Inter-Industry Spillover of R&D, Technological Opportunities, and Productivity Growth

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This paper attempts to examine the empirical significance of the technological opportunities and spillover effects in the relationship between industrial R&D and productivity growth. Estimation results are in favor of the general hypothesis that a given level of investment in knowledge stock will have a greater effect in industries with relatively rich technological opportunities. However, the explicit consideration of the spillover effects does not lead to a significant improvement in estimation results. Analytically, as Scherer (1982) argues, spillover effects should play an important role in explaining output elasticity, but the results of empirical tests in this paper suggest that the information in the spillover effects is embodied in its own R&D. (*JEL* Classification: O14)

I. Introduction

The relationship between industrial research and development (R&D), an important source of technological innovation, and productivity growth has been the subject of concern since the slowdown in productivity growth during 70' and 80's in the U.S. coincided with the slowdown in expenditure for R&D. A number of studies have been done to investigate the relationship. Some of these studies have taken a production function approach in which R&D expenditure is an input, analogous to investment in physical capital.[1] The studies have found that the empirical relationship between the flow of services from the R&D stock and the productivity of traditional inputs are positive and

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[1]Griliches (1979, 1980, 1994).

significant in various formulations, although it is hard to say whether the quantitative evidence is quite robust.

In this paper, we explicitly introduce the inter-industry spillover of R&D in a production function framework, and examine the empirical significance of the spillover effect to productivity growth. Due to the public good aspect of technological knowledge, the returns of R&D investment cannot be fully appropriated by the firms undertaking the R&D projects. Knowledge produced by R&D-performing industries spills over to other industries; the positive externality of the knowledge could be an important determinant of productivity growth in other industries.

This paper also examines the effect of technological opportunity on the inter-industry variation of the elasticity of productivity with respect to the service flow from the stock of knowledge. The productivity elasticity with respect to the service flow of knowledge stock is assumed to be a function of technological opportunity variables measuring the relevance of applied and basic science and of the presence of natural trajectories of innovation to the industry's progress. The general hypothesis is that a given level of investment in knowledge stock will have a greater effect in industries with relatively rich technological opportunities than in industries with relatively poor technological opportunities.

For the spillover effects, there are two channels through which they could occur. The first type is the spillover through input purchase. An improved production process lowers cost and therefore prices, to the benefit of downstream industries; the industries are also benefited by product innovations in upstream industries as long as the prices of the new products do not fully reflect their improved quality. A familiar example of this first type spillover would be the computer industry where product prices are falling while the quality of the products is improving.[2] The second type of spillover is through positive externality between two industries not necessarily related by input purchase. For example, suppose industry i and j are neither purchasing each other's products nor producing similar products. But the results of R&D achieved by industry j could produce positive externality for industry i's performance if these industries are working on similar research projects. In this paper we consider only the first type of spillover.

The spillover effect from industry j to industry i is determined by the extent that industry j's improvements are incorporated in the price of

[2]Bresnahan (1986).

its products and are appropriated within the industry. This view relates to how well rents are captured by the supplying industry, and how well input prices are measured in the buying industry. We assume here that deflators of capital inputs are mismeasured, and the measurement error is a function of R&D performed in the capital supplying industries. This seems to be a reasonable assumption in the sense that prices of products in R&D intensive industries tend to under-measure systematically the true values of the products because of the intrinsic characteristics of knowledge produced from R&D activity.

Scherer (1982), following Schmookler (1966), attempts to measure the inter-industry R&D spillover by constructing a technological matrix to trace the flow of technology from the industry in which a new product originates to the industries where the product is used. Scherer (1982) uses the average number of U.S. patents obtained per million dollars of company-financed R&D in 1974. He observes that three-fourths of all U.S. industrial R&D is concerned with creating new or improved externally-sold products, as distinguished from the development of production processes used internally by the R&D performing enterprise,[3] and he concludes contributions made by upstream industries are large and significant because the spillover effect is more likely come from the product R&D than the internal process R&D. This result, however, depends on a considerable number of arbitrary assumptions. And in general, there are many limitations to patent data as well described in Levin et al. (1987).[4]

Empirically, this paper shows that the inter-industry technological spillover does not play an important role in explaining output elasticity. The explicit consideration of the spillover effects does not lead to a significant improvement in estimation results, and the extent of the spillover effect is mainly embodied in each industry's own R&D. Sever-

[3]Scherer calculated this using the raw data on patent counts.

[4]Some results of industrial R&D are not patentable. The value and cost of individual patents vary enormously within and across industries. Many inventions are not patented, while some types of technologies are much more likely to be patented than others. Moreover, the role of R&D is more than an invention-producing activity. It would not be justifiable to disaggregate R&D expenditure simply into product and process R&D if a significant amount of R&D is spent for development and maintenance of a firm's capacity to assimilate external knowledge. Firms cannot simply integrate external knowledge into their production. They must learn how to make it a part of their organizational knowledge. This process will also be reflected in R&D expenditures however not in patent data.

al other tests also show weak or adverse evidence for the importance of spillover effects.

For the technological opportunity, the variable is formulated from a national survey of R&D managers conducted by Yale University's Research Program on Technological Change. Consisting of factors such as "Relevance of basic science to technological change in the industry," "Relevance of applied science," and etc., the technological opportunity variable is to measure the susceptibility of the industry to the innovations and R&D. This attempt, being the first of the many to follow. quantitizes what has been up to now an ill-defined source of residual variation.

In this paper, technological opportunity variable is regressed as an independent variable against the estimated elasticity of the productivity growth respect to the service of knowledge stock. The estimation results are in favor of the the general hypothesis that a given level of investment in knowledge stock will have a greater effect in industries with relatively rich technological opportunities. This result is robust subject to the treatments of multicollinearity and non-linearity.

II. The Model

Assume a Cobb-Douglas production function which includes the service flow from the R&D stock as a distinct factor of production:

$$Q = AL^{\alpha_1}M^{\alpha_2}E^{\alpha_3}K^{\alpha_4}X^{\beta}e^{\mu}, \tag{1}$$

where Q = output; A = a constant; L = labor input; M = non-energy intermediate material input; E = energy input; K = physical capital services; X = the flow of services from knowledge stock; α_1, α_2, α_3, α_4, β = elasticity coefficients; e^{μ} = all unmeasured factors.

Define total factor productivity (TFP) as a productivity of traditional inputs:

$$TFP = Q \,/\, L^{\alpha_1}M^{\alpha_2}E^{\alpha_3}K^{\alpha_4}. \tag{2}$$

Combining (1) and (2) gives

$$TFP = AX^{\beta}\, e^{\mu}. \tag{3}$$

Or

$$\ln TFP = \ln A + \beta \ln X + \mu. \tag{4}$$

The productivity of traditional inputs (*TFP*) is now expressed as a function of R&D investment. β is the elasticity of output with respect to the flow of services from R&D stock.

A variety of theoretical issues has been raised in the attempt to infer the contribution of R&D to productivity growth.[5] Since R&D is a choice variable, we expect more of R&D to be undertaken in the industries where the R&D productivity elasticity, β, is large. The problem of simultaneity results in difficulties of econometric inference. Variables involved in the equation of concern also move together over time and industry; the complicated error structure makes it hard to separate effects of different sources. Measures of outputs and those of inputs are also subject to measurement errors. There is in particular no good measure of real output in government and service sectors. Mismeasurement of output also comes from the poor quality of output price indices due to the complexity and changing characteristics of products. Problems in the definition of R&D input and its deflators constitute another source of measurement errors. Moreover, the long and variable lags in the effect of R&D on productivity growth, and other issues involoved in the diffusion of particular technological development, further complicates the already complex problem. There seems to be no reasonable way to untangle all these problems together. In this paper, we pay attention to the measurement errors in capital equipment industries. Actually many economists have observed that output in R&D intensive industries, such as those of capital equipment, is more likely to be subject to measurement problem than outputs in less R&D intensive industries.[6]

Suppose that capital inputs, K, are mismeasured due to errors in the prices of capital inputs. Let measured capital inputs be mirrored in deviations from true capital inputs to the extent of the mismeasurement in the deflators:

$$K_m = K_T P^T / P^m, \tag{5}$$

where K_m = measured K; K_T = true K; P^T = true deflator: P^m = measured deflator: $P^T \neq P^m$. That is,

$$K_T = K_m P^m / P^T = K_m P, \tag{6}$$

where $P = P^m / P^T$.

[5]The issues are well discussed in Griliches (1979, 1994).

[6]See Griliches (1987).

Assume that the mismeasurement of the jth input deflator is a function of R&D in the supplying industry j:

$$P_j = f(R_j) = \exp(-\, d_j R_j), \tag{7}$$

where $P_j = P_j^m / P_j^T$, the mismeasurement in the deflator of the jth capital equipment industry: R_j = R&D in the industry j; d_j = coefficient > 0; exp (z) = e^Z. P_j is decreasing in R_j, and lies between 0 and 1. If we assume that the productivity elasticity with respect to each capital input is the same over different types of capital, then we get a reasonable idea of how to represent the measurement errors in the 'aggregate' price index of capital inputs in terms of R&D in the capital supplying industries:

$$K_T = K_m \Pi_j P_j = K_m \exp(-\, \Sigma d_j R_j). \tag{8}$$

Measured *TFP* is:

$$TFP^m = Q \,/\, L^{\alpha_1} M^{\alpha_2} E^{\alpha_3} K_m^{\alpha_4} = AX^{\beta} \exp(\sum_j \gamma_j R_j + \mu) \tag{9}$$

$$\ln TFP^m = \ln A + \beta \ln X + \sum_j \gamma_j R_j + \mu \tag{10}$$

where $\gamma_j = -\, d_j \alpha_4$.

Rewrite (10) for industry i at time t,

$$q_{it} = a_i + \beta_i x_{it} + \sum_j \gamma_{ji} R_{jt} + \mu_{it}, \tag{11}$$

where $a = \ln A$, $q = \ln TFP^m$, $x = \ln X$. To have enough degrees of freedom, three groups of capital equipment industries—mechanical industry, electronic and electrical, and instruments are chosen. The choice of the industries are based on a priori notions about the extent of commonality in their technological base and advice from local experts.

The intercept in equation (11) is allowed to vary across industries to admit the possibility that some industries have higher measured productivity than others.[7] An additional industry effect is introduced by the error term μ_i. One approach to estimating (11) would be to treat both effects as random. The random effects model, however, will yield biased estimates of the coefficients unless the effects are independent of the regressors. For (11) this means that x_{it} and a_i must be independent. If there is any unobserved variable that affects both the knowledge stock and the shift parameter in the production function, the ran-

[7]In this brief statistical discussion, we ignore serial correlation in the error term. Since R&D is assumed to affect the trend in *TFP* but not the short term fluctuations, the error term presumably shows serial correlation. We will introduce the problem later.

dom effect estimates will be biased. But the independence seems unlikely. Alternatively, equation (11) can be treated as a fixed effects model. Fixed effects models yield unbiased estimates whether or not the independence condition is met.

The main problem in estimating (11) is that the R&D variables are very highly correlated. As a matter of fact, the collinearity problem has been typical among all types of R&D variables, for example, R&D performed in an industry, R&D attributed to an industry through its purchases from other industries, company-financed and government-financed R&D, product and process R&D, etc. When I drop some of the R&D variables in (11), the fit of the equation is fairly good.

Another way to solve the collinearity problem is to reinterprete the R&D input in each industry using the concept of knowledge stock. The knowledge stock of an industry i is assumed to be a functions of its own R&D and the spillover from upstream industries. Knowledge stock in industry i is affected not only by its own research and development but also by productivity improvements in industry j to the extent to which i's purchases are from industry j.[8] That is, X_i is the flow of services from the knowledge stock of each industry; it reflects both its own R&D and the R&D embodied in inputs purchased from R&D intensive industries. Therefore, the estimation equation in this framework would be similar to (11) under the assumption that the productivity elasticity for own R&D and that for R&D spillover are the same.

There might be several alternative ways to see the spillover effect of R&D. If possible, one would directly estimate the spillover parameter γ_{ji} using the maximum likelihood estimation, assuming that μ_{it}, given (β_i, γ_i), is normally distributed with mean zero and variance σ_μ^2. However the limitation of the data does not allow us the joint estimation of the parameters. Since each industry has only eighteen observations, the system would be under-identified.

Alternatively, γ_{ji} could be constructed by using available data. To quantify this spillover effect, a simple weighting scheme is used which depends on the input-output coefficients relating industries i and j. Input-output coefficients, i.e. the proportion of inter-industry purchases, are used to measure the "closeness" of industries. Let a proxy for the service flow from the stock of knowledge in each industry be constructed as follows:

[8]Jaffe (1986) and Levin and Reiss (1988) use the functional forms $Q_i = g(X_i)$; $X_i = h(R_i, R_j)$ where Q_i = output of industry i; R_i = R&D in industry i; R_j = R&D in industry j.

$$X_{it} = R_{it} + \sum_{j \neq i} \theta_{ji} R_{jt}, \tag{12}$$

where X_i = knowledge in industry i ; R_i = own industry R&D; $R_j(i \neq j)$ = other industry's R&D; $\theta_{ji} = \gamma_{ji}/\beta_i$. Let us assume that the weighting function θ_{ji} is proportional to the measure of closeness:

$$\theta_{ji} = w_{ji}, \tag{13}$$

where w_{ji} is an input-output coefficient that measures the proportion of industry i's purchase from industry j. The weighting function θ_{ji} can be interpreted as the effective fraction of knowledge in j transferred into industry i. Presumably θ_{ji} becomes smaller as the distance, in some sense, between i and j increases.

By assuming that the knowledge stock is determined as (12), we ignore various lags in both own industry R&D and inter-industry R&D. This may not be a conceptually justifiable assumption since a particular research and development project may take more than a year to complete. When complete and if successful, it may still take some time before a decision is made to use it or produce it. It also takes time for knowledge to spillover from one industry to another. An exact formulation might be represented as:

$$X_{it} = \sum_{l=0}^{L} h_l X_{i(t-l)}, \tag{14}$$

where L is the total lag periods. However, the length of R&D time series is inadequate to accomodate the reasonably long lags that probably characterize the process, and any short lag introduced would be totally ad hoc. With the limitation of R&D data, we not only allow for no lag in R&D, but also make the current knowledge stock depends only on the current R&D, which is a different troublesome issue. Pakes and Griliches (1984) however show that the relationship between R&D and patent application within a firm is close to contemporaneous, and that the lag effects are significant but relatively small and not well estimated. We assume a similar assumption for the industry's own R&D as well as the spillover effects.

III. The Data

The data used here are cross sectional-time series data for twenty-seven "two-and-a-half" digit manufacturing industries over an eighteen

TABLE 1
INDUSTRIES INCLUDED IN THE STUDY

DOWNSTREAM INDUSTRIES	NSF	SIC CODES
Ordnance & Accessories	1	348
Missiles and Spacecraft	2	376
Food & Kindred Products	3	20
Plastic Materials & Other Synthetics	5	282
Agricultural Chemicals	6	287
Other Chemicals	7	281, 284-6, 289
Drugs & Medicines	8	283
Petroleum Refining	9	29
Rubber & Miscellaneous Plastics	10	30
Stone Clay & Glass Products	11	32
Ferrous Metals & Products	12	331, 332, 339
Nonferrous Metals & Products	13	333-6
Fabricated Metals & Products	14	34
Motor Vehicles & Equipments	25	371
Other Transportation Equipments	26	3733-375, 379
Aircraft and Parts	27	372
CAPITAL SUPPLYING INDUSTRIES	**NSF**	**SIC CODES**
Engines & Turbines	15	351
Farm Machinery & Equipments	16	352
Construction, Mining & Material-handling Equipments	17	353
Metalworking Machinery & Equipments	18	354
Office Computing & Accounting Equipments	19	357
Other Machinery except Electrical	20	355, 356, 358, 359
Electric Transformers & Distribution Equipments	21	361
Electric Industrial Apparatus	22	362
Other Electric Equipments & Supplies	23	363, 364, 369
Communication Equipments & Electric Components	24	365-367
Instruments	28	38

year period (1959-76). To investigate the effect of R&D spillovers through capital purchase on the estimation of the productivity elasticity, we choose 11 industries to represent capital supplying industries, using a priori notions about the extent of commonality in their technological base and advice from local experts. The data for 11 capital supplying industries are embodied in the spillover term in (12), R_{jt}, and the analysis on the productivity elasticity and the opportunity variables is done in 16 downstream industries. The description of the industries included in the analysis is revealed in the Table 1.

Four types of data are used: data on investment in knowledge stock, data on total factor productivity, data on input-output coefficients, and data on technological opportunity. The R&D expenditure data were supplied by Frank Lichtenberg and are described in detail in Griliches and Lichtenberg (1984). The time series data on R&D expenditures are from the industrial R&D survey conducted by the National Science Foundation. The data record annual expenditures on applied R&D for twenty-eight "two-and-a-half" digit industries and include both privately and publicly funded R&D conducted by the private sector. The series classifies R&D expenditures by product line, not by the industry to which the conducting firm belongs. We transform R&D expenditures to a flow of R&D services by assuming that the flow is proportional to the stock. The R&D stock variable is constructed under two simplifying assumptions—zero depreciation rate and no lag between expenditures on R&D and additional productivity relevant to the stock. Lag problems have already been discussed above; a zero depreciation rate may not be a bad assumption for an eighteen year period, but it would be a poor approximation for industries of rapid technological change.

The total factor productivity data were developed by Fromm, Klein, Riply and Crawford (1979) based on the Annual Survey of Manufacturers. The data include current and constant (1972) dollar series on the value of output and capital, labor, energy and material inputs for four-digit SIC industries. Under the assumption of constant returns to scale, current dollar capital services are calculated as a residual, the difference between the current value of output and the sum of current expenditures on labor, energy and materials. Since some factors are omitted, the share of capital is probably exaggerated. The labor data developed by Fromm, et al. (1979) have been revised by Griliches and Lichtenberg to include non-production workers, but are not adjusted for any changes in the quality of labor over the period. The share of labor is probably understated. Total factor productivity is defined as the ratio of real output to a tornqvist-divisia index of inputs.[9]

The data on w_{ji} are from the input-output tables of 1977 which was constructed by the Bureau of Economic Analysis in the U.S. Department of Commerce. We aggregated input-output coefficients into 27 industries to make them consistent with other data aggregation levels.

The source of the opportunity variables is survey responses to questions about technological opportunity. The survey data are from a

[9]See Griliches and Lichtenberg (1984), pp. 486-8, for detail.

national survey of R&D managers conducted by Yale University's Research Program on Technological Change. The survey included 130 lines of businesses defined by the Federal Trade Commission. Characteristics of the data are well summarized in Levin et al. (1987). In this paper, the technological opportunity data are aggregated to the same level as R&D data. The survey data is not only extensive but also very informative for the characterization of inter-industry variations in technological opportunity. Until the survey data were developed, technological opportunity had been treated as an ill-defined source of residual variation. The survey provides the necessary empirical content for a more precise concept of technological opportunities. Since the survey data are cross-sectional, they are merged with time series data by assuming that the opportunity variables are constant over time.

The opportunity variable consists of six variables which are:

y_1 = the relevance of "basic" sciences to technological change in the industry

y_2 = the relevance of "applied" sciences

y_3 = process trajectory

y_4 = product trajectory

y_5 = contributions from government research laboratories and agencies

y_6 = contributions from university research

y_1 and y_2 are included as opportunity variables in order to capture the industry's potential for technological change resulting from close ties to science. The basic science included in the survey data are biology, chemistry, geology, mathematics, and physics. The applied science included are agricultural science, material science, computer science, applied math and operations research, medical science, and metallurgy. y_1 and y_2 are the maximum score of each group of sciences. In both cases respondents were asked to rate the relevance on a seven-point Likert scalé—a scale of one ("not relevant") to seven ("very relevant"). And because the absolute levels of the variables are from semantic scales, the data for the variables may be subject to substantial measurement errors

y_3 and y_4 are based on the concept of general natural trajectories in technologies (Nelson and Winter 1982). Natural trajectories are described as the direction and rate of incremental innovation, which are not technology specific but industry specific. Many industries observed have consistently pursued a certain type of improvement in products or production process. In these industries, there is a pattern of innovation related to these trajectories. The inclusion of the trajectory variables is based on the hypothesis that as an industry enters a trajectory, the probability of successful innovation increases and the cost declines; the productivity of R&D expenditures is enhanced. y_3 is the maximum score for a series of questions on process trajectories: changing the scale of the production process, mechanization/automation, improving yields, improving material inputs, and converting batch to continuous processes. y_4 is the analogous variable for product trajectories: improving the physical properties, improving the performance of the product, standardizing the product, designing the product for specific market segments, tailoring products for specific market segments, tailoring products for specific individual customer.

y_5 is included to reflect a positive relationship between publicly conducted research and the industries' oportunity for technological advance. The publicly conducted R&D is distinct from the publicly funded but privately conducted R&D that is counted in R&D expenditures. y_6 analogously measures the contribution of university research. The contributions of government and university research are discussed in Nelson (1982) and Thackray (1983), respectively.

IV. The Estimation and Result

The estimation equation is the same as (4), and β is the elasticity of output with respect to the flow of services from knowledge stock and is hypothesized to vary across industries in response to variations in technological opportunity. Let Y be a vector of opportunity variables such that $\beta = \beta(Y, c)$ where c is a matching vector of coefficients. Our main interest is in parameters of β and the vector c in the following equations:

$$q_{it} = \alpha_i + \beta_i x_{it} + \mu_{it} \tag{15}$$

$$\beta_i = F(Y, c) + \eta_i. \tag{16}$$

The analytical model predicts that all of these coefficients will be positive. To test this prediction, the β_i' s are estimated first using equation (15). The estimates of β_i' s are then used in equation (16) to estimate the opportunity coefficients, c. When equation (15) is run for each industry, the resulting estimates of β_i' s will be unbiased. If autocorrelation is present, the OLS parameter estimates are not efficient and the standard error estimates are biased. In this case, we will use maximum likelihood estimation with correction for serial correlation.

TABLE 2
OLS ESTIMATES OF ELASTICITIES BY INDUSTRIES

INDUSTRY	β_i (*t*-stat)	R^2	DW
Ordnance & Accessories	0.0823 (4.517)	0.5605	1.003
Missiles and Spacecraft	0.0896 (5.108)	0.6351	2.144
Food & Kindred Products	0.0137 (1.496)	0.1228	0.773
Plastic Materials & Other Synthetics	0.1571 (7.061)	0.7571	1.016
Agricultural Chemicals	0.1126 (6.030)	0.6944	1.007
Other Chemicals	0.0686 (3.611)	0.4491	0.794
Drugs & Medicines	0.2041(16.217)	0.9427	0.663
Petroleum Refining	0.0656 (2.114)	0.2183	0.292
Rubber & Miscellaneous Plastics	0.0856 (5.998)	0.6922	0.717
Stone Clay & Glass Products	0.0447 (5.657)	0.6676	0.930
Ferrous Metals & Products	0.0255 (1.732)	0.1578	0.779
Nonferrous Metals & Products	–0.0052 (–0.414)	0.0106	1.077
Fabricated Metals & Products	0.0206 (1.716)	0.1554	0.734
Motor Vehicles & Equipments	0.0856(10.652)	0.8764	1.914
Other Transportation Equipments	0.0664 (6.473)	0.7237	0.542
Aircraft and Parts	0.1019 (7.222)	0.7653	1.228

The ordinary least square estimates of β appear in Table 2 with the Durbin-Watson statistics, *t*-statistics, and R^2. The Durbin-Watson test at the five percent significance level shows the prevalence of serial correlation in most industries except two, the missiles and spacecraft industry and the motor vehicles and equipments industry. To produce better estimates in those industries that show serial correlation, maximum likelihood estimation with autocorrelation was done. We increased the order of autocorrelation until each Durbin-Watson statistic indicated that the null hypothesis of zero correlation could not be rejected at the five percent significance level. After the AR (1) correction, the Durbin-Watson statistics for two industries—petroleum refining, and transportation equipment (other than motor vehicles) industry—were still low. After the AR (2) correction, each Durbin-Watson statistic was high enough to accept the null hypothesis. Therefore the error structure of the equation (15) is assumed as follows:

$$\mu_{it} = \rho_1\mu_{it-1} + \rho_2\mu_{it-2} + v_{it}. \qquad (17)$$

The final result of the estimates of β_i's are summarized in Table 3. As expected, the elasticities are either positive or essentially zero. Twelve out of the sixteen industries have a significantly positive elasticity at the five percent level. The elasticity of output with respect to the knowledge stock varies from a very low number to about 0.16. Furthermore,

TABLE 3

ML WITH AR(2) ESTIMATES OF ELASTICITIES BY INDUSTRIES

Industry	β_i (t-stat)	R^2
Ordnance & Accessories	0.0803 (3.032)	0.3999
Missiles and Spacecraft	0.0899 (5.266)	0.6697
Food & Kindred Products	0.0216 (2.377)	0.3247
Plastic Materials & Other Synthetics	0.1609 (6.699)	0.7735
Agricultural Chemicals	0.1168 (5.344)	0.6830
Other Chemicals	0.0810 (5.579)	0.7143
Drugs & Medicines	0.1578 (6.117)	0.7281
Petroleum Refining	0.0687 (2.043)	0.2616
Rubber & Miscellaneous Plastics	0.0912 (7.019)	0.8081
Stone Clay & Glass Products	0.0452 (6.391)	0.7742
Ferrous Metals & Products	0.0259 (1.486)	0.1531
Nonferrous Metals & Products	−0.0108 (−0.914)	0.0572
Fabricated Metals & Products	0.0255 (1.781)	0.2236
Motor Vehicles & Equipments	0.0899 (15.961)	0.9460
Other Transportation Equipments	0.0599 (4.253)	0.6114
Aircraft and Parts	0.0969 (5.561)	0.6956

those industries with relatively high elasticities are, in general, those in which technological change has been particularly rapid: drugs, chemicals, plastics, missiles and aircraft and parts. The fit of the equation is fairly good. Some of the explanatory effect of the knowledge stock in the equations may be the result of the correlation between knowledge stock and time. If there is some other variable that also is correlated positively with time and measured *TFP*, the observed effect of the knowledge stock may be exaggerated. The four industries with insignificant β_i's seem to fall in the industry group with insignificant R&D activity or technological stagnation. Industry level R&D expenditure as a percentage of sales is presented in Table 4 to illustrate the inter-industry difference in R&D activity. In 1976, the last year of the sampling period, the R&D sales ratio varies from 0.2 percent to 8.3 percent across the industry. We applied a fixed effects model to see if the poor fit in those four industries is due to omitted variables that are industry specific and time-invariant. But the estimation result was not improved by using the fixed effects model. For those industries, the production function approach represented in equation (15) may not be an appropriate approach to explain the variance in total factor productivity.

To see the effect of technological opportunity on the elasticity of output, regression was run of the form:

TABLE 4
R&D/SALES RATIO BY INDUSTRIES(%)

Industry	1975	1976
Ordnance & Accessories	1.5	1.7
Missiles and Spacecraft	1.9	2.3
Food & Kindred Products	0.4	0.5
Plastic Materials & Other Synthetics	3.7	3.5
Agricultural Chemicals	2.6	2.8
Other Chemicals	2.1	2.0
Drugs & Medicines	8.7	8.3
Petroleum Refining	0.2	0.2
Rubber & Miscellaneous Plastics	2.3	1.8
Stone Clay & Glass Products	1.4	1.3
Ferrous Metals & Products	0.4	0.4
Nonferrous Metals & Products	0.7	0.7
Fabricated Metals & Products	1.1	1.3
Motor Vehicles & Equipments	1.8	1.4
Other Transportation Equipments	0.7	0.8
Aircraft and Parts	5.7	5.5

Source: Aggregation of the FTC line of business data to the level consistent with other data in the analysis.

$$b_i = F(Y, c) + \varepsilon_i, \tag{18}$$

where b_i is the estimate of β_i, $Y = (Y_{i1}, Y_{i2}, \ldots Y_{i6})$ and $c = (c_0, c_1, c_2, \ldots c_6)$. The error term ε_i contains the error term η_i from equation (16) and the error introduced by using an estimate of β as the left hand variable. Thus, the error in equation (18) might be heteroskedastic. Both White and Breusch-Pagan tests of heteroskedasticity were run. But these tests do not reject the null hypothesis of homoscedasticity at the 5% level. The OLS estimates of the opportunity variables are reported in Tabel 5. The fit of the equation is reasonably good, suggesting that the opportunity variables explain a substantial proportion of the variance in the elasticity. The estimates generally support the predictions of the analytical model. The coefficients on y_1 (basic sciences) and y_4 (product trajectory) are significantly positive. The coefficient on y_2 (applied sciences), y_3 (process trajectory), y_5 (government research), and y_6 (university research) are not significantly different from zero. The insignificant coefficients on these four opportunity variables could be the result of collinearity among the regressors. A detailed analysis including the eigenvalues of the $Y'Y$ matrix, condition indices, and the decomposition of the variances of estimates with respect to each eigenvalue indi-

TABLE 5
TECHNOLOGICAL OPPORTUNITY COEFFICIENTS

Variable	Coefficient	(*t*-stat)	
Intercept	−0.3171	(−2.269)	
y_1	0.0373	(2.891)	
y_2	0.0057	(0.411)	
y_3	−0.0412	(−1.986)	$R^2 = 0.7802$
y_4	0.0602	(3.133)	
y_5	−0.0104	(−0.698)	
y_6	0.0219	(1.188)	

TABLE 6
COLLINEARITY DIAGNOSTICS FOR THE OPPORTUNITY REGRESSION

Eigenvalue	Condition Number	Variance Decomposition						
		intercept	y_1	y_2	y_3	y_4	y_5	y_6
6.834	1.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000
0.118	7.591	0.002	0.001	0.003	0.003	0.003	0.094	0.031
0.026	16.282	0.000	0.044	0.008	0.000	0.002	0.299	0.226
0.010	25.821	0.043	0.473	0.002	0.012	0.035	0.100	0.199
0.006	33.688	0.014	0.057	0.828	0.000	0.170	0.010	0.003
0.003	43.547	0.019	0.276	0.156	0.665	0.196	0.097	0.012
0.002	65.651	0.923	0.149	0.003	0.319	0.574	0.399	0.528

TABLE 7
PEARSON CORRELATION COEFFICIENTS AMONG OPPORTUNITY VARIABLES

	y_1	y_2	y_3	y_4	y_5	y_6
y_1	1.00	0.32	0.53	0.02	0.37	0.46
y_2	0.32	1.00	0.42	0.34	0.36	0.14
y_3	0.53	0.42	1.00	0.19	0.09	−0.02
y_4	0.02	0.34	0.19	1.00	0.22	−0.20
y_5	0.37	0.36	0.09	0.22	1.00	0.79
y_6	0.46	0.14	−0.02	−0.20	0.79	1.00

cates linear dependencies among the y_i' s. The collinearity diagnostics are reported in Table 6. The range of the condition numbers indicates serious collinearity problems. The Pearson correlation coefficients reported in Table 7 further confirms the presence of collinearity. There are high correlations, especially between y_1 and y_3, and between y_5 and y_6; the null hypothesis of zero correlation was rejected at the five percent level for those two pairs. It is not surprising to discover multicollinearity among the opportunity variables since they measure different aspects of the same general phenomenon.

We used a linear function for $F(*)$ in the above estimation of equation (16), and therefore implicitly assumed separability of effects of opportunity variables on R&D productivity. One might want to do nonlinear regression assuming an 'ad hoc' functional form for $F(*)$. Instead of using an arbitrary nonlinear function, we would rather introduce a factor analysis to surmount the multicollinearity problem and to test the robustness of the positive relationship between R&D productivity and technological opportunity. Using the technological opportunity data to the level of the individual respondent, the six opportunity variables can be insightfully condensed to two principal components. The weights associated with the first two principal components are presented in Table 8. The table clearly shows that the first principal component gives substantial weights to y_5 and y_6, and also to y_1 and y_2; the weighting is reversed for the second principal component. The straightforward interpretation of the first two principal components would be, respectively, the technological opportunity reflected in research activity "outside the firm," and that embodied in the "innovation history of the firm." As Table 8 show, the first two components explain 54 percent for the variance in the six opportunity variables. For the investigation of R&D productivity, we need to calculate standardized principal component scores for each respondent and aggregate them to the industry level of the analysis. When b is regressed on the first two principal components, the coefficients of the "outside the firm" opportunity regressor is fairly high in absolute level, and also is significantly positive, as expected. But the regressor that represents the technological opportunity embodied in the "innovation history" is insignificant. When we consider the fact that the two components explain only 54 percent of the variance in the six opportunity variables, it is plausible that other aspects of technological opportunity are left out from the regression, hence the estimates may be overestimated. However, the results of the principal component analysis suggest a certain robustness in the productivity relationship to technological opportunity as determined by research activity outside the firm.

Finally, to see the importance of the spillover effect in the R&D productivity relationship, we repeat the same regressions performed in this paper, using an alternative proxy of the service flow of the knowledge stock. If we assume zero spillover effect, X would be the same as own industry R&D, R_{it}. The results of the estimation using R_{it} is almost

TABLE 8
PRINCIPAL COMPONENTS ANALYSIS OF TECHNOLOGICAL OPPORTUNITY

	Coefficients of	
	1st Prin. Comp.	2nd Prin. Comp.
y_1 Basic Science Relevance	0.60	0.16
y_2 Applied Science Relevance	0.64	0.11
y_3 Process Trajectory	0.36	0.64
y_4 Product Trajectory	0.25	0.66
y_5 Contribution of the Government	0.73	−0.40
y_6 Contribution of Universities	0.74	−0.38
Cumulative Variance Explained	0.34	0.54

the same as those with X_{it}. Using X_{it}, instead of R_{it} doesn't improve the regression results significantly.

The similarity in the coefficients of X_{it} and R_{it} seems to come from the high correlation between own R&D and others' R&D. We also estimated the equation (10) rewritten here as:

$$q_{it} = a_i + \delta_i R_{it} + \delta_j \sum_{i \neq j} \theta_{jt} R_{jt} + \mu_{it}. \tag{19}$$

Estimating the coefficients δ_i and δ_j, we observed the multicollinearity again.

The similarity in coefficients of X_{it} and R_{it} probably reflects the fact that an industry in rapid technological change both invests more in R&D and receives greater spillover from upstream industries. These results suggest that the information in the spillover term is embodied in its own industry R&D. Knowledge stock itself can be an input into production but it might not be separated conceptually into knowledge attained in its own industry and knowledge transferred from other industries.

Another way to investigate the significance of inter-industry technological flow in explaining output elasticity is to test a hypothesis that product R&D explains more of the productivity improvement than process R&D. This originates from the idea that product R&D is relatively more relevant to the inter-industry spillover effect than is process R&D. We ran three regressions: (i) correlate of *TFP* to product R&D, (ii) correlate of *TFP* to process R&D, and (iii) correlate of *TFP* to both product and process R&D. The result is that process R&D explains more of the variation in *TFP* than does product R&D. Thus, the evidence for R&D spillover effects remains tenuous.

V. Conclusion

Estimation results confirm the positive relationship between the flow of services from the R&D stock and the productivity of traditional inputs. To investigate the role of technological opportunity for productivity improvement, we used a two stage estimation method and a principal component analysis, and other auxiliary analyses of data characteristics. The analytical results were also in favor of the general hypothesis that a given level of investment in knowledge stock will have a greater effect in industries with relatively rich technological opportunities. Findings on the technological opportunity relationship are encouraging in general, but they also need to be interpreted carefully, because of the presence of substantial measurement errors in the survey data and in the proxy of the service flow of the knowledge stock, aside from other problems involved in the inconsistency between theoretical concepts and the data. The level of aggregation and the assumption of time invariance for the opportunity variables are also troublesome. Aggregation to the industry level consistent with time series data creates a considerable intra-industry variation in the relevant variables. If the opportunity variables have changed substantially over the sample period, it is not clear how the estimation results of coefficients are to be interpreted. However, these results do represent one of only a few attempts at measuring the effects of the opportunity variables that are conceptually interesting and empirically important but have been treated as ill-defined residual variations.

Using several different approaches, we attempted to verify the importance of inter-industry technological spillover in explaining output elasticity and to examine the significance of its conceptual distinction from own industry research. But the empirical significance of the spillover effects could not be established. The results suggest that the information in the spillover term is embodied in its own R&D. As Evenson and Kislev (1973) and Mowery (1983) observed, firms that invest in their own R&D are more capable of exploiting knowledge spillovers from external sources.

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