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Chapter Author: Zvi Griliches, Jacques Mairesse

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17 Productivity and R & D at the Firm Level

Zvi Griliches and Jacques Mairesse

17.1 Motivation and Framework

17.1.1 Introduction

Because of worries about domestic inflation and declining international competitiveness, concern has been growing about the recent slowdowns in the growth of productivity and R & D, both on their own merit and because of their presumed relationship. This paper tries to assess the contribution of private R & D spending by firms to their own productivity performance, using observed differences in both levels and growth rates of such firms.

A number of studies have been done on this topic at the industry level using aggregated data, but ours is almost the first to use time-series data for a cross section of individual firms, that is panel data.[1] The only similar

Zvi Griliches is professor of economics at Harvard University, and program director, Productivity and Technical Change, at the National Bureau of Economic Research. Jacques Mairesse is a professor at Ecole des Hautes Etudes en Sciences Sociales and Ecole de la Statistique et de l'Administration Economique, and a research affiliate of the National Bureau of Economic Research.

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1. M. Ishaq Nadiri and his associates have done important related investigations. In their work at the firm level they have estimated factor demand equations (including demand for R & D) but did not pursue the direct estimation of production functions (see, for example, Nadiri and Bitros 1980).

study at the firm level is Griliches's (1980a) use of pooled NSF and Census data for 883 R & D performing companies over the 1957–65 period. This study had to rely on various proxies (and on corresponding ad hoc assumptions) for the measurement of both physical (*C*) and R & D (*K*) capital. Furthermore, because of confidentiality requirements, the data were provided only in moment-matrices form, which made it both impossible to control for outliers and errors and difficult to deal with the special econometric problems of panel data. In spite of these limitations, the results were very (and somewhat surprisingly) encouraging, yielding an elasticity of output with respect to R & D capital of about .06 in both the time-series and cross-section dimensions of the data.

A major goal of our work described in this paper, was to confirm these findings using a longer and more recent sample of firms, while paying more attention to the definition and measurement of the particular variables and to the difficulties of estimation and specification in panel data. In spite of these efforts, under close scrutiny our results are somewhat disappointing. This paper includes, therefore, two very different parts: section 17.2 documents the various estimates in detail, while section 17.3 attempts to rationalize and circumvent the problems that are evident in these estimates. First, however, we shall set the stage in this first section by explaining our data and our model. A more detailed description of the variables used and a summary of results using alternative versions of some of these variables can be found in the appendix.

17.1.2 The Data and Major Variables

We started with the information provided in Standard and Poor's Compustat Industrial Tape for 157 large companies which have been reporting their R & D expenditures regularly since 1963 and were not missing more than three years of data. Because of missing observations on employment and of questionable data on other variables, we first had to limit the sample to 133 firms (complete sample), and then, in response to merger problems, to restrict it further to 103 firms (restricted sample). The treatment of mergers has an impact on our estimates. These two overlapping samples are fully balanced over the twelve-year period, 1966–77.[2]

Our sample is quite heterogeneous, covering most R & D performing manufacturing industries and also including a few nonmanufacturing

2. We also consider two corresponding subsamples (96 firms and 71 firms) with no data missing for the entire eighteen-year (1960–77) period. We focus in this paper on the larger, shorter samples because of potential errors in our R & D measures in the earlier years. Most of the interpolation and doctoring of R & D expenditures (for missing observations or changes in definition) occurred in the years before 1966. Also, we had to estimate an initial R & D capital stock level in 1958 by making various and somewhat arbitrary assumptions whose impact vanishes by 1966.

firms (mainly in petroleum and nonferrous mining). Since the number of firms is too small to work with separate industries, we have dealt with the heterogeneity problem by dividing our sample into two groups: *scientific firms* (firms in the chemical, drug, computer, electronics, and instrument industries) and *other firms*.

The measurement of the variables raises many conceptual issues as well as practical difficulties. These problems have been discussed at some length in Griliches (1979, 1980a), and we shall only allude to the most important ones in our context. We think of the unobservable research capital stock (K) as a measure of the distributed lag effect of past R & D investments on productivity: $K_{it} = \Sigma_{\tau} w_{\tau} R_{i(t-\tau)}$, where R is a deflated measure of R & D, and the subscripts t, $(t-\tau)$, and i stand for current year, lagged year, and firm, respectively. Ideally, one would like to estimate the lag structure (w_{τ}) from the data, or at least an average rate of R & D obsolescence and the average time lag between R & D and productivity. Unfortunately, the data did not prove to be informative enough. Various constructed lag measures and different initial conditions made little difference to the final results. We focused, therefore, on one of the better and most sensible looking measures based on a constant rate of obsolescence of 15 percent per year and geometrically declining weights $w_{\tau} = (1-\delta)^{\tau}$.

We measure output by deflated sales (Q) and labor (L) by the total number of employees. There is no information on value added or the number of hours worked in our data base. This raises, among other things, questions about the role of materials (especially energy in the recent period) and about the impact of fluctuations in labor and capacity utilization and the possibility that ignoring these issues may bias our results—see section 17.3 where we address these questions and the related question of returns to scale. Sales are deflated by the relevant (at the two- or three-digit SIC level) National Accounts price indexes.[3] We assume that intrasectoral differences in price movements reflect mostly quality changes in old products or the development of new products. Accordingly (and to the extent that this assumption holds), we are in principle studying here the effects of both process- and product-oriented R & D investments.

3. At least two problems arise in applying these price indexes to our data. First, our firms are diversified and a significant fraction of their output does not fall within the industry to which they have been assigned. Second, observations are based on the companies' *fiscal* years which often do not coincide with price index calendar years. Experiments performed to investigate these problems indicated that our conclusions are not affected by them. We used 1978 Business Segment data to produce weighted price indexes for about three-quarters of our sample, with the results changing only in the second decimal place. Similarly, a separate smoothing of the price indexes, to put them into fiscal year equivalents, has very little impact on the final results.

Finally, we have used gross plant adjusted for inflation as our measure of the physical capital stock (C). This variable (as in some of our previous studies) performs reasonable well; however, it tends to be collinear over time with the R & D capital stock K, especially for some sectors and subperiods. We have tried various ways of adjusting gross plant for inflation and have also experimented with age of capital and net capital stock measures. Since random errors of measurement are another issue, we made various attempts to deal with the errors in variables problem by going to three-year averages. All these experiments resulted in only minor perturbations to our estimates.

Table 17.1 provides general information on our samples and variables, while more detail is given in the appendix. Note the much more rapid productivity growth and the higher R & D intensiveness in the "scientific firms" subsample.

17.1.3 The Model and Stochastic Assumptions

Our model, which is common to most analyses of R & D contributions to productivity growth (see Griliches 1979, 1980b), is the simple extended Cobb-Douglas production function:

$$Q_{it} = Ae^{\lambda t} C_{it}^{\alpha} L_{it}^{\beta} K_{it}^{\gamma} e^{e_{it}},$$

or in log form:

$$q_{it} = a + \lambda t + \alpha c_{it} + \beta \ell_{it} + \gamma k_{it} + e_{it},$$

where (in addition to already defined symbols) e_{it} is the perturbation or error term in the equation; λ is the rate of disembodied technical change; α, β, and especially γ are the parameters (elasticities) of interest—in addition to the weights w_τ or the rate of obsolescence δ implicit in the construction of the R & D capital stock variable.

One could, of course, also consider more complicated functional forms, such as the CES or Translog functions. We felt, based on past experience and also on some exploratory computations, that this will not matter as far as our main purpose of estimating the output elasticities of R & D and physical capital (α and γ), or at least their relative importance (α/γ), is concerned. However, two related points are worth making.

First, an important implication of our model in the context of panel data is that in the cross-sectional dimension differences in levels explain differences in levels, while in the time dimension differences in growth rates explain differences in growth rates. An alternative model would allow γ to vary across firms and impose the equality of marginal products or rates of return across firms, $\partial Q/\partial K = \rho$, implying that the rate of growth in productivity depends on the intensity of R & D investment (rewriting $\gamma \dot{k} = (\partial Q/\partial K)(K/Q)(\dot{K}/K) = \rho\dot{K}/Q = \rho(R - \delta K)/Q \simeq \rho R/Q$ for

Table 17.1 **Sample Composition and Size, R & D/Sales Ratio, and Labor Productivity Growth Rate**[a]

SIC Industry Classification	Complete Sample: Number of Firms	Complete Sample: R & D Sales (%)	Complete Sample: Productivity Growth Rate (%)	Restricted Sample: Number of Firms	Restricted Sample: R & D Sales (%)	Restricted Sample: Productivity Growth Rate (%)
Scientific firms:						
28(−283)—chemicals	19	3.4	6.7	16	3.6	5.1
283—drugs	19	6.5	3.3	10	7.5	4.6
357—computers	10	5.3	7.8	6	5.3	8.0
36—electronic equipment	14	4.6	3.3	10	4.7	3.8
38—instruments	15	5.5	3.6	15	5.5	3.6
Subtotal	77	5.0	4.3	57	5.2	4.7
Other firms:						
29—oil	6	0.7	5.1	6	0.7	5.1
35(−357)—machinery	13	2.8	0.7	10	2.8	0.7
37—transportation equipment	8	2.2	1.8	8	2.2	1.8
Other manufacturing—mostly 20–32–33	20	2.3	0.2	17	2.3	0.8
Nonmanufacturing—mostly 10	9	2.0	−0.6	5	2.2	0.5
Subtotal	56	2.2	0.9	46	2.2	1.5
Total	133	3.8	2.9	103	3.8	3.3

[a]The restricted sample excludes firms with large jumps in the data, generally caused by known merger problems.

small δ). We have not pursued such an alternative here, but we may consider it again in future work.[4]

Second, we also have the choice of assuming constant returns to scale (CRS) in the Cobb-Douglas production function: $\alpha + \beta + \gamma + \mu = 1$, or not—which amounts to estimating the regression

$$(q_{it} - \ell_{it}) = a + \lambda t + \alpha(c_{it} - \ell_{it}) + \gamma(k_{it} - \ell_{it}) + (\mu - 1)\ell_{it} + e_{it},$$

with $(\mu - 1)$ left free or set equal to zero. In our data the constant returns to scale assumption is accepted in the cross-sectional dimension, but is rejected in the time dimension in favor of significantly decreasing returns to scale. Because of the large effects of this restriction on our estimates of γ, we shall report both the estimates obtained with and without imposing constant returns to scale.

A distinct issue, which may explain why not assuming constant returns to scale and freeing the coefficient of labor in the regressions causes a problem, is that of simultaneity. Actually, it seems to provide a better explanation of our results than left-out variables or errors of measurement. We have, therefore, estimated a two, semireduced form, equations model in which output and employment are determined simultaneously as functions of R & D and physical stocks, based on the assumption of short-run profit maximization and predetermined capital inputs. These estimates yield plausible estimates of the relative influence of R & D and physical capital on productivity in both the cross-sectional and time dimensions. We elaborate on this line of research in section 17.3.

These different specification issues are, of course, related to the assumptions made about the error term, e_{it}, in the production function. When working with panel data, it is usual to decompose the error term into two independent terms: $e_{it} = u_i + w_{it}$, where u_i is a permanent effect specific to the firm and w_{it} is a transitory effect. In our context u_i may correspond to permanent differences in managerial ability and economic environment, while w_{it} reflects short-run changes in capacity utilization rates, in addition to other sources of perturbation. The habitual and convenient way to abstract from the u_i's is to compute the *within-firm regression* using the deviations of the observations from their specific firm means: $(y_{it} - y_{i\cdot})$, which is equivalent to including firm dummy variables in the total regression using the original observation (y_{it}). While the way to eliminate the w_{it}'s (in a long enough sample) is to compute the *between-firm regression* using the firm means $(y_{i\cdot})$. The least-squares estimates of the *total regression* are in fact matrix-weighted averages of the least-squares estimates of the within and between regressions. If most of the

4. An important practical advantage of this alternative approach is that by assuming $\delta = 0$ a priori it does not require the construction of an R & D capital stock. See Griliches (1973), Terleckyj (1974), and Griliches and Lichtenberg (this volume) for estimates based on this approach.

variability of the data is between firms rather than within, as is the case here, the total and between estimates will be very close.[5]

Another manner of viewing the decomposition of the overall error into permanent and transitory components, and of interpreting the between and the within estimates, is to consider them as providing cross-sectional and time-series estimates, respectively. Both estimates will be consistent and similar if the u_i's and the w_{it}'s are uncorrelated with the explanatory variables. Very often, however, the two are rather different, implying some sort of specification error. This is, unfortunately, our case. Following the early work of Mundlak (1961) and Hoch (1962), the general tendency is to hold the u_i's responsible for the correlations with the explanatory variables and to assume that the within estimates are the better, less biased ones.[6] This leads to the discarding of the information contained in the variability between firms, which is predominant (at least in our samples), relying thereby only on the variability within firms over time, which is much smaller and more sensitive to errors of measurement. In fact, there are also good reasons for correlations of the w_{it}'s with the explanatory variables and, therefore, putting somewhat more faith in the between estimates. These reasons have been sketched in Mairesse (1978); they will be considered further in section 17.3 when we discuss the potential influence of misspecifications on our results.

17.2 Overall and Detailed Estimates

17.2.1 First Look at Results

Our first results were based on the complete sample of 133 firms for the 1966–77 period and various variants of our variables, especially R & D capital. Although the use of different measures had little effect, disappointing our hope of learning much about the lag structure from these data, the actual estimates looked reasonably good even if far apart in the cross-section and time dimensions. Table 17.2 gives the total, between, and within estimates (and also the within estimates with year dummies instead of a time trend), using our main variants for output, labor, and physical and research capital, both with and without the assumption of constant returns to scale. The total estimates of the elasticities of physical and R & D capital (α and γ) are about .30 and .06, respectively, similar to Griliches's (1980a) previous estimates. The more purely cross-sectional between estimates are nearly identical to the total estimates, .32 and .07, respectively. This follows from the fact that most of the relevant variability in our sample is between firms (about 90 percent, see table 17.A.1 in

5. An independent year effect $v_t (e_{it} = u_i + v_t + w_{it})$ can also be taken into account by adding year dummies instead of a time trend to the regression.

6. The model is then equivalent to the so-called fixed effects model.

Table 17.2 **Production Function Estimates (complete sample, 133 firms, 1966–77)**

Total Regressions						Within Regressions					
α	γ	$(\mu - 1)$	λ	R^2	MSE	α	γ	$(\mu - 1)$	λ	R^2	MSE
0.319 (0.009)	—	—	0.012 (0.002)	0.499	0.099	0.232 (0.017)	—	—	0.017 (0.001)	0.402	0.0211
0.310 (0.008)	0.073 (0.011)	—	0.011 (0.002)	0.514	0.097	0.160 (0.020)	0.150 (0.020)	—	0.018 (0.001)	0.422	0.0204
0.332 (0.009)	0.054 (0.011)	−0.032 (0.005)	0.011 (0.002)	0.524	0.094	0.150 (0.019)	0.080 (0.022)	−0.126 (0.019)	0.025 (0.002)	0.437	0.0199
Between Regressions						Within Regressions with Year Dummies					
α	γ	$(\mu - 1)$		R^2	MSE	α	γ	$(\mu - 1)$		R^2	MSE
0.324 (0.027)	—	—		0.522	0.079	0.250 (0.017)	—	—		0.420	0.0206
0.317 (0.027)	0.072 (0.034)	—		0.538	0.077	0.176 (0.019)	0.158 (0.020)	—		0.442	0.0198
0.341 (0.029)	0.053 (0.035)	−0.033 (0.017)		0.551	0.075	0.163 (0.019)	0.091 (0.022)	−0.121 (0.020)		0.455	0.0194

the appendix). The time-series within estimates are, however, rather different: α being about .15 and γ about .15 or .08 depending on whether constant returns to scale are imposed or not. It is also clear that using separate year dummy variables instead of a linear trend makes little difference.

Unfortunately, these first results did not improve with further analysis; on the contrary. While the measurement of variables (within the range of our experimentation) does not really matter, trying to allow for sectoral and period differences and cleaning the sample of observations contaminated by mergers sharply degraded our within estimates of the R & D capital elasticity γ. The pattern of results already evident in table 17.2 is much amplified, especially in the time dimension: a tendency of the estimated γ's to be substantial, whenever the estimated α's seem too low; and a tendency for them to diminish or even to collapse when constant returns to scale are not imposed. We shall now document these different problems in detail before considering their possible causes and solutions.

17.2.2 Alternative Variable Definitions and Sectoral Differences

One of the original aims of this study was to experiment with various ways of defining and measuring physical and R & D capital. Using all the information available to us, we tried a number of different ways of measuring these variables but to little effect. The resulting differences in our estimates, even when they were "statistically significant," were nonetheless quite small and not very meaningful. In particular, they did not alter the order of magnitude of our two parameters of interest, α and γ. The various measures we tried turned out to be very good substitutes for each other and the choice between them had little practical import. Our final choices were based, therefore, primarily on a priori considerations, external evidence, and convenience. The appendix describes these choices and some of our experiments.

Since our sample consisted of R & D performing firms in rather diverse industries, it was also of interest to investigate the influence of sectoral (industrial) differences. Table 17.3 gives our main estimates separately for firms in research-intensive industries (so-called scientific firms) and the rest of our sample.

Dividing the sample into two allows for much of the heterogeneity, bringing down the sum of square of errors (SSE) by about 20 percent for the total regressions and 10 percent for the within regressions (with the division corresponding to very high F ratios of about 100 and 70, respectively). The two groups are indeed a priori very distinct: as a matter of fact, the average rate of productivity growth is about four times higher for the scientific firms, while the average R & D to sales ratio is about twice as high (see table 17.1).

In spite of this sharp contrast, the differences in our estimates are not

Table 17.3 **Production Function Estimates Separately for the Scientific and Other Firms (complete sample, 77 and 56 firms, respectively, 1966–77)**

	Total Regressions						Within Regressions					
	α	γ	$(\mu - 1)$	λ	R^2	MSE	α	γ	$(\mu - 1)$	λ	R^2	MSE
Scientific firms	0.243	—	—	0.030	0.423	0.088	0.194	—	—	0.033	0.607	0.0170
	(0.012)			(0.003)			(0.020)			(0.002)		
	0.203	0.223	—	0.025	0.570	0.066	0.150	0.111	—	0.032	0.615	0.0167
	(0.011)	(0.013)		(0.003)			(0.022)	(0.026)		(0.007)		
	0.250	0.185	−0.051	0.026	0.604	0.061	0.140	0.021	−0.200	0.044	0.653	0.0151
	(0.011)	(0.013)	(0.006)	(0.002)			(0.021)	(0.026)	(0.020)	(0.002)		
Other firms	0.364	—	—	−0.008	0.609	0.093	0.243	—	—	−0.001	0.172	0.0202
	(0.011)			(0.003)			(0.028)			(0.002)		
	0.365	−0.007	—	−0.008	0.609	0.093	0.169	0.124	—	0.001	0.196	0.0196
	(0.012)	(0.018)		(0.004)			(0.032)	(0.028)		(0.002)		
	0.351	0.010	0.025	−0.008	0.614	0.092	0.133	−0.015	−0.207	0.011	0.223	0.0190
	(0.013)	(0.019)	(0.009)	(0.003)			(0.032)	(0.039)	(0.043)	(0.003)		

that large, except for the estimated time-trend coefficients (rates of technical progress λ). The within estimates of α and γ (and also μ) are, in fact, quite comparable, only the fit being much lower in the "other firms" equation. Yet the total estimates of γ are very large in the scientific firms and insignificant for the other firms. Part of this discrepancy can be accounted for by the higher estimates of α in the other firms group.

Disaggregating to the industrial level decreases the total and within sums of square of errors by another 20 percent or so. The main effect is, however, to worsen the collinearity between R & D and physical capital in the within dimension. Some of the within estimates actually fall apart: two extreme cases being the computer industry with an estimated α of -0.06 and an estimated γ of 0.50, and the instruments industry with an estimated α of 0.49 and an estimated γ of -0.32. Without a larger sample, we do not really have the option of working at the detailed industrial level.[7]

17.2.3 Differences between Subperiods

Current discussions of "the productivity slowdown" suggest that some of it may be due not only to "the slowdown in R & D," but also to a significant decrease in the efficiency of recent R & D investments (Griliches 1980b); hence, our interest in whether we could find any evidence of a decrease in the R & D capital elasticity γ over time. Table 17.4 shows what happens (for the scientific firms group) when we divide our data into two six-year subperiods, 1966–71 and 1972–77.[8] Table 17.5 explores the resulting differences further by presenting the within estimates for the two subperiods (as well as the overall period and "between subperiods") and comparing the estimated γ when α and λ are constrained to .25 and .025, respectively. Table 17.5 also lists the rates of growth of the main variables, their within standard deviations, and the decomposition of their within variability for the subperiods (the overall period and "between subperiods").

As might be expected, the total estimates differ only slightly, while the within estimates change a lot. Yet the striking feature is not a decrease in the estimated γ but rather in $\hat{\alpha}$. The decomposition of variance shows, however, that by breaking down our data into two subperiods we keep only about half of the within variability in the overall period (the other half being between subperiods.) Our capital stock variables as well as the time variable itself are slowly changing, trendlike variables, and there is not enough variability in them to allow us to estimate all of their coef-

7. An intermediate step, without going fully to the sectoral level, is to allow for separate sectoral time trends and intercepts. While the total and within estimates change only slightly for the scientific firms, the total estimates of γ and α for the other group move up and down respectively, making them less different from those of the scientific group.

8. We also looked at the preceding six-year subperiod (1960–65) for our longer but smaller subsample of firms. The estimates are very similar to those for 1966–71.

Table 17.4 **Production Function Estimates for Two Subperiods: 1966–71 and 1972–77 (scientific firms, complete sample, 77 firms)**

	Total Regressions						Within Regressions					
Periods	α	γ	$(\mu - 1)$	λ	R^2	MSE	α	γ	$(\mu - 1)$	λ	R^2	MSE
1966–71	0.219	—	—	0.013	0.264	0.103	0.250	—	—	0.011	0.307	0.0115
	(0.018)			(0.009)			(0.029)			(0.004)		
	0.169	0.241	—	0.007	0.463	0.076	0.106	0.250	—	0.013	0.380	0.0103
	(0.016)	(0.019)		(0.007)			(0.033)	(0.034)		(0.004)		
	0.235	0.189	−0.068	0.008	0.528	0.067	0.113	0.040	−0.307	0.041	0.501	0.0083
	(0.017)	(0.019)	(0.009)	(0.007)			(0.030)	(0.036)	(0.029)	(0.004)		
1972–77	0.273	—	—	0.033	0.434	0.071	0.083	—	—	0.043	0.459	0.0080
	(0.016)			(0.007)			(0.028)			(0.003)		
	0.242	0.207	—	0.029	0.578	0.053	−0.012	0.225	—	0.041	0.486	0.0076
	(0.014)	(0.017)		(0.006)			(0.034)	(0.047)		(0.003)		
	0.269	0.183	−0.032	0.028	0.594	0.051	−0.023	0.175	−0.076	0.044	0.488	0.0076
	(0.015)	(0.017)	(0.008)	(0.006)			(0.034)	(0.057)	(0.050)	(0.004)		

Table 17.5 Analysis of Subperiod Differences (scientific firms, complete sample, 77 firms)

Periods	Within Degrees of Freedom	Rates of Growth, (within standard deviations), [% within variability]				Within Regressions ($\mu = 1$)					
		$q - \ell$	$c - \ell$	$k - \ell$	ℓ	α	γ	λ	γ ($\alpha = 0.25$)	λ ($\alpha = 0.25$)	γ ($\alpha = 0.25$) ($\lambda = 0.025$)
1966–77	847	4.3 (0.22) [100.0]	6.2 (0.33) [100.0]	3.0 (0.22) [100.0]	4.6 (0.28) [100.0]	0.15	0.11	0.032	0.06	0.027	0.08
1966–71	385	3.3 (0.14) [19.0]	9.1 (0.25) [27.6]	4.5 (0.20) [38.3]	6.3 (0.24) [33.4]	0.11	0.25	0.013	0.17	0.003	0.09
1972–77	385	5.1 (0.13) [17.0]	4.3 (0.19) [15.1]	2.4 (0.13) [15.8]	2.4 (0.13) [10.2]	−0.01	0.23	0.041	0.02	0.034	0.08
Between subperiods	77	4.7 (0.58) [64.0]	6.2 (0.81) [57.3]	2.9 (0.50) [45.9]	4.2 (0.69) [56.4]	0.25	−0.02	0.032	−0.02	0.032	0.07

ficients separately and precisely. What we get are relatively wide gyrations in the estimated coefficients α, γ, and λ, with some of them going down as the others go up. If we impose a reasonable a priori value of $\alpha = .25$, which corresponds to estimating the impact of R & D capital on total factor productivity, (TFP), we do indeed get a large decline in γ, from .17 in the first period to effectively zero in the second. However, this decline is associated with a correspondingly large increase in λ, from .003 to .034. Since such an acceleration in "disembodied" technological change goes against all other pieces of information available to us, we reestimate again, imposing also an a priori $\lambda = .025$. With this new restriction everything falls into place: $\hat{\gamma}$ being estimated at approximately .08 for both subperiods (as well as between subperiods and for the overall period).

This, of course, does not mean that we have strong evidence that γ is about .08, but only that one should not interpret the data as implying a major decline in γ over time. What the data tell us is that one cannot tell and that there is not enough independent variation in the subperiods to estimate the contribution of physical capital, R & D capital, and trend separately. If, however, we are willing to impose a priori, reasonable values on α and λ, then the implied $\hat{\gamma}$ is both reasonable and stable. Moreover, the imposition of such constraints is not inconsistent with the data; while they are not "statistically" accepted given our relatively large sample size, the actual absolute deterioration in fit is rather small, the standard deviation of residuals changing by less than .01.[9]

This may not be all that surprising considering the other major fact that emerges from table 17.5: our "scientific firms" did not actually experience a productivity slowdown in 1972–77 relative to 1966–71 (as against the experience of manufacturing as a whole). There was a slowdown in the growth of both physical and R & D capital, but this was associated with an *accelaration* in labor productivity growth and, hence, also in total factor productivity growth. (The latter rises from about 0.6 percent in the first period to about 3.8 percent in the second.)[10] Given these facts, it is not surprising that correlation of productivity growth with capital input growth tends to vanish, leading to a collapse of the estimated α and γ. These strange events are not limited to the firms in our sample, they also actually happened in the science-based industries as a whole, as can be

9. Our estimated regression standard errors are about .1 in the within dimension, implying that we explain annual fluctuations in productivity up to an error whose standard deviation is about 10 percent. Imposing the a priori values of α and λ increases this error by less than one additional percent.

10. This is computed from the average yearly rates of growth given in table 17.5, using .65, .25, and .1 as relative weights for labor, physical capital, and R & D capital, respectively.

seen by examining the aggregate data collected by NSF and the BLS.[11] (Average TFP growth in "scientific" industries increases in these data from about .8 percent in 1966–71 to 3.2 percent in 1972–77.) If anything, the puzzle is why there was so little "exogenous" productivity growth in 1966–71. One possible answer would invoke errors of measurement in the dating of physical and R & D investments (longer lag structures); another might be based on different cyclical positions of the endpoints of these two periods. In any case, since there is no evidence that there has been a significant productivity slowdown in R & D intensive industries, it is unlikely that whatever slowdown did occur could be attributed to the slowdown in R & D growth.[12]

17.2.4 The Problem of Mergers

Starting from our original sample of 157 firms, we first eliminated 24, primarily because of missing observations (in the number of employees generally and in gross plant occasionally) or obvious large errors in the reported numbers. In the case of one or two missing observations we "interpolated" them. In some instances we managed to go back to the original source and obtain the missing figure or correct an error. Fortunately, most firms did not present such difficulties, and the construction of our "complete sample" was straightforward enough. We were still left with the important issue of mergers. About one firm out of five in our "complete" sample (as many as twenty among the seventy-seven "scientific" firms) appeared to be affected (at least for one year over the 1966–77 period) by considerable and generally simultaneous "jumps" (80 percent or more year-to-year increases) in gross plant, number of employees, and sales. We have been able to check and convince ourselves that most of these jumps do, in fact, result from mergers, although some may be the result of very rapid growth. Since the problem was of such a magnitude (as is bound to be the case in a panel of large companies over a number of years), we had to be careful about it.

11. The data are taken from sources given in Griliches (1980b). The numbers that correspond to those of table 17.5 are:

Scientific Industries Aggregate: Based on NSF and BLS Statistics
(Average yearly rates of growth)

Subperiods	$q - \ell$	$c - \ell$	$k - \ell$	ℓ
1960–65	4.3	2.0	8.2	2.8
1966–71	3.3	7.4	6.3	0.9
1972–77	3.8	2.0	0.6	2.3

Although the definitions and measures are quite different, and although our firms are much faster growing than the scientific industries as a whole, the growth patterns are very similar.

12. For possible contrary evidence, see Scherer (1981) who emphasizes the impact of R & D on productivity growth in the R & D *using* rather than R & D *doing* industries.

One way of dealing with this problem is simply to drop the offending firms. This results in what we have called the "restricted" sample. An alternative is to create an "intermediate" sample in which a firm before and after a major merger is considered to be two different "firms." If mergers were occurring precisely in a given year, we would have as many observations in the intermediate sample as in the complete one (and more "firms" but some of them over shorter periods), and we would eliminate only the "variability" corresponding to the "jumps." In fact, we lost a few observations because some mergers affect our data for more than one year (primarily because we chose gross plant at the beginning of the year as our measure of capital for the current year) or because they occur in the first or last years of the study period (since we decided not to have "firms" with less than three years of data in the intermediate sample). Estimates for the restricted sample and its complement, the "merger" sample, are given in table 17.6 for the scientific firms group. (Estimates for the other group behave similarly, although there were fewer mergers there.) Table 17.7 provides more detail, showing separately the results for the complete, intermediate, and restricted samples and decomposing the merger group into "jump" and "no-jump" periods. To facilitate interpretation, it also presents estimates of γ based on constraining α to .25 and λ to .025, and it lists the rate of growth, the standard deviations and the variance decomposition of the main variables.[13]

The total estimates (reported in table 17.6) manifest their usual stoutness, remaining practically unchanged whatever the sample. The within estimates are, on the contrary, very sensitive, and the estimated γ collapses, declining from 0.11 to 0.05 and -0.03 in the complete, intermediate, and restricted samples, respectively (even when constant returns to scale are imposed). It is clear from table 17.7 that the merger firms are responsible for the difference. They correspond to a major part of the within variability of our variables (much of it being from the "jumps"). Moreover, they seem to account for the significant, positive within estimates of γ in our complete sample, especially through their "no-jumps"

13. The variance decomposition of a variable y for a firm i going through a merger at the end of year t_0 is identical to its decomposition into the two subperiods before and after the merger, the "jump" component corresponding to the between subperiods component. It can be written

$$\sum_{t=1}^{T}(y_{it}-y_{i\cdot})^2=\sum_{t=1}^{t_0}(y_{it}-y_{i\cdot}^{(1)})^2+\sum_{t=t_0+1}^{T}(y_{it}-y_{i\cdot}^{(2)})^2$$
$$+\,t_0(y_{i\cdot}^{(1)}-y_{i\cdot})^2+(T-t_0)(y_{i\cdot}^{(2)}-y_{i\cdot})^2,$$

where $y_{i\cdot}, y_{i\cdot}^{(1)}$, and $y_{i\cdot}^{(2)}$ are the respective means of y_{it} over the whole period $(1, T)$, the before merger period $(1, t_0)$, and the after merger period (t_0+1, T). The practical way to run the regressions corresponding to the jump component is simply to substitute $(y_{i\cdot}^{(1)}-y_{i\cdot})$ and $(y_{i\cdot}^{(2)}-y_{i\cdot})$ for $(y_{it}-y_{i\cdot})$ in the before and after merger years.

Table 17.6 **Separate Production Function Estimates for the Restricted and the Merger Samples (57 and 20 firms respectively, scientific firms, 1966–77)**

	Total Regressions						Within Regressions					
Samples	α	γ	$(\mu - 1)$	λ	R^2	MSE	α	γ	$(\mu - 1)$	λ	R^2	MSE
Restricted	0.264	—	—	0.032	0.510	0.075	0.221	—	—	0.035	0.737	0.010
	(0.012)			(0.003)			(0.025)			(0.002)		
	0.230	0.210	—	0.028	0.645	0.054	0.239	−0.034	—	0.035	0.737	0.010
	(0.011)	(0.013)		(0.003)			(0.030)	(0.028)		(0.002)		
	0.278	0.170	−0.048	0.028	0.671	0.050	0.211	−0.062	−0.112	0.041	0.745	0.010
	(0.012)	(0.014)	(0.006)	(0.003)			(0.030)	(0.028)	(0.025)	(0.002)		
Merger	0.204	—	—	0.021	0.235	0.117	0.200	—	—	0.021	0.379	0.034
	(0.032)			(0.007)			(0.036)			(0.004)		
	0.146	0.292	—	0.017	0.462	0.093	0.	0.270	—	0.020	0.437	0.031
	(0.028)	(0.029)		(0.005)			(0.038)	(0.055)		(0.004)		
	0.171	0.265	−0.064	0.020	0.524	0.073	0.114	0.135	−0.229	0.042	0.506	0.027
	(0.027)	(0.028)	(0.011)	(0.006)			(0.036)	(0.057)	(0.040)	(0.005)		

Table 17.7 **Analysis of Merger Differences (scientific firms, 1966–77)**

Samples	Within Degrees of Freedom	Rates of Growth, (within standard deviations), [% within variables]				Within Regressions ($\mu - 1$)					
		$q - \ell$	$c - \ell$	$k - \ell$	ℓ	α	γ	λ	γ ($\alpha = 0.25$)	λ ($\alpha = 0.25$)	γ ($\alpha = 0.25$) ($\lambda = 0.025$)
Complete		4.3	6.2	3.0	4.6						
(1)	847	(0.22)	(0.33)	(0.22)	(0.28)	0.15	0.11	0.032	0.06	0.027	0.08
		[100.0]	[100.0]	[100.0]	[100.0]						
Intermediate		4.7	5.8	3.7	3.2						
(2)	783	(0.21)	(0.26)	(0.21)	(0.20)	0.79	0.05	0.035	0.01	0.033	0.09
		[82.5]	[58.6]	[79.6]	[49.2]						
Restricted		4.7	6.1	3.4	3.2						
(3)	627	(0.21)	(0.27)	(0.22)	(0.21)	0.24	−0.03	0.035	−0.04	0.045	0.05
		[67.3]	[50.4]	[63.6]	[42.6]						
Merger		3.3	6.5	2.0	8.6						
(4) = (1) − (3)	220	(0.24)	(0.45)	(0.26)	(0.41)	0.12	0.27	0.020	0.18	0.012	0.11
		[32.7]	[49.6]	[36.4]	[57.4]						
"Jump"		0.0	11.5	−4.8	21.9						
(5) = (1) − (2)	64	(0.33)	(0.76)	(0.36)	(0.72)	0.20	0.11	0.011	0.07	0.006	0.02
		[17.5]	[41.4]	[20.4]	[50.8]						
"No-Jump"		4.7	4.5	4.9	3.1						
(6) = (2) − (3)	156	(0.20)	(0.22)	(0.21)	(0.17)	−0.18	0.65	0.019	0.30	0.017	0.23
		[15.2]	[8.2]	[16.2]	[6.6]						

component. In other words, R & D seems most effective for firms growing rapidly through mergers, and both phenomena (mergers and R & D growth) are apparently related.

Merger firms have higher R & D than physical capital growth rates during their nonmerger ("no-jumps") periods, while the opposite is true for nonmerging ("restricted") firms. The labor productivity growth rates are about equal for both, but they are much more closely related to R & D growth for the merger firms. Actually, not enough variability is left to estimate the separate contributions of the two capital terms and the time trend term precisely. If one imposes $\alpha = .25$ and $\lambda = .025$ a priori, one gets back from the restricted subsample a reasonable though still low estimate of $\hat{\gamma} = .05$. The intermediate sample, however, is the most relevant one from our point of view, yielding a much higher $\hat{\gamma} = .09$, which can be interpreted as a weighted average of about .2 for the merger firms and .05 for the rest.[14]

Such a finding raises questions that deserve additional analysis: Who are these "merger" firms and why would their R & D investment be more successful? What kind of selectivity is at work here? How does one expand this type of analysis to allow for different R & D-related success rates by different firms? A random coefficient model does not, at first thought, appear to be the most appropriate way to go. Unfortunately, given the small size of our sample, we cannot pursue these questions further here.

Our tentative conclusion is that we should *not* exclude the merger firms from our sample entirely. These are firms whose R & D has apparently been very effective. Throwing them out would seriously bias our estimates of the contribution of R & D to productivity downward.

17.3 Misspecification Biases or an Exercise in Rationalization

17.3.1 Three Possible Sources of Bias

Our within estimates of the production function are unsatisfactory in the sense that they attribute unreasonably low coefficients to the physical and research capital variables and imply that most of our firms are handicapped by severely diminishing returns to scale. The simplest explanation is to impute these "bad results" to a major misspecification of our model. The trouble is that when we start thinking about possible misspecifications, many come to mind. The most important appear to be: (1) the omission of labor and capital intensity of utilization variables, such as hours of work per employee and hours of operation per machine; (2) the use of gross output or sales rather than value added or, alterna-

14. Here also the imposition of the a priori values of $\alpha = .25$ and $\lambda = .025$ does not result in an economically meaningful deterioration of fit.

tively, the omission of materials from the list of included factors; (3) overlooking the jointness (simultaneity) in the determination of employment and output.[15]

These three misspecifications are similar in the sense that they all imply the failure of the ordinary least-squares assumption of no correlation between the included factors, c, l, k, and the disturbance e in the production function, resulting in biases in our estimates of the elasticities of these factors (and in our estimate of the elasticity of scale). In all three cases the correlation of the disturbance e with the labor variable ℓ is likely to be relatively high in the time dimension, affecting especially our within estimates.

If we consider the "auxiliary" regression connecting e to c, ℓ, k:

$$E(e) = b_{ec\cdot\ell k}c + b_{e\ell\cdot ck}\ell + b_{ek\cdot c\ell}k$$

(where we suppress for simplicity the constant and trend terms by taking deviations of the variables from the appropriate means, i.e., respectively, $[y_{it} - y_{\cdot t}]$ and $[y_{it} - y_{\cdot t} - y_{i\cdot} + y_{\cdot\cdot}]$ for the total and within regressions), the specification biases in our estimates can be written in the following general form:

$$E(\hat{\alpha} - \alpha) = \text{bias}\,\hat{\alpha} = b_{ec\cdot\ell k},$$

$$E(\hat{\beta} - \beta) = \text{bias}\,\hat{\beta} = b_{e\ell\cdot ck},$$

$$E(\hat{\gamma} - \gamma) = \text{bias}\,\hat{\gamma} = b_{ek\cdot c\ell}.$$

If we assume more specifically that the physical and research capital variables c and k are predetermined and that only the labor variable is correlated with e, we can go one step further and formulate the biases in α and γ as proportional to the bias in β (see Griliches and Ringstad 1971, appendix C):

$$\text{bias}\,\hat{\alpha} = -(\text{bias}\,\hat{\beta})\,b_{\ell c\cdot k},$$

$$\text{bias}\,\hat{\gamma} = -(\text{bias}\,\hat{\beta})\,b_{\ell k\cdot c}.$$

There is no good reason why the coefficients $b_{\ell c\cdot k}$ and $b_{\ell k\cdot c}$ should be both small, or one much smaller than the other, or very different for the within and total estimates. One will expect them to be positive and less than one, but large enough to result in a significant transmission of an upward bias in $\hat{\beta}$ into downward biases in both $\hat{\alpha}$ and $\hat{\gamma}$. One would also expect the absolute biases in $\hat{\alpha}$ and $\hat{\gamma}$ to be of the same order of magnitude

15. Three other possible misspecifications are the following: (4) ignoring the possibility of random errors in our measures of labor and capital; (5) assuming wrongly that firms operate in competitive markets; and (6) ignoring the peculiar selectivity of our sample. We shall allude briefly to (4) and (5) in what follows, but continue to ignore the selectivity issue, postponing the investigation into this topic to a later study based on a much larger post-1972 sample.

and, therefore, to have a much larger relative effect on $\hat{\gamma}$ than on $\hat{\alpha}$ (assuming that the true γ is small relatively to the true α). For example, a bias of -0.1 might reduce $\hat{\alpha}$ from a true .3 to .2 but could wipe out $\hat{\gamma}$ if its true value were .1.

We can actually estimate such bias transmission coefficients in our sample. They are relatively large and of comparable magnitude, on the order of .3 to .4.[16]

To the extent that the correlation between labor and the disturbance in the production function is the main problem, we are left with the evaluation of the bias in labor elasticity and the question of whether we can ascertain the "within" bias to be positive and sizeable in contrast to a small "total" bias. This is much more difficult, and we have to consider specifically our three possible misspecifications. We shall say a few words about the first two and then concentrate on the simultaneity issue. This issue seems most important, and we have been able to progress further toward its solution by considering a simultaneous equations model composed of the production function and a labor demand function, and by estimating what we call the semireduced form equations for this model.

Consider first the omission of the hours worked per worker variable h (or machine hours operated per machine) and let the "true" model be:

$$q = \alpha c + \beta(\ell + h) + \gamma k + \epsilon,$$

where labor is measured by the total number of hours of work.

The disturbance in the estimated model is then $e = \epsilon + \beta h$, and we get for the labor elasticity bias: bias $(\hat{\beta}) = b_{e\ell\cdot ck} = \beta b_{h\ell\cdot ck}$. Cross-sectionally, hours per worker h should be roughly uncorrelated with any of the included variables c, ℓ, and k and, hence, cause no bias in the between regression or in the total regression (which is similar since the between variances of the variables dominate their total variance). In the time dimension, however, short-run fluctuations in demand (say a business expansion) will be met partly by modifying employment (hiring) and partly by changing hours of work (increase in overtime). Hence, $b_{h\ell\cdot ck}$ should be positive and rather large (perhaps .5 or higher), and therefore the within estimate of $\hat{\beta}$ should be biased upward and substantially so (perhaps by $.6 \times .5 = 0.3$). Considering then that the within correlations of h with c and k are likely to be negligible, we have seen that a significant

16. The auxilary regression of ℓ on c and k giving these coefficients is precisely what we shall call our semireduced form labor equation; tables 17.8, 17.9, and 17.10 provide their exact values for our various samples. Note that since the order of magnitude of the sum of these coefficients is less than one, we cannot explain the downward biases in $\hat{\alpha}$ and $\hat{\gamma}$ and also in the returns to scale $\hat{\mu}$ solely by the transmission of an upward bias in $\hat{\beta}$. Our second misspecification example, the omission of materials, does not assume that c and k are predetermined and hence that the biases are only caused by the correlation of ℓ and e; it provides, as we shall see below, a rationalization of the decreasing returns to scale estimates in the within dimension.

downward bias should be transmitted to the within estimates of $\hat{\alpha}$ and $\hat{\gamma}$ (about $-.3 \times .4$ or $-.3 \times .3 \simeq -.1$).

The same type of analysis applies to the exclusion of materials as a factor in the production function (or to not using value added but gross output or sales to measure production). The total estimates of $\hat{\alpha}$, $\hat{\beta}$, and $\hat{\gamma}$ should all move up roughly in proportion to the elasticity of materials δ [by $1/(1-\delta)$], while the within estimates $\hat{\alpha}$, $\hat{\beta}$, and $\hat{\gamma}$ will be raised in lesser proportions, with the plausible result of a negligible bias in the total and a large downward bias in the within estimates of the scale elasticity.

This time let the "true" model be:

$$q = \alpha c + \beta \ell + \gamma k + \delta m + \epsilon$$

(i.e., a generalized Cobb-Douglas production function where materials come in as another factor). Estimating a gross output equation ignoring m assumes implicitly that materials are used in fixed proportion to output. This may be a belief about the technical characteristics of the production processes (the form of the production function) or the consequence of assuming that materials are purchased optimally and that their price relative to the price of output remains roughly constant over firms and over time. In any case, omitting m where it should be included means that the error in the estimated model is $e = \epsilon + \delta m$, resulting in the following biases for our estimates:

$$\text{bias}\,\hat{\alpha} = \delta\, b_{mc\cdot \ell k}, \text{bias}\,(\hat{\beta}) = \delta b_{m\ell \cdot ck}, \text{bias}\,(\hat{\gamma}) = \delta b_{mk\cdot c\ell}.$$

Across firms, in the between dimension, it is quite likely that the sum of the auxiliary regression coefficients b's will not depart far from unity, so that the sum of estimates $\hat{\alpha} + \hat{\beta} + \hat{\gamma}$ will approach the relevant true scale elasticity $\mu = \alpha + \beta + \gamma + \delta$. If the proportionality assumption of q and m holds well enough, then the b's would be more or less proportional to the corresponding elasticities and the relative biases roughly the same:

$$\hat{\alpha} = \alpha/(1-\delta), \hat{\beta} = \beta/(1-\delta), \hat{\gamma} = \gamma/(1-\delta).$$

Over time, however, it is more likely that material usage may change less than proportionally, since it will respond incompletely or with lags to short-run output fluctuations. Hence, the sum of the b's might be much less than one in the within dimension, causing the misleading appearance of decreasing returns to scale. As a plausible example, we can take

$$b_{mc\cdot \ell k} = b_{mk\cdot \ell c} = 0, \text{ and } b_{m\ell \cdot ck} = .5,$$

and if the true coefficients are $\alpha = .15$, $\beta = .3, \gamma = .05$ and $\delta = .5$ $(\mu - 1 = 0)$, we get the following within estimates when m is omitted:

$$\hat{\alpha} = .15, \hat{\beta} = .55, \hat{\gamma} = .05, \text{and}\, \hat{\mu} - 1 = -.25.$$

Turning to the problem of simultaneity and assuming that firms try to maximize their profits in the short run, given their stocks of physical and R & D capital, the true model will consist of a production function and a labor demand function:

$$q = \alpha c + \beta \ell + \gamma k + e,$$

$$q = \ell + w + v,$$

where w is the real price of labor, and v is a random optimization error. We can assume that the errors in the two equations (e and v) are independent or, more generally, that they are of the following form: $(e + f)$ and $(v + f)$, where e and f are respectively the parts of the disturbance in the production function transmitted and not transmitted to the labor variable. The OLS bias in $\hat{\beta}$ can be written as

$$E(\beta - \hat{\beta}) = b_{el \cdot ck} = (1 - \beta)R,$$

where

$$R = \sigma_{e}^{2}/[\sigma_{e}^{2} + \sigma_{w}^{2}(1 - r_{w \cdot ck}^{2}) + \sigma_{v}^{2}]$$

is the ratio of the random transmitted variance in the production function to the sum of itself and the independent variance in the labor equation. Thus, to get some notion about the value of R and the bias in $\hat{\beta}$, we need to discuss the potential sources of variation in e, v, and w.

Schematically, we can think of the disturbance in the production function as consisting of: (1)long-term differences in factor productivity between firms; (2) short-run shifts in demand which are being met (partly) by changes in (unmeasured) utilization of labor and capital; and (3) errors of measurement in the deflators of output, errors arising from the use of gross rather than net output concepts, and errors arising from the use of sales rather than output concepts. Only items (1) and (2) matter as far as the formulas are concerned since (3) (errors of measurement) are not really transmitted to labor. Moreover, only (1) matters in the cross-sectional (between) dimension under the assumption that (2) cancels out over time, while only (2) matters in the time (within) dimension.

Similarly, the independent variation in the labor equation can be partitioned into: (4) the independent variation in real wage and (5) other short-run deviations from the profit-maximizing level of employment because of implicit contracts, shortages, or mistaken expectations. It is probably the case that most of the factor price variation to which firms respond is either permanent and cross-sectional or is common to all firms in the time dimension and hence is captured by the time dummies or trend coefficients. Thus, we anticipate that (4) manifests itself largely in the between dimension while (5) is all that is left in the within dimension.

On the basis of the estimated variances and covariances of the residuals for the semireduced form equations to be discussed below, we can give the following illustrative orders of magnitude (for $\beta \sim .6$):

$$\sigma^2_{(1)} = \sigma_e^{2(B)} = .004\,, \quad \sigma^2_{(2)} = \sigma_e^{2(W)} = .002\,,$$

$$\sigma^2_{(3)} = \sigma_f^{2(B)} + \sigma_f^{2(W)} = .04 + .008\,,$$

$$\sigma^2_{(4)} = \sigma^{2(B)}_{w\cdot ck} = .04, \quad \sigma^2_{(5)} = \sigma_v^{2W} = .002.$$ [17]

The R would equal $(.004/.044) \sim .10$ in the between dimension and $(.002/.004) \sim .50$ in the within dimension. With a true β of .6, the OLS between and within estimates $\hat{\beta}$ would be respectively biased upward by about .04 and .20.

17.3.2 The Semireduced Form Estimates

If one takes the simultaneity story seriously, it is not surprising that the OLS within estimates of the production function are unreasonable. We should be estimating a complete simultaneous equations system instead. We cannot do that, unfortunately, lacking information on factor prices. But we can estimate semireduced form equations (i.e., reduced form equations omitting factor price variables) which may allow us to infer the relative size of our two parameters of interest α and γ.

Let the true production function be (ignoring constants, time trends, or year dummies)

$$q = \alpha c + \beta \ell + \gamma k + \delta m + e\,,$$

where both c and k are assumed to be predetermined and independent of e, while q, ℓ, and m are endogenous, jointly dependent variables. Short-run profit maximization in competitive markets implies:

$$q - \ell = w + v, q - m = p + \epsilon\,,$$

where w and p are the real prices of labor and of materials, respectively, and v and ϵ are the associated optimization errors. Solving for q, ℓ, and m yields:

$$q = \frac{1}{1 - \beta - \delta}[\alpha c + \gamma k + e - \beta(w + v) - \delta(p + \epsilon)]\,,$$

17. The variances of the residual e' and v' in our semireduced form production and labor equations are respectively:

$$[\sigma_e^2 + \beta^2(\sigma_w^2 + \sigma_v^2)]/(1 - \beta)^2 + \sigma_f^2, \text{ and } (\sigma_e^2 + \sigma_w^2 + \sigma_v^2)/(1 - \beta)^2,$$

while the covariance is $[\sigma_e^2 + \beta(\sigma_w^2 + \sigma_v^2)]/(1 - \beta)^2$. For a given β, we can thus derive estimated values of σ_e^2, $(\sigma_w^2 + \sigma_v^2)$, and σ_f^2. However, these values are extremely sensitive to the value of β chosen and to small differences in the variances and covariance of the semireduced form equations residuals.

$$\ell = \frac{1}{1-\beta-\delta}[\alpha c + \gamma k + e - (1-\delta)(w+v) - \delta(p+\epsilon)],$$

$$m = \frac{1}{1-\beta-\delta}[\alpha c + \gamma k + e - \beta(w+v) - (1-\beta)(p+\epsilon)].$$

Since materials and factor prices are unobserved in our data, we have to drop the last equation and lump w and p with the other error components in these equations. We are thus left with two semireduced form equations for output and labor. Coming back for the sake of coherence to our previous notations of the production function with m solved out $[\alpha = \alpha/(1-\delta), \ldots, e = e - \delta(p+\epsilon)/(1-\delta)]$, we can rewrite these two equations more simply:

$$q = \frac{1}{1-\beta}(\alpha c + \gamma k) + e',$$

$$\ell = \frac{1}{1-\beta}(\alpha c + \gamma k) + v',$$

(where $e' = [e - \beta(w+v)]/(1-\beta)[e - \beta(w+v)]/(1-\beta)$ and $v' = [e - (w+v)]/(1-\beta)[e - (w+v)]/(1-\beta)$.

The semireduced form equation should provide unbiased estimates of $\alpha/(1-\beta)$ and $\gamma/(1-\beta)$ to the extent that factor prices w and p are more or less uncorrelated with the capital variables c and k. This condition seems quite plausible in the within dimension. There is little independent variance left in w and p in the within dimension after one takes out their common time-series components with time dummies or a trend variable. In the between dimension, however, one would expect that w and p might vary across firms and be positively correlated with c and k, leading to downward biases in $\alpha/(1-\beta)$ and $\gamma/(1-\beta)$ in both equations (and more so in the labor equation).

Tables 17.8, 17.9, and 17.10 present estimates of such semireduced form equations comparable to the production function estimates reported in the earlier tables 17.2–17.7: total and within estimates for all firms and for scientific and other firms separately; for the two subperiods 1966–71 and 1972–77 (and between these two subperiods); for the restricted and merger samples (and the merger-no-jump sample). Since the "theory" of the semireduced form equations implies that corresponding coefficients should be the same in the two equations, we also present the constrained system (SUR) estimates.

A first look at the results shows that they are in the right ball park. They are not very strikingly different in the two dimensions, and most remarkably, the within estimates of the research capital coefficient are quite significant and rather large. Also, the corresponding estimates in the two equations are rather close. Given the large number of degrees of freedom, all differences are "statistically" significant, but constraining the

Table 17.8 **Semireduced Form Equations Estimates (complete sample, 1966–77)**

Different Regressions		Total Regressions			Within Regressions		
		$\alpha/(1-\beta)$	$\gamma/(1-\beta)$	System R^2	$\alpha/(1-\beta)$	$\gamma/(1-\beta)$	System R^2
All firms ($N = 133$)	Output	.574 (.010)	.296 (.014)	.873	.407 (.022)	.265 (.027)	.559
	Labor	.415 (.013)	.416 (.017)		.400 (.021)	.288 (.026)	
	Constrained	.554 (.010)	.311 (.014)	.857	.403 (.019)	.278 (.024)	.558
Scientific firms ($N = 77$)	Output	.488 (.013)	.378 (.017)	.910	.321 (.025)	.291 (.031)	.711
	Labor	.464 (.019)	.375 (.024)		.283 (.025)	.423 (.030)	
	Constrained	.490 (.013)	.378 (.017)	.909	.301 (.023)	.395 (.028)	.706
Other firms ($N = 36$)	Output	.544 (.018)	.380 (.024)	.860	.510 (.037)	.067 (.052)	.340
	Labor	.290 (.021)	.558 (.029)		.559 (.036)	.122 (.051)	
	Constrained	.506 (.018)	.407 (.024)	.802	.536 (.033)	.096 (.041)	.337

Table 17.9 **Semireduced Form Equations Estimates for Subperiods: 1966–71 and 1972–77 and between Subperiods (scientific firms, complete sample)**

Different Regressions		Total Regressions			Within Regressions		
		$\alpha/(1-\beta)$	$\gamma/(1-\beta)$	System R^2	$\alpha/(1-\beta)$	$\gamma/(1-\beta)$	System R^2
Subperiod 1966–71	Output	0.480 (0.019)	0.363 (0.025)	0.902	0.350 (0.036)	0.164 (0.047)	0.582
	Labor	0.482 (0.027)	0.341 (0.035)		0.437 (0.043)	0.230 (0.057)	
	Constrained	0.480 (0.019)	0.363 (0.025)	0.902	0.371 (0.035)	0.180 (0.046)	0.571
Subperiod 1972–77	Output	0.500 (0.018)	0.394 (0.023)	0.917	0.060 (0.046)	0.622 (0.071)	0.418
	Labor	0.447 (0.026)	0.408 (0.033)		0.107 (0.040)	0.579 (0.062)	
	Constrained	0.506 (0.018)	0.392 (0.022)	0.915	0.093 (0.039)	0.592 (0.059)	0.417
Between subperiods	Output				0.413 (0.022)	0.264 (0.024)	0.830
	Labor				0.259 (0.020)	0.464 (0.022)	
	Constrained				0.320 (0.019)	0.385 (0.027)	0.822

Table 17.10 **Semireduced Form Equations Estimates for the Restricted, Merger, and Merger No Jump Samples (scientific firms, 1966–77)**

Different Regressions		Total Regressions			Within Regressions		
		$\alpha/(1-\beta)$	$\gamma/(1-\beta)$	System R^2	$\alpha/(1-\beta)$	$\gamma/(1-\beta)$	System R^2
Restricted Sample	Output	0.521 (0.014)	0.343 (0.019)	.923	0.500 (0.038)	0.146 (0.037)	.730
	Labor	0.481 (0.022)	0.343 (0.029)		0.392 (0.035)	0.281 (0.034)	
	Constrained	0.527 (0.013)	0.343 (0.017)	.921	0.433 (0.033)	0.230 (0.032)	.725
Merger Firms	Output	0.402 (0.028)	0.484 (0.031)	.896	0.208 (0.042)	0.434 (0.059)	.714
	Labor	0.461 (0.038)	0.438 (0.042)		0.179 (0.045)	0.572 (0.063)	
	Constrained	0.407 (0.028)	0.480 (0.031)	.895	0.196 (0.038)	0.492 (0.053)	.709
Merger: no-jumps sample	Output	0.460 (0.028)	0.414 (0.032)	.925	−0.117 (0.083)	0.652 (0.106)	.519
	Labor	0.521 (0.039)	0.355 (0.045)		0.178 (0.077)	0.372 (0.098)	
	Constrained	0.468 (0.027)	0.405 (0.031)	.924	0.049 (0.066)	0.495 (0.085)	.504

coefficients to be equal in the two equations results in a negligible loss of fit, changing the systemwide R^2 only in the third (or second) decimal place.

A more careful examination confirms, more or less, our previous production function findings. The estimates for the two, scientific and other firms, are close, given the collinearity between c and k, which causes the much lower within estimate of $\gamma/(1-\beta)$ for the other firms group to be largely counterbalanced by the higher estimates of $\alpha/(1-\beta)$. The estimates for the two subperiods are also quite comparable, since the higher within estimates of $\gamma(1-\beta)$ for 1972–77 can be explained, similarly, by the lower estimate of $\alpha/(1-\beta)$. Also, the merger firms do not seem to behave as differently as it appeared earlier. The within estimates of $\gamma/(1-\beta)$ for the nonmerger firms are significant, and the discrepancy between the estimates for the two types of firms may also be a result of the collinearity between c and k.

The remaining difficulty with our semireduced form estimates is their absolute size. It is different from our a priori expectations. If the true coefficients of the production function were $\alpha = .15$, $\beta = .3$, $\gamma = .05$, and $\delta = .5$, or in value-added terms $\alpha = .3$, $\beta = .6$, and $\gamma = .1$, the semireduced form coefficients should be about .75 and .25, respectively. The estimated physical capital coefficients should be about .75 and .25, respectively. The estimated physical capital coefficient is much smaller, being about .5 at best, while the estimated R & D coefficient is of the expected order of magnitude but often higher. Although the total and within estimates do not differ too strikingly, it should be noted that the estimated sum $(\alpha + \gamma)/(1-\beta)$ is about .8 or .9 cross-sectionally and about .5 to .7 in the time dimension. This is quite similar to what happened to our production function returns to scale estimates.

We can think of two possible explanations for these shortfalls: (1) errors in variables, and (2) failure of the perfect competition assumption.

To the extent that errors in measurement are random over time (which is a difficult position to maintain for *stock* variables), their effects can be mitigated by averaging and by trying to increase the signal-to-noise ratio in the affected variables. The between subperiods estimates given in table 17.9 represent an attempt to accomplish this by using differences between two six-year subperiod averages. It is clear from this attempt (and from others not reported here) that averaging does not solve the problem of the absolute magnitude of our estimates. Either our solution for the errors of measurement is not effective (because the errors are correlated over time) or the problem is caused by something else entirely.

The perfect competition assumption is especially dubious for our large firms and short-run context. To explore the consequences of such a misspecification, we have to expand our model by adding a demand equation:

$$q_{it} = \alpha_i + z_t + \eta p_{it} + \phi k_{it} + \epsilon,$$

where α_i is a permanent firm demand level variable, z_t is a common industry demand shifter, η is the relative price elasticity of demand (where the price of the firm's products p_{it} is measured relative to the overall price level in the industry), and ϕ is the direct effect of R & D capital on the demand for the firm's products.

Given this model, we reinterpret our output variable as sales (which it really is), make price endogenous, and use the demand equation to solve it out of the system. This yields comparable semireduced form equations, but the coefficients are now

$$\frac{\alpha\left(1 + \frac{1}{\eta}\right)}{1 - \beta\left(1 + \frac{1}{\eta}\right)} \quad \text{and} \quad \frac{\gamma\left(1 + \frac{1}{\eta} - \frac{\phi}{\eta}\right)}{1 - \beta\left(1 + \frac{1}{\eta}\right)}$$

for physical and research capital, respectively. With $\eta < 0$, the research capital coefficient is seen to be a combination of both its production and demand function shifting effects.

The introduction of the $(1 + 1/\eta)$ terms into these coefficients provides an explanation for the "shortfall" in our estimates. Assuming $\eta = -4$ (i.e., if a firm lowers the relative price of its product by 25 percent, it would double its market share) and $\alpha = .3$, $\beta = .6$, $\gamma = .1$, and $\phi = .1$, implies .4 and .18 as the respective coefficients in the semireduced forms. That is not too far off and the assumptions are plausible enough, but that is about all that we can say. We shall need more data and more evidence from other implications of such a model before we can put much faith in this interpretation of our results.

17.4 Summary and Conclusions

We have analyzed the relationship between output, employment, and physical and R & D capital for a sample of 133 large U.S. firms covering the years 1966 through 1977. In the cross-sectional dimension, there is a strong relationship between firm productivity and the level of its R & D investments. In the time dimension, using deviations from firm means as observations and unconstrained estimation, this relationship comes close to vanishing. This may be due, in part to the increase in collinearity between the trend, physical capital, and R & D capital in the within dimension. There is little independent variability left there. When the coefficients of the first two variables are constrained to reasonable values, the R & D coefficient is both sizeable and significant. Another reason for these difficulties may be the simultaneity of output and employment decisions in the short run. Allowing for such a simultaneity yields rather high estimates of the importance of R & D capital relative to physical capital. Our data do not enable us, however, to answer any detailed questions about the lag structure of the effects of R & D on productivity. These effects are apparently highly variable, both in timing and magnitude.

Appendix
Variables and Additional Results

In this appendix we present more information on our sample and summarize the results of various additional computational experiments.

Table 17.A.1 lists means, standard deviations, and growth rates for our major variables, and indicates that most of the observed variance in the data (90+ percent) is between firms, rather than within firms and across time. It also underscores the fact that these firms are rather large, with an average of more than 10,000 employees per firm.

Table 17.A.2 compares our main measure of physical capital stock C to four alternatives: C', CA, CN, and CD. C is gross plant adjusted for inflation, which we assume to be proportional to a proper capital service flow measure. Since our adjustment for inflation is based on a rough first-order approximation, assuming a fixed service life, a linear depreciation pattern, and an estimate of the age of capital (AA) from reported depreciation levels, we also tried different variants of it.[18] C' is one of them in which we assume the same average service life for plant and equipment of sixteen years for all our firms. The fit is somewhat improved, but the changes in the estimates are only minor. Actually, using the reported gross plant figure without any adjustment does not make that much difference either. CA is our C measure taken at the end of the year instead of the beginning of the year. The fit is slightly improved, and the within estimates of α are increased a little. This could indicate that end of the year measures are appropriate but may also reflect a simultaneity bias arising from the contemporaneous feedback of changes in production on investment. CN and CD are net plant and depreciation adjusted for inflation, respectively. CN can be advocated on the grounds that in some sense it allows for obsolescence and embodied technical progress, and CD on the grounds that it is nearer in principle to a service

18. To be precise C_t is computed as reported gross plant $\times$ $P(72)/P(t - \mathrm{AA}_t)$, where P is the GNP price deflator for fixed investment and AA_t (the average age of gross plant) is computed as reported gross plant minus reported net plant (i.e., accumulated depreciation) divided by an estimate of the average service life LL_t. LL_t itself is computed as the five-year moving average of reported gross plant/reported depreciation.

Table 17.A.1 Characteristics of Variables, Complete Sample (133 firms)[a]

		Scientific Firms (77)					Other Firms (56)				
				Percent Variability					Percent Variability		
Main Variables[b]		Geometric Mean	Standard Deviation	Between	Within	Rate of Growth (%)	Geometric Mean	Standard Deviation	Between	Within	Rate of Growth (%)
Q	Deflated sales	297.0	1.66	95.1	4.9	8.9	442.8	1.74	97.9	2.1	3.9
L	Number of employees	10.4	1.63	97.4	2.6	4.6	12.5	1.52	97.6	2.4	2.9
C	Gross plant adjusted for inflation	188.4	2.12	95.3	4.7	10.8	295.7	2.11	97.3	2.7	8.4
K	R & D capital stock computed using a 0.15 rate of obsolescence	58.1	1.64	95.7	4.3	7.6	39.6	1.53	82.3	17.7	4.4
Q/L	Deflated sales per employee	28.7	0.39	71.6	28.4	4.3	35.3	0.49	89.8	10.2	0.9
C/L	Gross plant adjusted per employee	18.1	0.85	86.6	13.4	6.2	23.6	1.05	93.2	6.8	5.4
K/L	R & D capital stock measure per employee	5.6	0.70	90.6	9.4	3.0	3.2	0.67	87.5	12.5	1.5

[a]Standard deviations and the decomposition of the variance are given for the logarithms of the variables.

[b]Deflated sales, gross plant adjusted, and R & D capital stock are in $\$10^6$ and constant 1972 prices. Number of employees is in 10^3 persons.

Table 17.A.2 Production Function Estimates for Different Measures of Physical Capital Stock and Output, All Sectors, Complete Sample (133 firms), 1966–77 (annual and three-year averages)

	Total Regressions			Within Regressions		
Different Regressions[a]	α	γ	MSE	α	γ	MSE
C	0.310	0.073	0.097	0.160	0.150	0.0204
	0.332	0.054	0.095	0.150	0.080	0.0199
C'	0.323	0.070	0.095	0.180	0.142	0.0202
	0.350	0.048	0.092	0.173	0.069	0.0197
CA	0.322	0.074	0.095	0.201	0.156	0.0201
	0.344	0.054	0.092	0.186	0.101	0.0197
CN	0.304	0.076	0.096	0.124	0.184	0.0204
	0.325	0.050	0.094	0.114	0.115	0.0199
CD	0.361	0.062	0.099	0.194	0.163	0.0202
	0.383	0.044	0.097	0.189	0.086	0.0196
QC	0.305	0.073	0.100	0.102	0.127	0.0229
	0.325	0.055	0.098	0.093	0.060	0.0224
Three-year averages	0.313	0.074	0.091	0.195	0.154	0.0153
	0.336	0.055	0.090	0.187	0.092	0.0149

[a]Constant returns to scale are imposed for estimates reported in the first line of each cell but not in the second.

flow measure. CN results in a small decrease of the within estimate of α and a corresponding increase in γ, while CD results in an increase in both total and within estimates of α with no noticeable effect on γ. We have also run regressions including an age of capital variable, AA. While our estimates of α and γ are not affected by its inclusion, this variable in conjunction with our gross capital measure C (but not so in conjunction with the net capital measure CN) is clearly significant both in the cross-sectional and time dimensions, tending to indicate a rate of embodied technical progress of 5.5 percent per year (see Mairesse 1978).

Table 17.A.2 also gives the estimates obtained with an alternative measure of deflated sales, QC, tentatively corrected for inventory change. The correction, however, is problematic since it is based on all inventories and not just finished products. In any case, QC performs much worse both in terms of fit and in terms of the order of magnitude of the within estimates. Finally, we also list estimates based on three-year averages of the observations. While errors of measurement appear to be a priori an important issue (if they were random and uncorrelated, going to averages should reduce the resulting biases), the changes are not striking and the discrepancy between total and within estimates remains. Yet there is a sizeable increase (about 20 percent) in the within estimate of α, which might reflect an error in the capital-labor ratio accounting for about 30 percent of the observed "within" variance in this ratio.

Because we did not want to give up hope of gaining some evidence on the lag structure of R & D effects, we experimented with a large number of R & D capital stock measures, but mostly in vain. Table 17.A.3 compares K, the measure we finally settled on based on a 15 percent depreciation rate, to six rather different alternatives. $K00$ and $K30$ are computed similarly to K but assuming 0 and 30 percent per year obsolescence rates instead. K' and $K'00$ differ from K and $K00$ respectively in assuming that R & D vintages older than eight years are completely obsolete. Since information on R & D is available only from 1958 (i.e., for eight years before 1966), this is also a way to test our initial condition assumption. In the K and $K00$ measures, the 1958 R & D capital levels are based on extrapolating R & D expenditures back to 1948, using the 1958–63 individual firm R & D growth rate shrunk toward the overall industry rate. KP is also a summation of past R & D expenditures over eight years but with a very different peaked lag structure: $w_{-1} = w_{-8} = 0.05$, $w_{-2} = w_{-7} = 0.10$, $w_{-3} = w_{-6} = 0.15$, and $w_{-4} = w_{-5} = 0.20$. Finally, K, P_{-34}, P_{-56}, P_{-78}, P_{-9+} is one of the free-lag version experiments we have attempted. The P variables are the following proportion of past R & D expenditures (over two years plus the tail) to total cumulated expenditures (with a .15 rate of obsolescence):

$$(R_{-3} + R_{-4})/K,\ (R_{-5} + R_{-6})/K,\ (R_{-7} + R_{-8})/K,$$
$$(R_{-9} + R_{-10} + \ldots)/K.$$

Table 17.A.3 Production Function Estimates Based on Different Measures of R & D Capital, Complete Sample (133 firms), 1966–77

Alternative R & D Capital Measures[a]	Total Regressions α	Total Regressions γ	Total Regressions MSE	Within Regressions α	Within Regressions γ	Within Regressions MSE
K	0.310	0.073	0.097	0.160	0.150	0.0204
	0.332	0.054	0.095	0.150	0.080	0.0199
K'	0.311	0.075	0.096	0.173	0.119	0.0206
	0.333	0.057	0.094	0.153	0.064	0.0199
$K00$	0.309	0.059	0.098	0.152	0.172	0.0202
	0.334	0.040	0.095	0.154	0.081	0.0199
$K'00$	0.311	0.070	0.097	0.178	0.106	0.0207
	0.333	0.051	0.095	0.158	0.050	0.0200
$K30$	0.311	0.079	0.096	0.167	0.137	0.0204
	0.332	0.061	0.094	0.147	0.084	0.0198
KP	0.311	0.065	0.097	0.195	0.070	0.0209
	0.334	0.046	0.095	0.165	0.027	0.0200
K and	0.318	0.070	0.094	0.149	0.205	0.0197
P_{-34}, P_{-56}, P_{-78}, P_{-9+}	0.340	0.051	0.092	0.152	0.120	0.0196

[a]First line regressions assume constant returns to scale, second line regressions do not.

Hence, the coefficients of the P's should give an indication of how far the respective true weights are from the assumed declining weights in K: 1, .85, .72, .61, .52, . . . , etc.

As was the case for the different physical capital measures, the total estimates are almost unaffected by all this experimentation, while the within estimates are more sensitive. The initial conditions seem to matter very slightly, showing some influence of a truncation remainder or tail effect. The within regressions with the K and $K00$ measures perform a little better in terms of fit than those with the corresponding K' and $K'00$ measures (which assume no effective R & D before 1958), and the estimated γ is a bit higher. The assumption about the order of magnitude of the rate of obsolescence δ is even less important. Still, there is some tenuous evidence here for a rather rapidly declining lag structure. The KP measure (which assumes a peaked lag structure) has the lowest fit and the lowest within γ, while the "free lag" version in the neighborhood of the K measure performs best on both grounds. The estimated P coefficients (within) are:

$$P_{-34}: \underset{(0.09)}{-0.35}, \quad P_{-56}: \underset{(0.07)}{-0.17}, \quad P_{-78}: \underset{(0.07)}{-0.10}, \quad P_{-9+}: \underset{(0.02)}{0.05},$$

implying that around lag 3 and 4 the weight of past R & D is about .22 rather than .57, around lag 5 and 6 it is .24 rather than .41, around lag 7 and 8 it is .20 rather than .30, and around lag 11 it is .22 rather than .17. That is, there is a reasonably strong immediate effect in the first two years which then drops sharply and stays constant through most of the rest of the observable range.

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