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During the 1970s, the United States experienced a sharp decline in the rate of growth of industrial productivity. Had productivity in the private business sector continued to grow at its average 1947-68 rate, output per worker hour in 1980 would have been 21 percent greater than the actually measured value. Numerous explanations for the productivity growth slump have been advanced. Denison's argument (1980) that the causes were complex and multi-faceted is well taken. This paper is nevertheless concerned primarily with a single explanatory variable, industrial research and development (R&D) expenditure, whose role is particularly poorly understood.

One reason why R&D is of special interest in the productivity puzzle is that its growth slowed shortly before the protracted productivity growth decline. Had real (i.e., GNP deflator-adjusted) privately-financed industrial R&D spending continued to grow at 1960s trend rates following a peak in 1969, real 1979 outlays would have been roughly 50 percent higher than

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their actually observed values. The slowdown in R&D spending appears to have been a reaction to a fall in the profitability of R&D,[1] which in turn may have been associated with diminished productivity impacts.

Despite a considerable amount of research, the links between R&D and productivity growth are poorly understood. There are two main reasons. First, the "R&D" done by industrial corporations consists of two rather different things -- work on new and improved internal production processes that should have a direct impact on productivity within the firm performing the R&D, and work on new or improved products sold to other enterprises or consumers. Except in extreme and implausible cases, at least some benefits from product R&D are passed on to those who buy the products, and if the forces of competition are strong, most of the productivity-enhancing benefits will be passed on. Product R&D should be associated with productivity growth in the industry performing the R&D only if there are increases in monopoly power as a consequence of the R&D or certain errors in measuring productivity.[2] Since roughly three-fourths of all industrial R&D is directed toward product innovation and improvement,[3] to assume that R&D in industry i leads to productivity growth in industry i is likely to entail serious specification error. Second, the data available for testing R&D - productivity hypotheses leave much to be desired. A distinction between product and process research is seldom made; the most comprehensive and consistent data are published by the National Science Foundation only at a high level of aggregation; and until recently, R&D data were collected only for whole companies, with no reliable disaggregation across the various lines of business in which a company operates. As an example of this last point, R&D conducted by General Motors on earth-moving equipment, diesel locomotives, and missile guidance systems would be lumped together with GM's motor vehicle work for reporting purposes. Since the average manufacturing company in 1972 had a third of its employment outside its primary line of business,[4] the mismeasurement associated with the whole-company approach to R&D data collection could be quite serious.[5]

I. Technology Flow and Productivity Data

In an attempt to overcome these problems and shed new light on the links between R&D and productivity growth, a novel and unusually rich data set was developed. The starting point was the Federal Trade Commission's 1974 Line of Business survey, which obtained inter alia from 443 large U. S. corporations data on applied research and development expenditures broken down into some 262 manufacturing "lines of business" (LBs), typically at the four- or three-digit SIC level, along with 14 nonmanufacturing LBs. Data for both privately-financed and contract (mostly Federal) R&D were available. After inflation by industry sales coverage ratios that ranged from 6 to 99 percent, the sample's 1974 private R&D outlays of $10.6 billion totalled $14.7 billion, which corresponds almost exactly with the analogous aggregate figure from National Science Foundation surveys.

Linked to the R&D expenditure data were 15,112 U.S. invention patents issued to the same corporations during an appropriately lagged ten-month period in 1976 and 1977. Each such patent was individually examined to determine inter alia the industry of origin (on the basis of which the R&D link was effected), the industry(ies) in which use of the invention was anticipated, whether the invention entailed a process internal to the originating firm or a product to be sold externally, and whether the invention's subject matter was better characterized as capital goods or materials technology. Once this was done, the linked R&D associated with each invention was flowed through a novel kind of input-output matrix from industries of origin to as many as 287 industries of use (including personal consumption).[6] R&D dollars for inventions of widespread or general use (such as more versatile adhesives or general-purpose computers) were flowed out to using industries in proportion to the sales of the origin industry to other industries, as ascertained from the 1972 U.S. input-output tables, modified to integrate capital formation with current transactions and to deal with numerous other special problems encountered in measuring inter-industry technology flows. Taking row and column sums, the end result was a set of vectors tracing R&D (as well as several subdivisions thereof) to any of 263 industries in which it originated and 287 industries in which its use was anticipated.

To minimize the likelihood of spurious inferences despite well-known measurement difficulties, three quite differently compiled productivity data sets were analyzed. One, which has been used in several other R&D studies, is the set of two-digit manufacturing industry productivity indices originally compiled by John Kendrick and updated by Kendrick and Grossman.[7] A second set is the Bureau of Labor Statistics series published annually under the title, Productivity Indexes for Selected Industries. Those indices of output per labor hour are based primarily upon physical output quantities with fixed period (usually employment) weights. As such, the series is limited in coverage, but is believed to be of particularly high quality. Matches between my industry definitions and the series (hereafter, the BLSPQ series) were achieved for 37 manufacturing industries originating 29 percent of total 1974 manufacturing value added [8] and four nonmanufacturing industries -- coal mining, railroads, air transport, and telephone communications. However, the nonmanufacturing industries had to be omitted from many analyses because comparable capital stock data could not be obtained. The third data set, blending disaggregative detail with comprehensiveness, comes from a new Bureau of Labor Statistics series organized according to input-output industry definitions (for which reason it will be called the BLSIO series).[9] It includes 81 manufacturing branches originating 94 percent of 1973 manufacturing sector output plus six nonmanufacturing sectors -- agriculture, crude oil and gas production, railroads, air transport, communications, and the combined electric - gas - sanitary utilities sector. Seven other nonmanufacturing sectors (metal mining, coal mining, other mineral mining, local transit, trucking, water transportation, and pipelines) were included in some analyses despite incomplete capital stock data. Other sectors were excluded because of inadequate data matches or patently deficient productivity measurements. The BLSIO productivity indices are measured by taking total industry output value and deflating it by the most closely corresponding industry price indices.

II. The Theory

The theory underlying the analyses that follow is in most respects conventional. We assume a production function of the Cobb-Douglas variety:

$$(1) \quad Q_{it} = \phi e^{\lambda t} R_{it}^{\delta} K_{it}^{\alpha} L_{it}^{\beta} M_{it}^{\gamma} \epsilon_{it},$$

where Q_{it} is the output of the i^{th} industry in period t, R is some measure of the R&D capital stock, K is the capital stock, L is labor input, M is materials usage, λ is an exogenous shift variable, and ϵ is an error term. Since most of our productivity data are in terms of output per unit of labor rather than total factor usage, we can, assuming that $\alpha + \beta + \gamma = 1$ and suppressing subscripts, write:

$$(2) \quad \left(\frac{Q}{L}\right) = \phi e^{\lambda t} R^{\delta} \left(\frac{K}{L}\right)^{\alpha} \left(\frac{M}{L}\right)^{\gamma} \epsilon.$$

Taking logarithms and differentiating with respect to time, we obtain:

$$(3)\quad \Delta LP = \lambda + \delta\Delta R + \alpha\Delta\kappa + \gamma\Delta m + \ln\epsilon ,$$

where ΔR is the percentage change in the R&D stock (i.e., $\dot{R}/R \times 100$), ΔLP is the percentage change in labor productivity, other Δ variables are similarly defined, $\kappa = K/L$, and $m = M/L$. For the R&D variable, we have no stock data, but only 1974 expenditures. Noting that $\delta = \frac{\partial Q}{\partial R} \frac{R}{Q}$, Terleckyj (1974) has shown that the R&D term can be rewritten $\frac{\partial Q}{\partial R} \frac{\dot{R}}{Q}$, where the first ratio is the marginal product of R&D, which can be estimated as a regression coefficient. On the further assumption that the R&D stock depreciates only slowly, $\dot{R}$ is approximated by the flow of R&D in a given time period, e.g., a single year, as in our data set. Thus $\dot{R}/Q$ becomes the ratio of 1974 R&D expenditures RE to 1974 dollar output (or value added for the Kendrick and BLSPQ regressions). We therefore estimate:

$$(4)\quad \Delta LP = \lambda + \left(\frac{\partial Q}{\partial R}\right)\left(\frac{RE}{Q}\right) + \alpha\Delta\kappa + \gamma\Delta m + \ln\epsilon .$$

Since reliable data on Δm were not available, γ cannot be estimated and we shall have an omitted variable problem (or, since other relevant variables are surely omitted, an additional problem).

The availability of cross-sectional R&D data for only a single year poses a further challenge. We wish to estimate the impact of R&D on productivity growth and also to test whether the fall in productivity growth during the 1970s might have come in part from a decrease in the fecundity of R&D -- e.g., because the stock of promising technical opportunities became depleted or because new technologies of the early 1970s were less than optimally suited to the altered economic environment of the late 1970s. The impact of 1974 R&D on productivity can be expected to occur with a lag of at least several years.[10] Given data constraints and the need to minimize the impact of business cycle disturbances, the best approximation attainable to a correct lag was to measure productivity changes between 1973 and 1978, both business cycle peak years.[11]

To test whether the fecundity of R&D declined, we employ what can be called a "wrong lag" hypothesis. The intensity of R&D performance by industries of origin has been quite stable over time. For 15 broadly-defined manufacturing industry groups on which comparable National Science Foundation survey data are available, the simple correlation between privately-financed R&D / sales ratios is 0.98 for the years 1973 and 1963 and 0.90 for 1973 and 1958. Assuming without direct quantitative evidence that there has also been gross stability of R&D <u>use</u> patterns over time, the "wrong lag" hypothesis predicts that one will also observe a positive association between 1974 R&D flows and productivity growth during the 1960s. To be sure, there will be more mismeasurement of these "wrong lag" relationships, so the associations should be weaker than for a correctly specified lag relationship. Stronger associations in "wrong lag" regressions than in "correct lag" regressions can be interpreted as evidence of a breakdown in the ability of industrial R&D to drive productivity growth.

With this in mind, the principal "wrong lag" period was defined as 1964-1969. This five-year interval terminates with an end-of-the-year business cycle peak, maximizing comparability with the "correct lag" period.

III. Two-Digit Manufacturing Group Results

The relationship between R&D and productivity growth in two-digit manufacturing industry groups, as measured by Kendrick and Grossman, has been examined by a number of scholars.[12] Table 1 presents a comparable analysis. Equations 1.1 through 1.4 take total factor productivity growth as the dependent variable. Two results stand out. First, for the long "wrong lag" 1948-66 period emphasized in most prior studies, R&D variables have significant explanatory power. Of the two, R&D flowed through to industries of use (USERD) is more powerful than R&D classified by industry of origin (ORGRD). In a multiple regression with both variables (not shown), R^2 rises to 0.497 and USERD plays the dominant role while ORGRD falls to insignificance. Second, strong support emerges for the "wrong lag" hypothesis. Both variables lose their explanatory power for the 1973-78 period, with r^2 values indistinguishable from zero to three digits. This result, which is consistent with similar findings by Kendrick and Grossman (1980, pp. 109-111) and Terleckyj (1980), suggests that something went wrong with the linkages between R&D and productivity growth during the 1970s.

Table 1. Two-Digit Manufacturing Group Regressions Using Kendrick-Grossman Data (N = 20)

Regression Number	Dependent Variable Measure	Period	Constant	R&D Coefficients# ORGRD	R&D Coefficients# USERD	r^2
1.1	ΔTFP	1948-66	2.52	0.194* (2.24)		.218
1.2	ΔTFP	1948-66	1.70		0.872** (3.79)	.444
1.3	ΔTFP	1973-78	0.86	0.001 (0.91)		.000
1.4	ΔTFP	1973-78	0.82		0.038 (0.07)	.000
1.5	ΔLP	1948-66	2.54	0.190 (1.64)		.130
1.6	ΔLP	1948-66	1.85		0.878** (2.64)	.279
1.7	ΔLP	1964-69	1.75	0.210 (1.61)		.126
1.8	ΔLP	1964-69	1.78		0.359 (0.83)	.037

#All R&D variables are divided by 1974 industry group value added. t-ratios are given in subscripted parentheses.

*Statistically significant in one-tail test at the .05 level.

**Statistically significant in one-tail test at the .01 level.

To facilitate comparison with later analyses using labor productivity ΔLP as dependent variable, four additional regressions are presented in Table 1.[13] For 1948-66, the results are quite similar to their total factor productivity counterparts, except with somewhat lower r^2 values.[14] Regressions 1.7 and 1.8 reveal a deterioration of the relationship when the shorter and later "wrong lag" period used in subsequent analyses is substituted as dependent variable. By 1973-78 (not explicitly reported), the labor productivity results are virtually identical to those of regressions 1.3 and 1.4. The r^2 values are 0.006 for ORGRD (with a negative coefficient sign) and 0.000 for USERD.

IV. Disaggregated Data Results

We turn now to the disaggregated productivity data sets BLSIO and BLSPQ. Since one objective is to investigate the links between R&D and the productivity growth slump of the 1970s, it is useful to examine the slump's magnitude in the context of our samples. We must also anticipate a potential problem. The BLSIO productivity data are based upon price index-deflated output value statistics. As such, they can be no more reliable than the deflators used. Before any regressions were run, the Producer and Consumer Price Index manuals were consulted to separate the sample into two parts -- industries for which the price deflators were reasonably comprehensive and those for which they were not. Although other things can also go wrong in measuring real output, the main BLSIO sample (excluding industries without complete capital stock indices) was divided on the basis of this analysis into two subsets: 51 industries with "well-measured" and 36 with "poorly measured" productivity indices. Simple averages of annual labor productivity growth indices for the full BLSIO sample, its two subsets, and the BLSPQ sample are as follows:

	ΔLP64-69	ΔLP73-78	Percentage Drop
Full BLSIO sample	2.81 %	2.03 %	27.7 %
Well-measured subset	2.53	1.93	23.5
Poorly-measured subset	3.21	2.18	32.2
BLSPQ sample	2.99	2.54	15.0

Although the BLSIO subsample means are not significantly different from one another for either period,[15] there is at least a suggestion that measured productivity growth fell more in the 1970s, the less well-measured the productivity indices were.[16] This complication will reappear in a different context shortly.

The data developed through our patent - R&D - input-output flows link are extraordinarily rich. They make it possible to examine a number of hitherto unexplored questions. Four require immediate attention before further analysis can proceed. First, it is hypothesized that R&D dollar measures explain productivity growth better than raw invention patent counts. Second, as indicated earlier, R&D dollars flowed out to industries of use are expected to explain productivity growth better than R&D dollars assigned to industries of origin.[17] Third, in flowing indicia of technological advance out to using industries, a difficult conceptual problem had to be solved. When there is more than one industry of use, should the invention or its accompanying R&D dollars be treated as a public good, with use by industry j not diminishing the dollars or patents used by industry k, or should they be treated as private goods, with industry of use values summing to equal origin industry values? Both concepts were implemented, the public goods assumption by letting the largest using industry have unit weight and scaling down all smaller using industries by the ratio of their purchases from the origin industry to the largest using industry's purchases.[18] Which concept is preferred, public or private goods, was left an open hypothesis. Fourth, for certain component inventions such as new large-scale integrated circuits, one might suppose that the main productivity benefits will accrue not, e.g., to the computer manufacturers who buy them, but to the computer users who buy the computers embodying the improved components. For all or part of 22 component-supplying industries, use vectors were computed incorporating such second-order (and in selected cases third-order) flow relationships as an alternative to first-order technology flow indices.

Table 2 presents a set of results on the basis of which three of these hypotheses were resolved. Listed for six alternative technology flow indices[19] are simple correlations with 1973-78 productivity growth for both the BLSPQ and 87 industry BLSIO sample as well as t-ratios for the technology flow variables in multiple regressions with a 1973-78 gross

Table 3. PRODRD and USERD1 Multiple Regressions, BLSIO and BLSPQ Samples

Regression Number	Sample	Number of Industries	Time Period for Dependent Variable ΔLP	Constant	Δ(K/L)	R&D Variable Coefficients PRODRD	R&D Variable Coefficients USERD1	R^2
3.1	BLSIO:A	87	1973-78	-.142	.347** (3.30)	.289* (2.01)	.742* (1.89)	.193
3.2	BLSIO:A	87	1964-69	1.90	.149* (2.01)	.133 (1.05)	.643* (1.84)	.118
3.3	BLSIO:C	51	1973-78	-.162	.400** (2.90)	-.182 (0.54)	1.039** (2.53)	.241
3.4	BLSIO:C	51	1964-69	1.09	.309* (2.27)	.095 (0.35)	.741* (2.06)	.260
3.5	BLSIO:S	36	1973-78	.084	.310* (1.82)	.431* (2.10)	.096 (0.10)	.197
3.6	BLSIO:S	36	1964-69	2.94	.161 (1.52)	.071 (0.39)	.049 (0.06)	.074
3.7	BLSPQ#	37	1973-78	-1.50	.268* (2.05)	.089 (0.46)	.711* (2.03)	.247
3.8	BLSPQ#	37	1964-69	2.43	-.041 (0.30)	.051 (0.34)	.401 (1.42)	.086

#Four nonmanufacturing industries (coal mining, railroads, air transport, and telecommunications) are deleted owing to the lack of capital stock measures. Results for the sample including nonmanufacturing, but without capital/labor variables, are similar to those reported here.

capital stock / labor ratio change variable also included. We see that the patent count and public good R&D use variables are dominated by their private good R&D dollar counterparts.[20] Thus, patent count and public goods variables will be excluded from further analyses. In the Table 2 regressions and others, the USERD2 variable (i.e., without second-order component flows) weakly but consistently outperformed USERD1. However, because the a priori grounds for favoring second-order component flows are strong, only variables embodying such flows will be used in subsequent analyses.[21]

The relative strength of ORGRD vs. USERD variables varies with the samples. This ambiguity persists in multiple regressions including both variables. USERD1 has higher t-ratios than ORGRD for both 1973-78 and 1964-69 with the BLSPQ sample and for 1964-69 with BLSIO, but ORGRD dominates with BLSIO for 1973-78. However, only the 1973-78 BLSIO ORGRD coefficient is statistically significant at the 5 percent level. Nonsignificance of the other R&D coefficients is attributable in part to multicollinearity, since both ORGRD and USERD contain in common the process (i.e., internally used) component of firms' R&D. A more precise insight is obtained by focusing on the variables USERD1 (encompassing both internal process R&D and R&D "imported" through product purchases from other industries) and PRODRD, representing originating firms' R&D on products sold to others.[22] This split is implemented in the multiple regressions of Table 3. Both the correct and wrong lag periods are covered for the BLSIO and

Table 2. Simple Correlations and Partial Regression Coefficient t-ratios for Selected Technology Flow Variables, 1973-78; Labor Productivity Growth Rate as Dependent Variable

Variable and Description	Simple r, BLSPQ Sample, N = 41#	BLSIO Sample, N = 87: Simple r	BLSIO Sample, N = 87: t-ratio with $\Delta(K/L)$ also included
ORGRD: R&D by industry of origin	.238	.260**	2.61**
ORGPAT: Patent count by industry of origin	.181	.161	1.78*
USERD1: R&D by industry of use, private goods, with second-order component flows	.374**	.223*	2.35*
USERD2: R&D by industry of use, private goods, without second-order component flows	.385**	.249**	2.60**
USEPUB1: R&D by industry of use, public goods assumption, with second-order component flows	.247	.160	1.92*
USEPAT1: Patent count by industry of use, private goods, with second-order component flows	.238	.130	1.38

#Includes four nonmanufacturing industries.

*Statistically significant in one-tail test at the .05 level.

**Statistically significant in one-tail test at the .01 level.

BLSPQ samples. The BLSIO sample is also subdivided into groups of industries with well-measured output deflators (BLSIO:W) and with poorly-measured deflators (BLSIO:P).

Several points stand out. First, in sharp contrast to the results with aggregated Kendrick-Grossman data, there is no clear support for the wrong lag hypothesis.[23] For both full samples and one of the two BLSIO subsamples, R^2 values and R&D regression coefficient values are larger for the 1973-78 period than for the "wrong lag" 1964-69 period, and for exceptional BLSIO:W equations, the differences are small. In all four 1973-78 regressions, there is at least one significant R&D coefficient. It must follow that the 1970s productivity slump did not result from a deterioration of the fecundity of industrial R&D,[24] or errors of measurement rise sharply when the "wrong lag" hypothesis is tested.

In principle, one would not expect to find a significant relationship between <u>product</u> R&D and productivity growth unless there are rising price/cost margins associated with monopoly power and/or mismeasurement. That expectation is confirmed for all but two of the regressions in Table 3. Of the two exceptions, regression 3.5, for the industries with poorly-measured price deflators, is the stronger.[25] Its significant product R&D effect in turn dominates the PRODRD coefficient of full-sample regression 3.1, for when the subset of well-measured industries is broken out (regression 3.3), the PRODRD coefficient becomes negative but insignificant. The poorly-measured subset, it will be recalled, also experienced the sharpest productivity growth rate drop in the 1970s. A plausible explanation for the PRODRD variable's performance in regression 3.5 is productivity measurement error, although variations in the degree of monopoly power exercised in pricing new products cannot be ruled out. It is in any event clear and important that for samples with reasonably well-measured productivity, product R&D conforms to the prediction of having no significant productivity effect.

Even those regressions in Table 3 with the greatest explanatory power (notably, those using the best-measured productivity data) exhibit considerable noise. Nothing like the r^2 of 0.44 obtained with aggregated Kendrick 1948-66 TFP data is obtained. One apparent contributor to the relatively low degree of variance explanation is measurement error associated with the shortness of the time periods over which productivity growth is analyzed. When annual productivity growth over the 14-year 1964-78 period is taken as dependent variable, R^2 rises to 0.299 and 0.330 in the analogues of regressions 3.1 and 3.3.[26] Evidently, productivity growth does not follow from R&D in any tightly deterministic way, or both our dependent and independent variables suffer from considerable measurement error. Both inferences are probably apt.

From equation (4), it can be seen that regression coefficients on the R&D variables can be interpreted as steady-state marginal returns on investment in research and development. There are, however, several interpretational problems. For one, the BLSIO and BLSPQ R&D coefficients have different denominators -- output value and value added, respectively, with the former being roughly twice as large on average as the latter. A larger denominator forces the regression coefficient and hence the estimated rate of return to be larger, all else equal. It is not certain a priori which denominator is preferable in general, although with BLSIO output measurement in gross terms, the use of a gross output denominator appears clearly warranted. A related problem is the omission of a material input growth variable. If real material input growth were positively correlated with used R&D, the latter's coefficient is likely to be biased upward, especially with a gross output denominator.[27] Grounds for doubting the existence of such a positive correlation, at least with the BLSIO sample, will be presented shortly. Errors in measuring the R&D variables are likely to bias R&D coefficient estimates downward, while the assumption of fixed effects when a random coefficients approach, if implementable, might be more appropriate, leads to inefficient estimates.[28] For one more complication, productivity growth in the 1973-78 period undoubtedly reflects the effects of R&D in years prior to 1974 to some extent. R&D was clearly not experiencing steady-state growth during the early 1970s. With U. S. industrial R&D/sales ratios falling from a 1970 peak, this implies a modest upward bias in the rate of return estimates.

In view of these problems, the most that can be said is that the social rate of return on R&D investment during the 1970s was probably quite high. From the USERD coefficients alone, it appears to have been somewhere in the range of 70 to 100 percent. Returns trapped as monopoly rents by product innovators appear to have added as much as 40 percent, but probably a good deal less, to the total.

As noted earlier, the R&D covered by USERD1 consists of both process research done by firms to improve their own production operations and technology "imported" across industry lines (i.e., the off-diagonal column element sums in a technology flows matrix). Our data permit a decomposition of USERD1 into these two components PROCRD and OUTRD. For the full BLSIO sample, the well-measured subsample, and the BLSPQ sample, the most interesting coefficient estimates on 1973-78 productivity growth, t-ratios (in parentheses), and increases in R^2 relative to the analogous Table 3 regressions are as follows:

Sample	PRODRD	PROCRD	OUTRD	Change in R^2
BLSIO:A	.321* (2.20)	.368 (0.74)	1.472* (2.04)	0.014
BLSIO:W	-.154 (0.44)	.932 (1.60)	1.184* (1.71)	0.001
BLSPQ	.076 (0.38)	.648 (1.49)	.874 (1.19)	0.002

The decomposition provides very little new explanatory power; even for the BLSIO:A regression, the incremental F-ratio is only 1.45. The estimates are also imprecise. Yet the decomposed coefficient values are both plausible and imply substantial social returns to both process R&D and R&D embodied in products purchased from other industries.

Also available was a variable FEDRD measuring contract R&D (mainly from Federal government contracts) devoted to internal process improvement or embodied in products purchased by sample industries. This contract R&D was flowed through to using industries only on the public goods assumption, which complicates the interpretation of regression coefficients as rates of return. The results from introducing this variable into productivity regressions were erratic. The simple correlations between FEDRD and productivity growth were in some cases high, especially for the wrong lag 1964-69 period.[29] However, substantial values of FEDRD were concentrated in a very few defense-oriented manufacturing industries along with airlines, and when FEDRD was included in multiple regressions, it usually faded to statistical insignificance despite coefficient values ranging as high as 2.00 to 4.00. Thus, no solidly-based conclusions concerning the impact of Federal R&D on productivity growth appear warranted.

V. The Embodiment Hypothesis and Federal Regulation

There is a substantial literature on the question of whether technological progress is "disembodied," as implied in equations (1)-(4) above, or whether it is embodied in the capital equipment firms acquire or modify through non-R&D investment outlays.[30] Our technology flow data permitted a series of embodiment hypothesis tests. They are most easily

Quite apart from the role of R&D, it was hypothesized that productivity growth would be explained better using capital/labor change variables whose capital change component emphasizes gross additions to the capital stock, that is, new investment without deductions for retirements or depreciation.[31] The reason for favoring this capital/labor change index, which we shall now call ΔINV, is that the embodiment of new technology, measured or unmeasured, is directly proportional to the amount of new investment. Substituting ΔINV into 1973-78 productivity regressions with ORGRD and USERD1 as other explanatory variables led to R^2 increases of 0.025 and 0.082 in the 87 industry BLSIO and 37 industry (manufacturing only) BLSPQ samples respectively. For the well-measured BLSIO sample, there was a slight decline of 0.002. Because of the preponderantly superior performance of the ΔINV capital/labor variable and for other reasons that will become clear, we use it in the remaining embodiment tests.

Our next step is to replace USERD1 with variables better suited to testing the embodiment hypothesis. Specifically, USERD1 was broken into two mutually exclusive and exhaustive compoments, USECAP, which accounts for process or imported R&D pertaining to capital goods, and USEMAT, which measures materials-oriented used R&D. Regressions 4.1-4.3 introduce USECAP only.[32] For the full BLSIO sample, R^2 jumps by 0.034 relative to regression 3.1 or by 0.010 relative to a regression with ΔINV, USERD1, and PRODRD as variables. For the well-measured subset, the R^2 increase is 0.057 relative to a regression with USERD1, ΔINV, and PRODRD. However, for the BLSPQ sample, R^2

Table 4. Embodiment Hypothesis Test Regressions, 1973-78 Only

ression Number	Sample	N	Capital Stock Variable	ΔK/L Coefficient	R&D Variable Coefficients PRODRD	USECAP	USEMAT	μ	R^2
4.1	BLSIO:A	87	ΔINV	.431** (3.84)	.287* (2.02)	1.017* (2.36)			.227
4.2	BLSIO:W	51	ΔINV	.473** (3.19)	-.134 (0.42)	1.542** (3.44)			.296
4.3	BLSPQ	37	ΔINV	.272* (2.03)	.129 (0.66)	.728 (1.62)			.216
4.4	BLSIO:A	87	ΔINV	.438** (3.85)	.280* (1.96)	1.067** (2.40)	-.676 (0.49)		.230
4.5	BLSIO:W	51	ΔINV	.502** (3.40)	-.077 (0.24)	1.689** (3.73)	-1.98 (1.51)		.329
4.6	BLSPQ	37	ΔINV	.267* (2.00)	.081 (0.41)	.593 (1.29)	1.013 (1.23)		.251
4.7	BLSIO:A	87	Nonlinear USECAP embodied	.464** (4.00)	.313* (2.21)	.741* (1.74)		.100	.237
4.8	BLSIO:W	51	Nonlinear USECAP embodied	.519** (3.39)	-.074 (0.24)	1.192 (2.70)		.115	.311
4.9	BLSIO:A	87	ΔINV(1-E)	.445** (3.94)	.288* (2.03)	1.056** (2.45)			.233
4.10	BLSIO:W	51	ΔINV(1-E)	.485** (3.28)	-.098 (0.31)	1.547** (3.47)			.302
4.11	BLSIO:A	87	Nonlinear embodied ΔINV(1-E)	.487** (4.14)	.322* (2.28)	.696 (1.64)		.130	.246
4.12	BLSIO:W	51	Nonlinear embodied ΔINV(1-E)	.553** (3.57)	-.014 (0.31)	1.085** (2.46)		.150	.326

the materials R&D variable is added in regressions 4.4-4.6, it has an unexpected negative sign and is insignificant with the BLSIO samples. It is positive but insignificant with the BLSPQ sample, also causing the USECAP coefficient to drop into insignificance. Given the differences in results between samples, support for the embodiment hypothesis from the introduction of USECAP must be considered equivocal.

The next test involved only the more comprehensive BLSIO sample. The new capital investment component I of ΔINV was multiplied by the level (not the output-deflated ratio) of used capital goods R&D raised to the power μ, and iterative techniques were used to find the value of μ that minimized the residual sum of squares.[33] This specification multiplicatively embodies capital goods R&D in the new capital investment component of the capital/labor ratio change variable. Regressions 4.7 and 4.8 give the results. Relative to otherwise comparable regressions 4.1 and 4.2, there are R^2 increases of 0.010 and 0.015. A better fit was obtained with the embodied capital/labor variable over μ values ranging from just above zero to 0.225 for the full sample and to 0.250 for the 51 industry subsample. The free-standing (i.e., disembodied) USECAP variables continue to be significant, although with coefficient values reduced by roughly one-fourth.[34]

Summing up the analysis thus far, introducing a capital/labor variable that emphasizes new investment, or substituting used capital goods R&D for all used R&D, but not necessarily both changes together, leads to improved productivity growth explanations. So also does the explicit embodiment of capital goods R&D in the new investment variable. Thus, there is support for the embodiment hypothesis, although it is not completely consistent, nor are the changes large enough to be statistically significant.

An explicit premise of the Reagan Administration's economic policy is that governmental regulation has led to reduced productivity growth.[35] A sub-hypothesis readily incorporated into our embodiment tests is that regulation has diverted investment from activities that enhance measured productivity growth to the control of environmental pollution and the improvement of occupational health and safety (all together, EHS activities). To test this hypothesis, regulatory impact variables were developed. For the BLSIO sample, the relevant variable E is the fraction of 1974-77 new capital investment outlays devoted to EHS mandates.[36] The BLSPQ sample was too finely disaggregated to apply this approach, so a dummy variable REG was created with a value of 1 if the industry had pollution control outlays greater than 10 percent of its mid-1970s investment (as seven sample industries did) <u>or</u> (like motor vehicles and all four nonmanufacturing industries) was otherwise heavily regulated during the 1970s.

One method of testing the regulatory impact hypothesis is simply to add the regulation variable to regressions of the form already estimated. For the BLSIO sample, the coefficient on (1 - E) (that is, the fraction of investment not devoted to regulatory mandates) in the analogue of regression 4.1 is 3.67, with a t-ratio of 0.57.[37] Since the mean level of (1 - E) was .928, this means that moving from the average level of regulation-mandated investment to no such investment ((1-E) = 1.0) would be accompanied on average by a rise in the annual labor productivity growth rate of 0.26 percentage points. For the BLSPQ sample, the dummy variable coefficient in the analogue of regression 4.3 is -1.24, with a t-ratio of 1.43.[38] Given the unit value of the dummy variable, this means that the absolute impact on productivity growth of having been heavily regulated was dramatic, even if erratic in view of the failure to pass conventional significance tests. Taking the average of the BLSPQ dummy variable values, the mean impact over all manufacturing industries is estimated to be a productivity growth shortfall of 0.27 percentage points per annum -- quite close to the BLSIO estimate.

An alternative and theoretically better-based test implementable with the BLSIO sample is to multiply the new investment component of ΔINV by (1 - E) so that what is measured is investment net of mandated EHS outlays. This is done in regressions 4.9 and 4.10. In both cases, the amended capital/labor change variable does a slightly better job explaining productivity growth than otherwise analogous regressions 4.1 and 4.2. The R^2 increases are 0.006 in both instances. Regressions 3.11 and 3.12 then retest the nonlinear capital goods R&D embodiment hypotheses with capital/labor change variables adjusted to exclude mandated EHS outlays. The R^2 improvements for the best-fitting values of μ are 0.013 and 0.024 -- somewhat greater than the increases with respect to capital variables unadjusted for EHS investments.

The weight of the regulation hypothesis evidence appears to imply that regulation has made a difference and perhaps, in a few cases, a large difference. But the statistical support for this conclusion is rather fragile.

VI. Conclusions

An unusually rich new set of data has been tapped here to explore the relationships between R&D and productivity growth. Without doubt the most important finding is that using disaggregated data, the "wrong lag" hypothesis is not supported: there is no evidence that the productivity slump of the 1970s resulted from a decrease in the fecundity of R&D. If anything, the evidence points more toward problems in measuring productivity, since the smallest average declines occurred in industries whose productivity growth was best measured. Product R&D is found to have yielded at best weak and erratic productivity gains in the industries performing the R&D. Apparently, the forces of competition prevent firms from realizing consistent price-cost margin increases as a result of product innovation. Internal process R&D, however, exhibits appreciable social returns on investment, as do new products in their use by purchasing industries. These distinctions are important. Studies that fail to make them must suffer from serious specification errors, especially in view of the fact that three-fourths of industrial R&D is product-oriented. Support for the capital goods embodiment hypothesis is mixed, although there is some evidence of both embodied and disembodied effects. Materials R&D is less clearly conducive to measured productivity growth. There were also indications of an adverse impact on 1970s productivity growth from mandated environmental health and safety investments, but the effects were apparently erratic, since the relevant variables were in no instance statistically significant.

FOOTNOTES

[1]See Ravenscraft and Scherer (1981).

[2]For an early recognition of the problem, see Gustafson (1962). For a detailed analysis see Griliches (1979).

[3]For the sample analyzed in this paper, internal process R&D expenditures amounted to 24.6 percent of total R&D outlays. The rest (by definition) was product R&D.

[4]See Scherer (1980), pp. 76-77.

[5]For a similar conclusion, see Sveikauskas (1981), pp. 278-279.

[6]Details of the linking and technology flow procedures are described in Scherer (1981a) (1981b).

[7]See Kendrick and Grossman (1980). Extensions to 1978 were kindly provided by the authors.

[8]Twenty-five of the manufacturing industries consisted of one or two four-digit industries. Ten were defined at or near the three-digit SIC level and two at a level broader than three digits. Thus, the degree of disaggregation is relatively high.

[9]The original productivity data and a discussion of methodology are found in U. S. Bureau of Labor Statistics (1979a). Nearly matching capital stock data are published in U. S. Bureau of Labor Statistics (1979b). Both series were updated in computer printouts kindly provided by BLS, although a special effort had to be made to extend the capital stock series by one

year and in a few cases by several years. The productivity series was also extended by the author to 1978 using 1978 Annual Survey of Manufactures data. The results were generally similar to those reported here, but because of splice problems, are believed to be less reliable.

[10]See Ravenscraft and Scherer (1981), where the mean lag between R&D and performing firm profitability is found to be four to six years.

[11]The peak actually occurred in 1979, although its exact timing is arguable. After January 1979, the industrial production series, which is most closely comparable to our sample coverage, was quite flat.

[12]See Kendrick (1973), pp. 140-143; Kendrick and Grossman (1980), pp. 102-111; Terleckyj (1974) (1980); and Mansfield (1980).

[13]There is also a comparison problem within regressions 1.1 - 1.4, since total factor productivity is measured with a deduction for net capital inputs over the 1948-66 period and for gross capital inputs in the later period. The 1948-66 relationships tend to be weaker when gross capital TFP values published by Kendrick and Grossman in 1980 are substituted for the original Kendrick data.

[14]A plot of the data revealed the rubber and plastic products group to be an extreme outlier in the USERD regression, with R&D use (mostly for synthetic rubber and plastic resin materials) much greater than for any other industry. Such materials R&D use , we shall see later, may have little productivity growth effect.

When the observation for that group is deleted from regression 1.6, the r^2 value jumps to 0.577. The ORGRD regression remains essentially unchanged.

[15]An F-ratio test for differences in subsample means yielded values of 2.06 for 1964-69 and 0.17 for 1973-78. The 5 percent point is 3.95.

[16]For the 37 manufacturing industries in the BLSPQ sample, the mean drop was 9.3 percent, revealing that the four nonmanufacturing industries were more heavily impacted. When the five largest manufacturing industries (motor vehicles, steel, pulp and paper, petroleum refining, and sawmills) are also excluded, the mean drop falls further to 3.4 percent. This plus the results that follow suggests that the 1970s productivity growth slump was specific to certain typically large industries rather than general.

[17]These two hypotheses were stated explicitly in the proposal dated September 1978 underlying this research.

[18]For details, see Scherer (1981b).

[19]In these and all other regressions that follow, the BLSPQ technology flow variables are divided by a 1974 value added output measure, while the BLSIO variables are divided by gross 1974 output value.

[20]The correlations for USEPUB are 0.028 to 0.051 higher than their private goods counterparts in BLSPQ regressions for 1964-69. USEPAT1 also had a correlation 0.066 higher than USERD1

in a BLSPQ 1964-69 regression with manufacturing industries only, but the relationship reversed when the four nonmanufacturing industries were added. These were the principal departures from a prevailing pattern favoring private goods dollar-denominated variables.

[21]The regressions in Table 1 also incorporate second-order component flow USERD variables.

[22]With the 87 industry BLSIO sample, the simple r between ORGRD and USERD1 is 0.419. Between USERD1 and PRODRD it is 0.222, and between ORGRD and PRODRD 0.968. The correlation between a variable measuring internal process R&D PROCRD and ORGRD is 0.514; between USERD1 and PROCRD it is 0.849. All variables here are deflated by 1974 gross output value.

[23]The change in results does not appear to come from using different data sets. When the 81 BLSIO manufacturing industries were aggregated to 20 two-digit groups, the results were quite similar to those obtained using Kendrick-Grossman labor productivity data. Both simple and partial (holding capital/labor changes constant) correlations were minute for 1973-78 productivity. As in regression 1.7 of Table 1, the strongest R&D variable correlation was for ORGRD in 1964-69; its coefficient in a bivariate regression was 0.272 with a t-ratio of 1.85 (compared to 0.190 and 1.61 in regression 1.7). Evidently, support for the wrong lag hypothesis stems mainly from some aggregation effect.

[24]Contrast the findings of Griliches (1980), pp. 346-347, who aggregated BLSIO data for 1969-77 to 39 sectors.

[25]The average value of PRODRD is 2.22 percent for the poorly-measured subset of BLSIO compared to 0.74 for the well-measured subset. This is probably no coincidence. It is hard to maintain good price index coverage in industries with considerable product innovation, and especially in the high-R&D industries making complex capital goods. The USERD1 indices are identically 0.73 for both subsets.

[26]Because of capital/labor variable limitations, no regression analogous to 3.7 was run. However, the simple correlation between 1964-78 BLSPQ productivity growth and USERD1 was 0.041 higher than for 1973-78; for USERD2, it was 0.067 higher.

The strength of the USERD results is also impaired by a relatively low variance of that variable's values. Although the maximum USERD1 value is 3.99 percent (for electronic components), all but 15 of the 87 BLSIO sample values are clustered in a narrow range of from 0.06 to 1.2 percent.

Despite the evident skewness of USERD, the regression estimates were not dominated in any simple way by outlying observations. Plotting the data did reveal several interesting ad hoc relationships. For instance, the communications industry (mostly telephonic) and (in the BLSIO regressions) agriculture have much higher productivity growth than one would expect on the basis of their used R&D/output ratios. This suggests the realization of scale economies in providing specialized but fairly standardized capital goods to huge using industries. Other high productivity outliers in the BLSPQ sample are corn milling, which experienced a boom during the 1970s involving inter alia a high-fructose syrup process pioneered in Japan, and the hosiery industry, for which the best machines come from Europe. Our used R&D variables do not cover R&D done overseas. On corn milling, see Harvard Business School (1978).

[27]See Maddala (1977), pp. 155-157.

[28]See Maddala (1977), pp. 400-403.

[29]For the BLSIO:P subsample, the simple r with 1964-69 productivity growth was +0.56. For the same subsample in 1973-78, it was 0.01. The highest 1973-78 correlation was 0.26, for the BLSIO:W subsample.

[30]See for example Nelson (1964), Jorgenson (1966), and Mansfield (1968), pp. 74-80.

[31]If K_o is the beginning capital stock, I is new investment (a flow), W represents retirements, and D is depreciation, the gross stock concept used in previous BLSIO regressions views the ending stock as $K_o + I - W$. The net stock concept tested with slightly less explanatory power and not reported here views the ending stock as $K_o + I - W - D$. The ΔINV concept we now adopt (and which was used earlier for the BLSPQ regressions in place of Annual Survey of Manufactures gross book value change indices) views the ending stock as $K_o + I$.

[32]The BLSIO:P subsample is excluded because neither USERD1 nor its components were significant.

[33]Specifically, where LCAP is the level of used capital goods R&D, the capital/labor ratio change variable employed for this analysis is given by

$$\left[\ln\left(\frac{K_o + I\cdot LCAP^{\mu}}{L_{end}}\right) - \ln\left(\frac{K_o}{L_o}\right)\right] \Big/ 5.$$

[34]In interpreting this result, it is important to note that the embodied capital/labor and USECAP variables were not collinear. Their intercorrelations were 0.02 and 0.11 in regressions 4.7 and 4.8.

[35]See for example President Reagan's first state of the economy address delivered February 5 , 1981.

[36]The sources are Rutledge et al. (1978) and an unpublished McGraw-Hill Department of Economics survey. Since the source data were more aggregated than our sample, some estimated interpolations had to be made. In the absence of additional information, the same ratio was applied for each component of a more aggregated industry.

[37]For the well-measured subsample, the coefficient is 2.16 and the t-ratio 0.32.

[38]When the four nonmanufacturing industries are added and the capital/labor ratio is excluded, the regulation coefficient is -0.89 with a t-ratio of 1.03.

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