period distribution vectors, while those for 1978 use proximities based on the second period distributions. For estimation, I took the log of these variables and subtracted off the mean, so that the R&D coefficients are mean R&D elasticities.

The firm's market share and capital and R&D stocks (and hence the ratio of the R&D and capital stocks) are treated as endogenous variables. Jaffe (1985) presents estimates of a more complete system, in which the market share depends on the firm's R&D, industry R&D and industry sales, and its (optimal) R&D stock depends on its capital stock, the spillover pool, and industry R&D, sales and growth rate. This implies that these industry variables are potential instruments for the firm's R&D and market share. In addition, the industry minimum efficient scale (MES) is added as an instrument for the capital stock. The interaction between the firm's own R&D and the spillover pool makes the equations non-linear in the variables, which means that there is no optimal non-linear function of the exogenous variables which should be used as instruments (Amemiya (1983)). I utilize the industry variables, the spillover pool, and interactions between the pool and all the industry variables.

Industry sales and concentration at the 4-digit level from the 1972 Census of Manufactures were used to form weighted averages of (the logs of) these variables for the firms. The weights are the fraction of the firms' sales in each 4-digit SIC in 1972, taken from the PICA database. The industry growth rate was taken to be the logarithmic difference in deflated sales, 1967-72 and 1972-77. The industry R&D numbers are only available from the FTC for 193 industries that are approximately 3½ digit SIC's, so it was necessary to assume that the R&D/Sales ratio is constant across 4-digit SIC's within the FTC industries. The industry R&D numbers are for 1974.

Means and variances for all the important regression variables are presented in Table Three.

I assume that the six-element residual vector ϵ_i is independent of all the instruments, that $E(\epsilon_i \epsilon_j') = \underline{0}$ for all $i \neq j$, and that $Var(\epsilon_i)$ is an arbitrary matrix Σ_i. Thus I allow for unconstrained covariance across equations and time and conditional heteroskedasticity. The appropriate estimation procedure in this circumstance is three-stage least squares, with the use of the procedure described by White (1982) to calculate standard errors that are robust under conditional heteroskedasticity.

The estimation of the two cross-sections as a system makes the question of the constancy of parameters across time one of cross-equation constraints. I group these constraints into two sets: equality of the slope coefficients (β's and γ's) and equality of the

TABLE THREE

SIMPLE STATISTICS FOR REGRESSION VARIABLES

	1972		1978	
	MEAN	VARIANCE	MEAN	VARIANCE
LOG(ACCOUNTING ROR)	-1.619	0.180	-2.081	0.202
LOG(Tobin's q)	-0.140	0.482	-0.847	0.288
LOG(PATENTS)	2.512	2.600	2.192	2.853
WEIGHTED AVERAGE LOG(MARKET SHARE)	0.885	1.252		
LOG(CAPITAL STOCK)	5.542	2.163	6.232	2.313
LOG(R&D STOCK)	3.357	2.723	3.581	2.605
LOG(R&D FLOW)	1.708	2.639	1.866	2.889
LOG(POOL FLOW)	0	0.212	0	0.239
LOG(POOL STOCK)	0	0.220	0	0.212

technological cluster dummy coefficients. This yields six sets of constraints. The χ^2 statistics for testing each of these sets of constraints against the unconstrained model are:

	ROR	q	Patents
β's and γ's	3.8 (6 d.f.)	5.2 (7 d.f.)	.63 (3 d.f.)
intercepts (20 d.f.)	75.4	83.1	16.2

The constraints on the slope coefficients are easily accepted for all equations,[23] as are the constraints on the intercepts in the patent equation. The intercept constraints in the ROR and q equations are strongly rejected.[24] Based on these tests, I will proceed to analyze estimation results in which the slope constraints are imposed (except on market share), but all of the intercepts are left free.

B. Results

The main regression results are presented in Table Four. Looking first at the patent equation, the estimates imply close to constant returns with respect to the firms' own R&D; the elasticity varies from about .73 to about 1.03 as the pool varies plus or minus two standard deviations from its mean. The pool has a significant positive effect, both directly and through its influence on the R&D elasticity. For the firm with mean log(R&D), the elasticity of patents with respect to others' R&D is about 1.1. If everyone increased their R&D by 10%, total patents would increase by 20%, with more than half the increase coming from the spillover effect.

TABLE FOUR

3SLS ESTIMATES OF PATENT, ROR AND q EQUATIONS FOR 1972 AND 1978

(432 Observations)

	log(Patents)	log(ROR)	log(Tobin's q)
log(R&D)	.875 (.183)	.180 (.042)	
R&D/Capital			3.31 (.209)
log(R&D)*log(Pool)	.352 (.048)	.058 (.020)	
(R&D/Capital)* log(Pool)			.803 (.098)
log(Pool)	.509 (.104)	-.095 (.053)	-.058 (.031)
log(Capital)		-.175 (.044)	
log(72 Share) (72 Equation)		.188 (.055)	.310 (.053)
log(72 Share) (78 Equation)		.057 (.055)	.123 (.054)
log(4-firm Concentration Ratio)		-.220 (.045)	-.525 (.083)
χ^2_{20} on technological cluster effects	89.5	82.5	95.8
$\hat{\sigma}$ (1972)	.842	.325	.652
$\hat{\sigma}$ (1978)	.912	.327	.420

All equations also include 21 technological cluster dummies. The instrument set consists of the cluster dummies, the spillover pool flow and the spillover pool stock for both years; 1974 industry R&D, 1972 and 1977 industry shipments and concentration, 1972 minimum efficient scale, industry growth rates 1967-72 and 1972-77; and interactions of the pool variables with the contemporaneous industry variables. All instruments are used in all equations.

Numbers in parentheses are heteroskedasticity-consistent standard errors calculated according to White (1982).

At first glance, this may seem like an implausibly large spillover effect. It is, however, consistent with a reasonable picture of R&D as a partial public good. In terms of marginal products evaluated at the mean of the data, the coefficients imply a return of 2.0 patents per million dollars of own R&D, and .06 patents per million dollars of other firms' relevant R&D. Because the total relevant R&D is large relative to any firm's own spending, spillovers are important even though the implied value for Spence's θ is only .03.[25]

The results from the ROR and q equations are best considered together. Note first that the ROR equation estimates imply constant returns in R&D and capital for firms with the average spillover pool. The R&D share is about 20% of the capital share. (Recall that the capital share is the reported capital coefficient plus one.) Converted to average gross rates of return at the mean of the data, we get 27% for R&D and 15% for capital, which are consistent with the conventional wisdom that the economic depreciation rate for knowledge is higher than that for physical capital (Pakes and Schankerman(1984)).

The q equation imposes constant returns by assumption; we estimate only the relative implicit price of the R&D and capital stocks. The market apparently places more than 3 times as much value on a dollar of R&D stock as on a dollar of capital stock, for firms with the average pool. Given the average returns implied by the profit equation, it would appear that R&D spending conveys some sort of signal about long-run returns over and above its direct contribution to measured profits.

Turning to the spillover effects, we find a slightly different pattern than in the patent equation. The direct effect of the pool is to lower profits and market value. There is, however, an interaction between own and others R&D that implies that the return to own R&D is increased by the spillovers. For the firm with mean log(R&D), the net elasticity of profits with respect to the pool is about plus .1. If everyone increased their R&D by 10%, the aggregate profits would increase by about 3%, with about one-third of the net increase coming from the spillovers. For firms whose log(R&D) is about .6 standard deviations below the mean, the net effect of the pool is zero; for those with less R&D it has a net negative effect.

The pool effect in the q equation is quite similar, though much more significant statistically. Evaluated at the average log(R&D) and log(capital), the net elasticity of value with respect to the pool is about .05. Note that the "competitive" (i.e. negative) effect of the pool is not significantly different from zero in either equation at conventional significance levels. The data do, however, reject at the 1% level the hypothesis that the log(pool) coefficient is zero in both equations. It appears that both technological spillovers and competitive effects of others' R&D come into play when we consider the economic returns to the firm's research. Comparing firms whose neighbors do a lot of R&D to those whose neighbors do little, the former are characterized by lower profits and market value if they do no R&D themselves, but a higher return to doing R&D. For firms with the average R&D budget, the net effect of others' R&D is positive.

Finally, a brief comment is in order on the effect of market share and concentration on profits and market value. Table Four shows that higher market shares are associated with higher profits and market value, but increasing the 4-firm concentration lowers the profits and market value of the average firm. Results not reported here show that each of these effects remains if the other variable is dropped, and interactions do not appear to be important. These results are consistent with other studies finding negative effects of concentration on profits at the firm or line-of-business level (Demsetz (1974), Ravenscraft (1983)). They imply that the larger firms in a given industry have systematic advantages over their smaller rivals. It is not possible, with these aggregate firm data, to determine the extent to which the advantages are on the cost side, and the extent to which large market shares confer or reflect market power.

V. ANALYSIS OF TECHNOLOGICAL OPPORTUNITY EFFECTS

The coefficients on the technological cluster dummies in the ROR, q and patent equations measure, in some sense, the average excess returns (positive or negative) experienced by the firms in the group. In the patent equation, it is the average excess return to R&D, in terms of patents. In the ROR and q equations, it is the average excess profits or market value remaining after controlling for the average rate of return on all of the firms' observed assets. These include R&D, capital, the spillover pool, market share and industry concentration. The motivation for including these dummies in all the equations has been to allow for variations in technological opportunity, defined above as exogenous, technologically determined variations in the productivity of R&D. The χ^2 statistics reported in Table Four show clearly that the cluster dummies are important in all equations. It is difficult to know, however, whether technological opportunity is really the driving force behind the cluster effects. One way to investigate this question is to analyze and compare the patterns of coefficients across equations.

Table Five presents the correlation matrix across the ROR, q and patent equations for the 21 intercept coefficients. Consistent with the test statistics reported above, the correlation across time is .62 for the patent equation, .25 for the ROR equation and .05 for the q equation. Within cross-sections, the ROR-q correlation is high (.84 for 1972, .80 for 1978), while the patent equation intercepts are relatively uncorrelated with those from the ROR and q equations (.15 and .23 for 1972, .14 and .01 for 1978). It appears that the ROR and q intercepts share a common influence that is relatively fleeting; the patent intercepts are driven by something else that is relatively stable over time.

There are two possible interpretations of these results, one sympathetic to the technological opportunity story and one not. The sympathetic interpretation is that ROR, q and patents are all responding to technological opportunity, but that in the case of patents this response is drowned out by the pattern of the propensity to patent, which is stable over time. The other view is that the absence of any

TABLE FIVE

CORRELATION MATRIX FOR TECHNOLOGICAL CLUSTER INTERCEPTS

	ROR (72)	q (72)	ROR (78)	q (78)	Patents (72)
q(72)	.84				
ROR(78)	.26	.16			
q(78)	.11	.05	.80		
Patents(72)	.23	.15	.22	.15	
Patents(78)	.15	-.01	.00	.14	.62

correlation between the effects on patents and profits suggests that the cluster effects in the ROR and q equations come from somewhere else. Implicit in the model as formulated is an assumption that all relevant influences from the market or demand side are captured by the industry variables that are in the model. To the extent that this is not true, then the cluster dummies could be capturing industry effects, since there is some correspondence between the clusters and industry groups.

Some additional insight can be gained by comparing these results to analagous ones where I substitute dummies based on industry groups for those based on technological clusters. I have relevant data on the industry distribution of firms' sales only for 1972, so I can look only at the contemporaneous correlations. I find that the ROR-q correlation is .88, while the patent intercepts are correlated .09 with those from the ROR equation and .07 with those from the q equation. Thus, when looking at industries, patents are even less correlated with ROR and q, which are still highly correlated with each other. This is at least consistent with the view that there is a small "piece" of the variation in profits that is related to technological opportunity. If this piece accounts for the .15 to .2 correlation of patents to ROR and q in Table Five, it would make sense that it is reduced when we look at the industry grouping, since this does not control for technology directly.

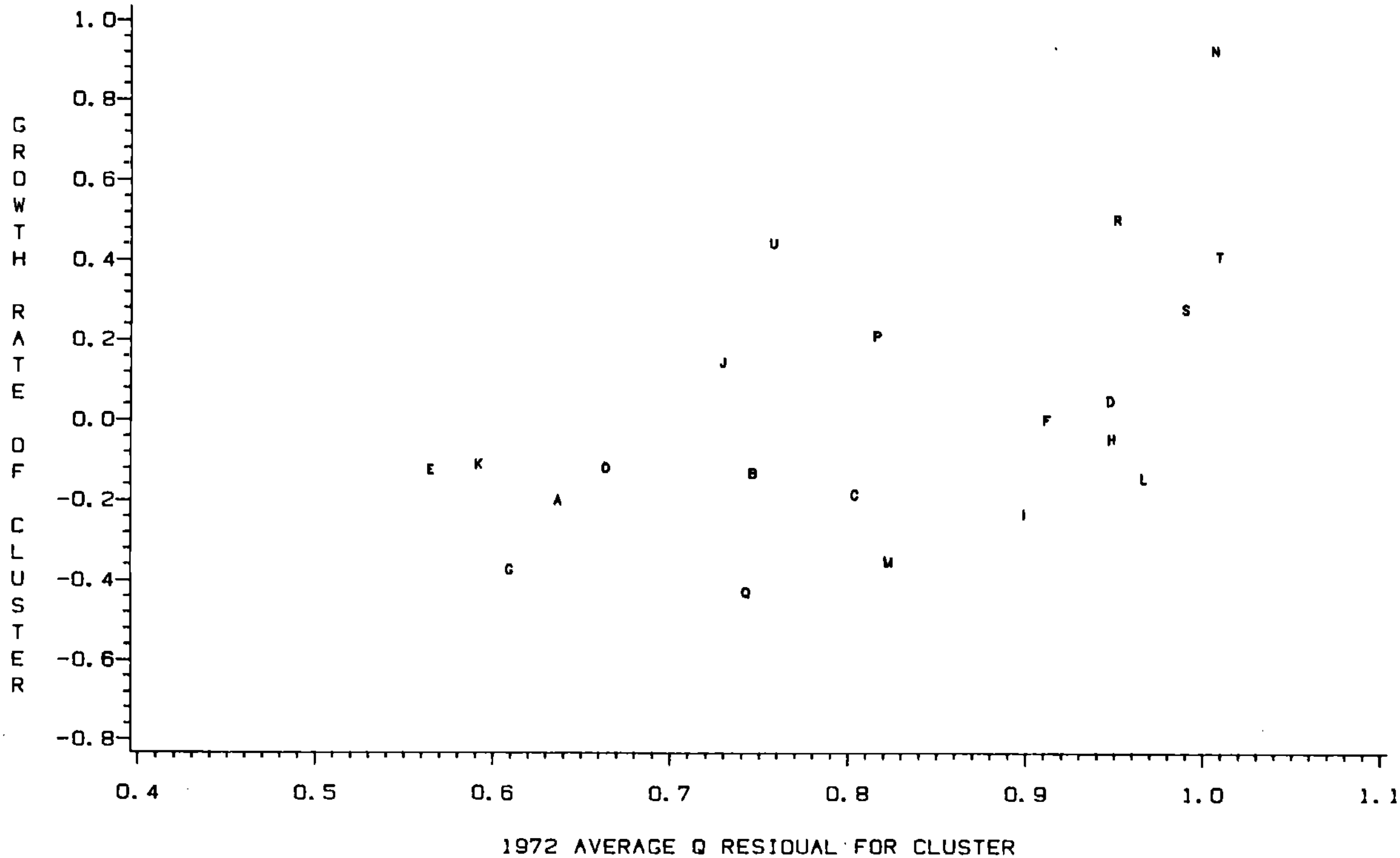
Regardless of whether excess profits or value are associated with industries or technological positions, it is interesting that they do not appear to be persistent over time; the correlations between the ROR and q intercepts in each cross-section are much larger than the correlation across time for either. This is consistent with the absence of significant mobility barriers, allowing firms to move eventually to join high profit clusters. Such movements would tend to compete away the excess returns. We would expect that, over time, the economic return to R&D in a "hot" area would fall, even if the potential of the area in a strictly technological sense remained high. This appears to be exactly what happened.

As discussed above, I take the view that firms cannot change their position in technology space overnight, but that over some horizon they do move in response to perceived profit possibilities. The results presented here suggest an obvious test of this view. Did the movements in the firms' patent distributions between the 1965-72 period and the 1973-79 period bear any relation to the pattern of excess returns?

Figure One shows a plot of the proportional growth rate[26] of the number of firms in each technological cluster against the cluster intercepts in the 1972 q equation. There is a clear positive relationship. The correlation coefficient for the 21 observations is .53, which is significantly positive at the 1% level. The correlation of the growth rate with the intercepts from the 1972 ROR equation is .35. It appears clear that entry and exit were driven by the contemporaneous profit opportunities.

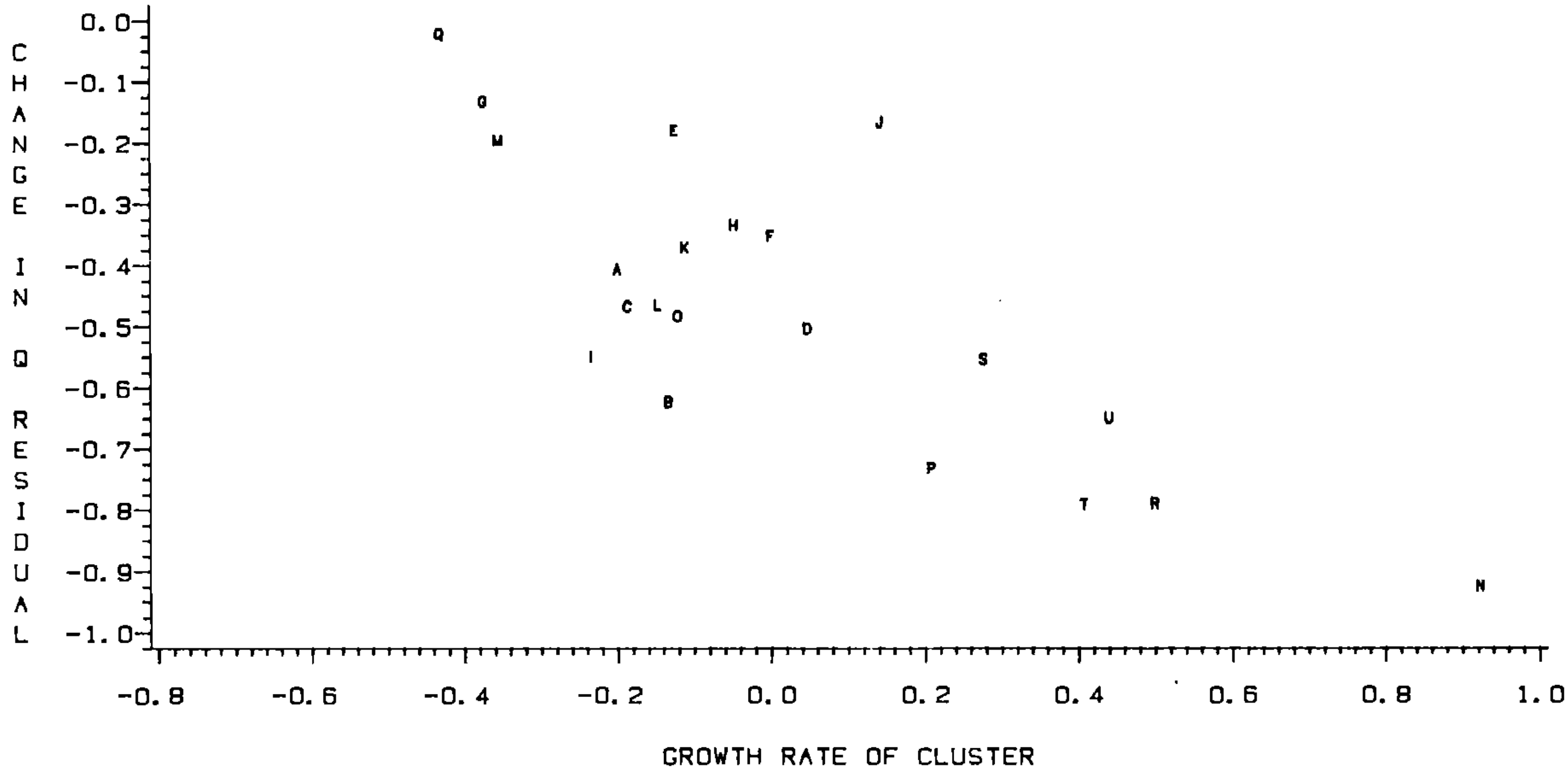
We would expect that this entry and exit would have an effect on

FIGURE ONE



GROWTH RATE OF CLUSTER
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
0.4
0.5
0.6
0.7
0.8
0.9
1.0
1.1
N
R
U
T
S
P
J
D
F
H
E
K
O
B
L
A
C
I
G
M
Q
1972 AVERAGE Q RESIDUAL FOR CLUSTER

FIGURE TWO


CHANGE IN Q RESIDUAL
0.0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
-0.7
-0.8
-0.9
-1.0
-0.8
-0.6
-0.4
-0.2
0.0
0.2
0.4
0.6
0.8
1.0
GROWTH RATE OF CLUSTER
Q
G
M
E
J
H
F
K
A
C
L
O
D
I
S
B
U
P
T
R
N

the future realized profitability of the clusters. Again, the results seem to be consistent with this prediction. Figure Two shows a plot of the change in the q equation intercept between the two cross-sections against the growth rate of the cluster. The correlation coefficient is -.79, which is again highly significant. Even the 1978 intercepts themselves are negatively correlated with the growth rate, though somewhat less so (-.56). Thus there is a clear association between entry (exit) into a cluster and a decrease (increase) in the average returns.

In interpreting these results, it is important to keep in mind that we are looking at snapshots, while the true process takes place in continuous time. It appears as if the firms do not have rational expectations, because they choose to move toward what will be, on average, low profit clusters. Such moves may well be rational, however, because the firms may make sufficient profits during the transition to make the move worthwhile--and they may well be in the process of moving on again to greener pastures.

One interesting question raised by these results is whether the "movers" are fundamentally different as a group from the firms that stay put. The above results regarding the effects of entry could be explained without reference to competitive forces if it were the case that the firms that move are, on average, low profit firms. One way to get at this is to examine the mean residuals for the two groups from the ROR and q equations. The two equations for the two cross-sections yield four such comparisons. In every case, the movers are actually higher profit firms (though in three out of the four comparisons one cannot reject the hypothesis that the groups have the same mean). Thus, instead of weakening the entry story, this effect only strengthens it. Entrants are, on average, good firms; despite this fact, entry is associated with a fall in the average returns for the group.

VI. CONCLUSION

I have presented an analysis of the effect on the productivity of R&D of certain factors from the "supply-side" of innovation. In particular I find evidence of spillovers of R&D from several indicators of technological success. Firms whose research is in areas where there is much research by other firms have, on average, more patents per dollar of R&D and a higher return to R&D in terms of accounting profits or market value, though firms with very low own-R&D suffer lower profits and market value if their neighbors do a lot. All of these effects remain after controlling for the possibility that the technological areas themselves are associated with variations in the productivity of R&D.

I view these results as demonstrating that "there is something to" the spillover phenomenon. Understanding the implications for industrial structure and public policy will require more detailed work that focuses on the variations in the extent of spillovers in different areas, as well as examining the spillovers in a context where their implications for firms' strategic behavior are recognized.

The results regarding technological opportunity are less satisfactory. The patent class distribution data clearly contain useful information about the composition of firms' research activities. Further, I find clear evidence that firms adjust their technological positions in response to profit possibilities, and that these adjustments tend to dissipate excess returns. It is not yet clear, however, to what extent the exogenous variations in profit potentials can really be attributed to technological opportunity rather than demand-side effects. More careful examination of the "movements" of firms in technology space, combined with similar analysis of changes in firms' market positions, should provide more complete understanding of the inter-relations among technological opportunity, changes in the structure of demand, profitability, and firms' actions in positioning their research and their sales.

NOTES

1. This paper is based on my PhD dissertation (Jaffe (1985)). More detailed derivations and further empirical results are contained therein. I am indebted to Zvi Griliches, Richard Caves, Mark Schankerman and workshop participants at Harvard and the NBER for many helpful comments. Financial support was provided by the NSF under grant PRA81-08635 and by an Alfred P. Sloan Doctoral Dissertation Fellowship.

2. One might ask whether it is the technological nature of the firm's research program or that of its current production technology that really matters. To the extent that the two do differ, it would seem that what matters most for the effects of technological opportunity and spillovers is the nature of the research program.

3. There are eight classes in which these firms took no patents, including "Land vehicles, animal draft" and "Whips and whip apparatus."

4. Classifying the patents by date of application rather date of issue is preferable because that is when the firm perceived itself to have generated new knowledge, and because there are long and variable lags in the patent office's processing of applications. Recall, however, that the dataset consists of all patents granted to these firms between 1969 and 1979. Because of the lags in granting, this includes essentially all of the successful applications filed between 1968 and 1976, but only some of those filed 1977-79, and also includes some from 1965-67 and a sprinkling from before. If we can view the patents we do have for the incomplete years as a random sample of all applications, then the incompleteness doesn't matter for this purpose. If, however, some patent classes have systematically long or short processing lags, then the early period totals are biased towards long lag categories and the later period towards short lag categories.

5. This is the basic approach suggested by Griliches (1979). Bernstein and Nadiri (1983) measure spillovers using a cost function approach and time series data for the chemical industry. Their pool variable is the unweighted sum of the R&D of all other firms in the industry.

6. This measure of proximity is purely directional; that is, it is not directly affected by the length of the F vectors. The length of the vector depends on the degree of focus or concentration of the firm's research interests. (It is actually the square root of the Herfindahl index of concentration of the category shares.) Other proximity measures, notably the Euclidean distance between the vector endpoints, are very sen-

sitive to the length. For example, all pairs of relatively diversified firms are "close" by the Euclidean measure, because they are close to the origin of the coordinate system, even if the vectors are orthogonal. If the vectors are all normalized to have the same length, then $(1 - P_{ij})$ is proportional to the squared Euclidean distance between the endpoints of the vectors F_i and F_j.

7. In matrix terms, if n is the number of firms, define $\underline{F}$ as the nx49 matrix whose rows are the F_i's. Let $\underline{F}_N$ be the matrix derived from $\underline{F}$ by normalizing each row so its sum of squares is unity. Then the column n-vector S is given by $S = (\underline{F}_N\underline{F}_N' - I)R$ where R is the n-vector of firms' R&D spending.

8. The units of s_i are arbitrary anyway, because there is no natural normalization of the proximity weights. This does not matter because I am primarily interested in elasticities. Of course, if $\theta = 0$, then this pool is a mere illusion and should have no direct effect on firm i.

9. The algorithm used was derived from the K-means algorithm (McQueen (1967) and Hartigan (1975)), modified to exploit the multinomial structure of the elements of the F-vectors. For more detail see Jaffe (1985).

10. For more detail, see Jaffe (1985).

11. See Pakes and Griliches (1984), Pakes (1985) and Hall, Griliches and Hausman (1983).

12. Actually, we expect knowledge production to depend on a distributed lag of R&D, but this lag structure is difficult to identify, and much of the weight appears to fall on the contemporaneous R&D. See Pakes and Griliches (1984) and Hall, Griliches and Hausman (1983).

13. Throughout this paper, lower case letters will represent the logs of variables. β's indicate coefficients of endogenous variables and γ's those of exogenous variables.

14. If there is covariance across firms in the productivity of R&D, then that is precisely what we mean by patterns of technological opportunity. Hence we assume that this will be picked up by the terms $\delta_{1c}D_{ic}$.

15. There has been a long debate on the general question of the usefulness of patent data as an indicator of inventive output. For present purposes, suffice it to say that patents have repeatedly passed tests of their economic relevance. See Schmookler (1966), Pakes and Griliches (1984), Bound, et al (1984), Pakes (1985), and Hirschey (1982).

[16]. For a related approach, see Siu (1984).

[17]. The concentration and market share effects are not the focus of this paper, but they are included because they were found to be significant in Jaffe (1985).

[18]. For a similar view, see Hirschey and Wichern (1984). Other papers using q to measure profitability include Griliches (1981), Lindenburg and Ross (1981) and Pakes (1985).

[19]. See Posner (1975).

[20]. Demsetz (1973) makes exactly this argument to explain why profits due to "success" are persistent despite the absence of entry barriers.

[21]. This differs from the treatment in Salinger (1984).

[22]. For more detail on the construction of the capital stock and market value variables, see Cummins, et al (1984).

[23]. Because the 1978 market value variable (in the ROR and q equations) is "wrong," its coefficient is left free and not included in the tests. Note that each equation also has a free intercept even in the constrained versions; the test on the dummy coefficients is testing equality over time of the deviations from the reference group. The 99.5% critical value for χ^2_{20} is 40.0.

[24]. Note that the cluster assignments of 35% of the firms change between the two cross-sections. Given the persistence of firm-specific effects (discussed below), one might be concerned that the rejection of stability of the cluster effects is due simply to the changing populations in each cluster. To check for this, the test was rerun using the 1972 cluster assignments in both equations. This yielded χ^2_{20}'s of 52.3 for the ROR equation and 57.8 for the q equation.

[25]. This number should be taken with a large grain of salt. As noted above, the units of the pool variable are essentially arbitrary. The "true" relevant R&D for each firm could be 10 times smaller; this would not affect the elasticity estimates, but would lead us to conclude that Spence's θ is .3.

[26]. $(N_{78} - N_{72})/N_{72}$

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