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Exploring the relationship between R&D and productivity in French manufacturing firms

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Abstract

Using a newly available dataset on the R&D investment of individual French manufacturing firms for the 1980s, we replicate and update a series of studies on French R&D and productivity at the firm level from the 1970s, and evaluate the robustness of methods currently used to measure the private returns to R&D. Our main findings are: Having a longer history of R&D expenditures helps improve the quality of the R&D elasticity estimates, but the choice of depreciation rate for R&D capital makes little difference. The correction for double-counting of R&D expenditures in capital and labor is important and may be interpreted under certain conditions as converting a measured 'excess' rate of return to a total rate of return to R&D. We show that the direct production function approach to measure returns to R&D capital is preferred on several grounds over the rate of return variation used in the past. Finally, as in the 1970s, the productivity of R&D capital for French manufacturing firms in the 1980s is positive; how strong and robust depends on whether we control for potential industry and firm effects.

Key words: R&D; Productivity; Panel data; Manufacturing; Firm level
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1. Introduction

This paper uses a newly available dataset on the R&D performance of individual French manufacturing firms for the 1980s to replicate and update a series of studies on French R&D and productivity at the firm level during the 1970s by Griliches and Mairesse (1983), Cuneo and Mairesse (1984), Mairesse and Cuneo (1985), and Mairesse and Sassenou (1991a). These studies, along with most other studies using individual firm data for the United States and Japan, have been surveyed by Mairesse and Sassenou (1991b). This survey documented the widely varying estimates of the contribution of R&D to productivity across samples, model specifications, and estimation methods. The purpose of the present paper is to further explore the reasons for these different estimates using a single dataset, but varying specifications of the model. This facilitates interpretation of the differences by eliminating the source of variability due to the data samples.

A justification for the present study is the fact that the new dataset provides us with a longer time series (1971 to 1987) on many of the firms, and also with data on a larger number of firms for the nineteen-eighties.[1].The data contain enough information to allow us to correct for the 'double-counting' of the inputs to R&D expenditures in labor, capital, and value added.[2] The longer history allows us to explore in more detail the effect of various assumptions used in constructing the stock of R&D capital. We also have on this dataset labor shares to enable us to calculate partial factor productivity at a firm-specific level rather than relying completely on production function estimates.

Another justification for our study is that the period of the 1970s, on which the previous studies were based, was not a 'favorable' period from the perspective of measuring the contribution of R&D investment to growth. The data in most of the OECD countries during this period are dominated by the stagnation and upheavals induced by the oil price shocks of 1973–74 and 1978–79. This has implications particularly for the growth rate (first-differenced) specifications of the productivity growth equations, where the heterogeneity of the individual units tends to reveal itself as a substantial downward measurement error bias. That is, in a period where there is little overall growth, the variance in the right-hand-side variables of the regression is dominated by such heterogeneity or 'measurement error' and we obtain the usual result that coefficients are imprecisely measured when there is little *true* dispersion in the regressors. By

[1] The data on research and development expenditures used in this paper come from the *Enquetes annuelles sur les moyens consacrés à la recherche et au developement dans les entreprises* conducted by the French Ministry of Research and Technology. This file has been augmented with data on value added, capital, labor, and other variables from the *Enquete annuelle d'entreprises* and the *Systeme Unifie de Statistiques d'Entreprises* at INSEE.

[2] See Schankerman (1981). A useful discussion of the biases introduced by such 'double-counting' and an evaluation of their effects on estimates with French data may also be found in the appendix to Cuneo and Mairesse (1984).

moving to the less troubled period of the 1980s, we hope to achieve more real dispersion in our regressors, and hence better estimates.

We begin by describing the new dataset and then outline the production function framework within which we are working and the measurement issues which it raises for R&D capital. We then present our basic set of estimates of the production function coefficients for French manufacturing during the 1980s. Two sections which present estimates using variations on the basic model follow: the first takes a partial productivity approach to correct for the simultaneity of output and labor, and the second uses a rate of return to R&D capital formulation of the production function. The results of the three approaches to estimating the elasticity of output with respect to R&D capital are summarized in the concluding section.

2. Data and variables

Our raw dataset consists of 351 French manufacturing firms in a slightly unbalanced panel from 1980 to 1987, among which 210 had R&D information available back to 1971 from the previous studies. When performing a comparative measurement analysis such as ours, it is important that the sample of data with which one is working be held fixed, so that any differences in estimates can be attributed to the change in measurement techniques rather than a slight change in sample. Accordingly, we defined at the outset a 'clean' sample according to a set of criteria which are given in Appendix A. Briefly, we trimmed outliers in both levels and growth rates, required that value added be positive, and removed observations for which the double-counting corrections were more than 50 percent of the total.

After cleaning, there were 340 firms left with good data and 206 with data back to 1971; 197 of these 206 remain when we require that the panel be fully balanced for 1980 to 1987. The results in the next several sections are based primarily on this balanced panel of 197 firms (and $1576 = 197 \times 8$ observations). Some of the results of estimating our preferred specifications are also given for the largest clean sample of 340 firms. This sample, which is slightly unbalanced, consists of 2670 observations pertaining to the 197 firms in the balanced long panel and 143 firms with shorter or incomplete R&D histories.

Table 1 shows the sectoral breakdown of the large and long samples into industries; it also compares their R&D to sales ratios to those for manufacturing as a whole, and gives their coverage ratios in proportion to total manufacturing R&D expenditures. The average ratios are reasonable overall (55 and 45 percent respectively for the large and long samples) and the R&D to sales ratios are also quite similar overall; these comparisons, however, are less satisfactory in several industries.

Table 2 gives simple statistics for our key variables for these two samples. The key variables are value added, which is our output measure, the physical capital

Table 1
Industrial sector breakdown

Sector	No. of firms		No. of obs.		R&D–sales ratio[a]			Share of R&D[b]	
	Large sample	Long sample	Large sample	Long sample	French total (percent)	Large sample	Long sample	Large sample (percent)	Long sample
1 Food & Agriculture	32	2	252	16	1.0	0.5	0.5	17.9	0.9
2 Textiles, Apparel, Leather, & Wood	40	15	313	120	2.4	3.9	5.5	53.4	43.7
3 Chemicals	13	9	104	72	3.2	3.3	3.4	22.6	21.4
4 Const. Materials & Glass	18	12	141	96	2.5	0.5	0.6	23.5	15.6
5 Metals & Fabrication	31	17	246	136	1.5	1.3	1.3	33.0	26.8
6 Nonelectrical Machinery	56	36	441	288	3.4	2.3	1.8	32.8	20.0
7 Electrical Machinery	33	25	261	200	3.2	4.0	4.0	109.7	97.8
8 Autos, Aircraft	28	20	212	160	6.3	5.1	4.6	80.7	71.5
9 Pharmaceuticals	56	36	441	288	9.2	4.5	5.1	60.2	47.8
10 Electronics	33	25	259	200	9.9	7.1	6.3	41.8	31.7
Total Manufacturing	340	197	2670	1576	4.5	4.2	4.2	55.4	46.2

[a]This is the *industry* R&D to sales ratio (in percent), not the average of individual firm ratios. It is computed for the year 1985. The numbers for France as a whole come from *La Recherche dans les Entreprises*, Direction Générale de la Recherche et de la Technologie, Ministère de la Recherche et de l' Enseignement Supérieur, 1985.

[b]This is the coverage ratio of our samples relative to the universe (French manufacturing) in terms of total R&D performed by manufacturing enterprises.

Table 2
Statistics on the variables (after cleaning and deflation), 1980–1987

		Large sample		Long sample		Large sample	
Variable	Name	Median	IQ range[a]	Median	IQ range[a]	Minimum	Maximum
No. of observations		2670		1576		2670	
Value added (MM of 1980 FF)	*VA*	146.2	76/358	198.8	85/458	8.06	15,174.0
VA adj. for R&D (MM of 1980 FF)	*VADJ*	150.6	77/369	202.5	89/465	8.31	15,642.0
Net capital stock (MM of 1980 FF)	*C*	305.0	115/816	395.0	125/1189	10.01	44,902.0
Cap. stock adj. for R&D (MM of 1980 FF)	*CADJ*	300.7	110/806	385.4	122/1135	9.26	43,881.0
R&D capital[b] (MM of 1980 FF)	*K71*	40.7	14/113	64.7	23/154	1.06	17,916.0
R&D capital[b] (MM of 1980 FF)	*KH71*	26.8	9/72	40.7	16/100	0.68	11,908.0
R&D capital[b] (MM of 1980 FF)	*KS78*	38.7	14/100	61.0	23/148	1.06	17,390.0
R&D expenditures (MM of 1980 FF)	*R*	7.3	2.5/20.3	11.1	4.7/29.8	0.17	3,535.0
Number of employees (beg. of year)	*L*	964.0	533/2304	1251.0	584/2957	68.00	106,740.0
No. empl. adj. for R&D (beg. of year)	*LADJ*	924.0	499/2193	1134.0	524/2817	65.00	103,042.0
VA growth rate[c]	(percent)	1.17	− 6.5/9.46	0.86	− 6.7/8.95	− 81.0	226.0
C growth rate[c]	(percent)	2.76	0.38/5.73	2.79	0.28/5.06	− 22.0	92.0
L growth rate[c]	(percent)	− 0.99	− 4.6/2.02	− 1.21	4.8/1.73	− 44.0	189.0
K growth rate[c]	(percent)	3.96	0.15/8.57	3.97	0.07/8.63	− 13.0	159.0

[a]The IQ range is the interquartile range, the value of the variable at the 25 percent and 75 percent level of the univariate distribution.

[b]The three types of R&D capital are calculated as described in Section 3 of the paper.

[c]The growth rate average is over seven observations per firm rather than eight (2344 observations in columns 3, 4, 7, and 8, and 1379 in columns 5 and 6).

stock of the firm, the knowledge or R&D capital, and the number of employees. Value added, capital stock, and the number of employees are shown both unadjusted and adjusted for the double-counting of R&D inputs.[3] All variables (except employment) are deflated; the deflators are output deflators at the ten-industry level for value added, and the capital stock is based on gross book value adjusted for inflation using an overall investment deflator. R&D expenditures are simply deflated by the manufacturing sector level value added deflator.[4] In the next section of the paper we will say more about how the R&D capital variable was constructed.

Table 2 shows that the median firm in the large sample has around 1000 employees (of whom 40 are R&D employees), physical capital worth 300 million 1980 French francs (approximately 50 million 1980 dollars), and produces 150 million 1980 French francs in value added per year. The firms in the long sample are larger (averaging around 1250 employees of whom 120 are R&D employees); they also have a slightly higher capital–labor ratio, and substantially higher value added per worker (170 thousand 1980 French francs as compared with 150 thousand). Both sets of firms have average rates of growth of value added, labor, and physical and R&D capital stock which are approximately equal, and higher growth rates of R&D capital. The firms are clearly becoming more capital-intensive over time, since employment is declining substantially over the whole period, implying an average increase in the capital–labor ratio of about $3\frac{1}{2}$ percent per year.

3. The production function framework and the measurement of R&D capital

In this section, we remind the reader of the by now familiar theoretical framework in which we are working and discuss our measures of the R&D capital stock variable. We assume that the production function for manufacturing firms can be approximated by a Cobb–Douglas function in the three inputs, physical capital C, labor L, and R&D or knowledge capital K:

$$Y_{it} = Ae^{\lambda t}C_{it}^{\alpha}L_{it}^{\beta}K_{it}^{\gamma}e^{\varepsilon_{it}}, \tag{1}$$

where Y is value added, ε is a multiplicative disturbance, i denotes firms, and t years. λ is the rate of disembodied technical change; however, as we discuss later in this section, the time trend λt will be replaced with time dummies in

[3] These adjustments are performed by subtracting R&D employment from employment, subtracting an 'R&D capital stock' constructed from the capital investment component of R&D expenditure from the capital stock, and adding the materials component of R&D expenditure back into value added.

[4] Later work by Bruno Crepon and Jacques Mairesse has shown that using a total manufacturing R&D deflator does not affect our basic results.

actual estimation. α, β, and especially γ (the elasticity of value added with respect to R&D capital) are the parameters of interest.

As usual, to implement the estimation of the Cobb–Douglas function, we take logarithms and obtain the following linear regression equation (where lower case letters denote the logarithms of variables):

$$y_{it} = a + \lambda t + \alpha c_{it} + \beta l_{it} + \gamma k_{it} + \varepsilon_{it}. \tag{2}$$

Under constant returns to scale with respect to the three inputs, the sum $\mu = \alpha + \beta + \gamma$ of factor elasticities will be unity. For interpretive reasons, we prefer to rewrite Eq. (2) so that the deviation from constant returns is measured explicitly, by subtracting labor from both sides of the equation:

$$(y_{it} - l_{it}) = a + \lambda t + \alpha(c_{it} - l_{it}) + \gamma(k_{it} - l_{it}) + (\mu - 1)l_{it} + \varepsilon_{it}. \tag{3}$$

The coefficient of the logarithm of labor $(\mu - 1)$ now measures the departure from constant returns.

The econometric and theoretical assumptions necessary to justify the use of this equation to estimate the parameters of the production function do not include perfect competition in output or factor markets, but they do include some kind of predeterminedness of the inputs with respect to output. By using input measures from the beginning of the year for which the output is measured, we hope to minimize the effects of simultaneity between factor choice and output, but this could still be a problem.

Finally, we note that ε_{it} includes any errors in the specification which arise because firms have different production functions (or because we have not disaggregated the inputs enough), as well as pure measurement error on all the variables. The most important component of ε_{it} is likely to be due to the heterogeneity across firms in their technologies and type of output, and this will introduce a 'firm effect' in our disturbance.[5] To the extent that this firm effect is correlated with our regressors, as seems not unlikely, we will have an omitted variable bias in our coefficient estimates. We follow the usual route of estimating equations 'within firm', as well as in first and long (1980 to 1987) differences to attempt to assess the extent of this bias.

Another component of ε_{it} may be due to changes over time in the rate of productivity growth which are common to all firms. Although economists commonly label these 'disembodied technical change' and model them with a deterministic (or stochastic) trend, they also include any errors in the price deflators common across firms, or other macro influences which may affect

[5] See Mairesse and Griliches (1990) and Mairesse (1988, 1990) for discussions of the extreme heterogeneity in these kinds of data.

measured outputs and inputs.[6] Although our model as written in Eqs. (1) to (3) contains only a time trend to summarize these effects, we have used individual dummies for each year in the estimation, since we do not believe they are constant over time.[7]

To construct the stock of R&D or knowledge capital for the firm, we follow a perpetual inventory method like that commonly used for physical capital.[8] The equation defining R&D capital K is the following:

$$K_t = (1 - \delta)K_{t-l} + R_{t-l}, \tag{4}$$

where K_t is beginning of period capital stock and R_t is R&D expenditures during the period. This computation has two obvious problems: first, we have very little idea what the appropriate depreciation rate δ is (if indeed it is constant across firms and over time), and second, our history of *measured* R&D expenditures is frequently not very long, so we need a way of starting the process presample. Using our long balanced sample of 197 firms, we explore the effects of uncertainty about both these factors on our calculation of K_t.

Our base case (*K71*) set of assumptions are those which have been most frequently used previously in this type of estimation: we assume a depreciation rate of 15 percent, a presample growth rate of 5 percent in real R&D expenditures, and we start the perpetual inventory accumulation process with the earliest year of R&D data available (1971 for our long history sample).[9] That is, if our R&D series starts in year $t = 1$ and the presample accumulation of knowledge capital is given by Eq. (4) with R&D growing at a rate of g, the knowledge capital at the beginning of the first year is defined by the following equation:

$$\begin{aligned} K_1 &= R_0 + (1 - \delta)R_{-1} + (1 - \delta)^2 R_{-2} + \cdots \\ &= \sum_{s=0}^{\infty} R_{-s}(1 - \delta)^s = R_0 \sum_{s=0}^{\infty} \left[\frac{1 - \delta}{1 + g}\right]^s = \frac{R_1}{g + \delta}. \end{aligned} \tag{5}$$

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[6] As written, the model in levels contains a deterministic trend (λt), but after differencing this is indistinguishable from a stochastic trend with constant drift. The only way these two models differ in their implications for a panel of growth rates might be in the variance components structure of the disturbance, since a common stochastic trend would guarantee that the time component of the disturbance is increasing, while a deterministic trend does not.

[7] An F-test for the equality of the year dummies in the first-differenced version of the model rejects in all specifications and for both samples of firms. For example, the values of $F(6,...)$ for the four columns of Table 5 are 4.46, 3.69, 6.22, and 5.38, respectively, with denominator degrees of freedom equal to 2643, 1633, 2644, and 1634.

[8] This method for measuring R&D capital has been discussed by Griliches (1979).

[9] The presample growth rate of 5 percent is approximately the mean growth rate for the firms which we observe during the nineteen-seventies. In any case, the precise choice of growth rate affects only the initial stock, and declines in importance as time passes, unlike the choice of depreciation rate. For this reason, we do not report the results of experimentation with this assumption.

We vary this by using a depreciation rate of 25 percent, which is the high end of the orders of magnitude obtained by Pakes and Schankerman (1984) or Hall (1988) using different methods (*KH71*). We also compare results obtained for the long history sample when we assume that the observable R&D process began in 1978, two years before our estimations begin and one year before the first value of R&D capital that we use (*KS78*). We capitalize the R&D spending in that year at the depreciation rate 15 percent plus a growth rate of 5 percent. Finally, we use the most extreme version of a short R&D history, by assuming that the previous year's R&D expenditures are the best indicator of the quality of its knowledge capital (*KR*). Note that because of the logarithmic formulation we are *not* necessarily assuming a depreciation rate of 100 percent, but rather that this year's expenditures are a better *measure* of the knowledge capital contained within the firm. This assumption is supported by some of the patent productivity evidence of Hall, Griliches, and Hausman (1986), for example.

4. The productivity of R&D

In this section, we discuss our basic production function results for both samples of firms. First we present a complete set of estimates for the long balanced panel in Tables 3 and 4 and then selected estimates for the larger sample in Table 5. Table 3 shows the estimates obtained when constant returns to scale are not imposed, using our different measures of R&D capital and different estimation techniques. It also gives the estimates with the measures of value added, labor, and physical capital which have not been corrected for double counting of R&D expenditures (and our preferred measures of R&D capital). Table 4 shows the same estimates with constant returns to scale imposed. The key results in these tables can be summarized as follows:

1) The hypothesis of constant returns to scale is accepted for the within and long-differenced estimates, rejected in the totals with a very small coefficient and in first differences with a large coefficient (where this large size suggests substantial downward biases probably due to the magnification of random measurement error).[10] In all cases, the effect on the fit of imposing constant returns to scale is quite small: Only for the first-differenced estimates does the standard error of estimate rise by even as much as 1 percent.

2) The adjustment for double-counting of R&D expenditures produces the most important differences across the columns of the tables with the possible exception of the first-differenced estimates (compare columns 1 and 2). These corrections tend to increase the total and long-differenced R&D capital coefficients by about 0.07 and the within coefficients by about 0.04–0.06. This increase

[10] See Griliches and Hausman (1986).

Table 3

Production function estimates, long sample, 1980–1987, 197 firms (1576 observations)

Dependent variable: Log(Value added/Employee), constant returns to scale not imposed

	Unadjusted *K71*	Adjusted *K71*	Adjusted *KH71*	Adjusted *KR*	Adjusted *KS78*
Totals					
log(C/L)	0.207 (0.013)	0.199 (0.013)	0.214 (0.013)	0.217 (0.012)	0.207 (0.013)
log(K/L)	0.180 (0.009)	0.252 (0.008)	0.254 (0.008)	0.248 (0.008)	0.246 (0.008)
logL	− 0.030 (0.007)	− 0.035 (0.007)	− 0.035 (0.007)	− 0.037 (0.007)	− 0.035 (0.008)
R^2(s.e.)	0.996 (0.336)	0.996 (0.344)	0.996 (0.338)	0.996 (0.335)	0.996 (0.345)
Within					
log(C/L)	0.121 (0.059)	0.174 (0.057)	0.178 (0.058)	0.102 (0.036)	0.187 (0.057)
log(K/L)	− 0.001 (0.036)	0.069 (0.035)	0.050 (0.028)	0.051 (0.016)	0.004 (0.031)
logL	− 0.095 (0.052)	− 0.055 (0.053)	− 0.070 (0.051)	− 0.132 (0.042)	− 0.090 (0.053)
R^2(s.e.)	0.075 (0.188)	0.103 (0.186)	0.103 (0.186)	0.104 (0.185)	0.101 (0.186)
Long differences					
log(C/L)	0.137 (0.137)	0.199 (0.133)	0.202 (0.133)	0.164 (0.084)	0.209 (0.132)
log(K/L)	0.064 (0.085)	0.129 (0.029)	0.122 (0.069)	0.122 (0.049)	0.086 (0.077)
logL	0.131 (0.115)	0.165 (0.116)	0.150 (0.112)	0.095 (0.097)	0.149 (0.118)
R^2(s.e.)	0.011 (0.0510)	0.030 (0.0507)	0.034 (0.0506)	0.050 (0.0502)	0.022 (0.0509)
First differences					
log(C/L)	0.203 (0.096)	0.233 (0.092)	0.239 (0.092)	0.071 (0.040)	0.234 (0.092)
log(K/L)	0.045 (0.072)	0.051 (0.070)	0.034 (0.051)	0.022 (0.019)	0.025 (0.065)
logL	− 0.607 (0.099)	− 0.600 (0.098)	− 0.611 (0.091)	− 0.754 (0.060)	− 0.621 (0.098)
R^2(s.e.)	0.157 (0.197)	0.183 (0.193)	0.183 (0.193)	0.181 (0.193)	0.183 (0.193)

K71 = knowledge capital constructed with $\delta = 0.15$, using R&D history to 1971.
KH71 = knowledge capital constructed with $\delta = 0.25$, using R&D history to 1971.
KR = knowledge capital = R_{-1} divided by $\delta = 0.15$.
KS78 = knowledge capital constructed with $\delta = 0.15$, using R&D history to 1978.

Table 4

Production function estimates, long sample, 1980–1987, 197 firms (1576 observations)

Dependent variable: Log(Value added/Employee), constant returns to scale imposed

	Unadjusted *K71*	Adjusted *K71*	Adjusted *KH71*	Adjusted *KR*	Adjusted *KS78*
Totals					
$\log(C/L)$	0.190 (0.012)	0.179 (0.012)	0.193 (0.012)	0.195 (0.012)	0.187 (0.012)
$\log(K/L)$	0.176 (0.009)	0.251 (0.008)	0.253 (0.008)	0.247 (0.008)	0.245 (0.008)
R^2(s.e.)	0.996 (0.338)	0.996 (0.346)	0.996 (0.341)	0.996 (0.337)	0.996 (0.347)
Within					
$\log(C/L)$	0.181 (0.040)	0.209 (0.047)	0.229 (0.044)	0.161 (0.031)	0.246 (0.045)
$\log(K/L)$	0.032 (0.035)	0.080 (0.033)	0.057 (0.028)	0.056 (0.016)	0.022 (0.030)
R^2(s.e.)	0.074 (0.188)	0.103 (0.186)	0.102 (0.186)	0.099 (0.186)	0.099 (0.186)
Long differences					
$\log(C/L)$	0.058 (0.119)	0.103 (0.159)	0.103 (0.110)	0.127 (0.075)	0.121 (0.113)
$\log(K/L)$	0.038 (0.082)	0.093 (0.079)	0.105 (0.068)	0.117 (0.048)	0.053 (0.072)
R^2(s.e.)	0.004 (0.0511)	0.019 (0.0509)	0.025 (0.0507)	0.045 (0.0502)	0.014 (0.0510)
First differences					
$\log(C/L)$	0.558 (0.077)	0.575 (0.073)	0.674 (0.067)	0.324 (0.036)	0.611 (0.071)
$\log(K/L)$	0.252 (0.065)	0.266 (0.061)	0.156 (0.049)	0.075 (0.020)	0.227 (0.057)
R^2(s.e.)	0.134 (0.199)	0.161 (0.195)	0.157 (0.196)	0.088 (0.204)	0.159 (0.195)

K71 = knowledge capital constructed with $\delta = 0.15$, using R&D history to 1971.
KH71 = knowledge capital constructed with $\delta = 0.25$, using R&D history to 1971.
KR = knowledge capital = R_{-1} divided by $\delta = 0.15$.
KS78 = knowledge capital constructed with $\delta = 0.15$, using R&D history to 1978.

Table 5
Production function estimates, 1980–1987
Dependent variable: Log(Value added/Employee)

	CRS not imposed		CRS imposed	
	Large sample	Long sample	Large sample	Long sample[a]
Totals				
$\log(C/L)$	0.167 (0.010)	0.199 (0.013)	0.156 (0.010)	0.179 (0.012)
$\log(K/L)$[b]	0.198 (0.006)	0.252 (0.008)	0.198 (0.006)	0.251 (0.008)
$\log L$	− 0.080 (0.006)	− 0.035 (0.007)	–	–
R^2(s.e.)	0.995 (0.368)	0.996 (0.344)	0.995 (0.369)	0.996 (0.346)
Within				
$\log(C/L)$	0.183 (0.037)	0.169 (0.057)	0.258 (0.032)	0.209 (0.047)
$\log(K/L)$	0.070 (0.024)	0.055 (0.035)	0.105 (0.023)	0.080 (0.033)
$\log L$	− 0.138 (0.034)	− 0.055 (0.053)	–	–
R^2 (s.e.)	0.123 (0.177)	0.103 (0.186)	0.118 (0.178)	0.103 (0.186)
Long differences				
$\log(C/L)$	0.113 (0.080)	0.199 (0.133)	0.126 (0.073)	0.103 (0.115)
$\log(K/L)$	0.077 (0.056)	0.129 (0.082)	0.086 (0.052)	0.093 (0.079)
$\log L$	− 0.032 (0.073)	0.165 (0.116)	–	–
R^2(s.e.)	0.026 (0.0490)	0.030 (0.0507)	0.025 (0.0489)	0.019 (0.0509)
First differences				
$\log(C/L)$	0.225 (0.053)	0.233 (0.092)	0.476 (0.047)	0.575 (0.073)
$\log(K/L)$	0.067 (0.047)	0.051 (0.070)	0.320 (0.039)	0.266 (0.061)
$\log L$	− 0.594 (0.065)	− 0.600 (0.098)	–	–
R^2(s.e.)	0.196 (0.185)	0.183 (0.193)	0.161 (0.188)	0.161 (0.195)

[a]The long sample contains 1576 observations and 197 firms; the large sample contains 2670 observations and 340 firms.

[b]The knowledge capital K is calculated using all of the history available for each firm and a depreciation rate of 15 percent (*K71*). Value added, capital, and labor have been corrected for R&D double-counting in all cases.

comes primarily at the expense of the labor coefficient, which typically falls by about the same order of magnitude (again except in the first-differenced estimates).[11] On the other hand, changes in the physical capital coefficient are ambiguous and depend on which specification is chosen: they are more frequently positive than negative in the within and long-differenced estimates, but zero in the totals. These results are consistent with the observation that the

[11] The labor coefficient is calculated as one minus the sum of the two capital coefficients plus the scale (log L) coefficient $[1-\alpha-\gamma+(\mu-1)=\mu-\alpha-\gamma=\beta]$.

average double-counting adjustment to labor is four times that to capital (4 percent of the total as compared with 1 percent).[12]

Contrary to the results in Cuneo and Mairesse (1984), the bias in the estimated elasticity of R&D capital caused by the lack of double-counting correction is almost as important in the within-firm dimension as in the total estimates. The implication is that the within-firm share of capital and labor which is devoted to R&D in fact varies enough over our period of study so that the estimated coefficient of knowledge capital remains biased downward even when 'permanent' differences across firms are controlled for.

3) Having a longer history of R&D available when constructing R&D capital (compare the columns with *K71* and *KS78)* makes little difference to the total estimates, as one would expect if these were dominated by cross-sectional variation across firms in overall R&D intensity. However, using the longer history raises the coefficient of the within-firm estimates by about 0.06, and the first- and long-differenced estimates by 0.03–0.04. Although the fit improves by only a tiny amount, a more precise estimate of the initial knowledge capital starting point seems to help in estimating the true growth rate of R&D capital at the firm-specific level, and in providing a better estimate of the coefficient in the within-firm dimension.

4) In the same way, using a higher depreciation rate when constructing the R&D capital variable (compare the columns with *K71* and *KH71*) makes no difference to the total estimates, but gives slightly lower coefficients for the within and differenced estimates. This result is expected, since the estimates which control for overall firm effects are essentially growth rate estimates: the growth rate of *KH71* is higher during the period, since the initial stock is lower, and this implies a coefficient which should be lower by approximately the ratio of the depreciation rates, $0.15/0.25 = 0.6$. In fact the coefficient of *KH71* is generally slightly higher than predicted, especially in the long-differenced estimates, where the fit is also slightly better. Although these results might imply some preference for a depreciation rate of 25 percent rather than 15 percent, the differences are not significant enough to give a definite conclusion.

To underline the insensitivity of the results to the choice of depreciation rate, we note that the most extreme version of R&D capital, one based solely on the

[12] As Schankerman (1981) has shown, the interpretation and prediction of the effects of the double-counting bias on the productivity regression are not simple, and depend in various ways on the actual pattern of covariances across the regressors. The only solid prediction one can make is that, under the reasonable assumption that the double-counting corrections for capital and labor are positively correlated with the measured R&D itself, the coefficient on R&D capital will be biased downward if uncorrected data are used (and the coefficients on labor and capital biased upwards). The relative magnitudes of the biases to labor and capital which are observed here are not necessarily implied by the observation that the double-counting adjustment is larger for labor than for capital.

previous year's level of R&D expenditures (a depreciation rate of 100 percent), gave approximately the same coefficients as *K71* in all specifications.[13] Disentangling the appropriate depreciation rate with the available data using the production function approach may be an impossible dream.

5) It is apparent that the R&D capital *K* is far more correlated with the overall firm effect than is ordinary capital. This is seen in the decline of the former coefficient relative to the latter coefficient when moving from total to within and differenced estimates.

6) Finally, the most important finding is that the R&D capital coefficient remains fairly high and marginally significant even when we control for firm effects, particularly when we take advantage of the longer history of R&D expenditures available to us. The magnitudes of our within estimates are quite comparable with those of Cuneo and Mairesse (1984) and Mairesse and Cuneo (1985) for the 1970s. However, they are somewhat higher than those earlier estimates in the cross-section and for the long growth rates. In comparison to the U.S. estimates for the 1960s and 1970s, given in Griliches (1980, 1986) and Griliches and Mairesse (1984), they are quite a bit higher (by about 0.1) in the totals; the within and long-differenced estimates are roughly comparable. This remains true when data corrected for double-counting is used for both countries (Schankerman, 1981).

We now turn briefly to the discussion of related estimates using our large slightly unbalanced sample of firms. In the absence of compelling evidence to the contrary, we based these estimates on our best measure of R&D capital (*K71*), which is constructed with a depreciation rate of 15 percent and as much history of R&D expenditures as available. These estimates are shown in columns 1 and 3 of Table 5; in columns 2 and 4 the corresponding estimates on the long sample are repeated for comparison.

The most striking discrepancy between the two sets of estimates is that in totals (as well as long differences without constant returns imposed) the R&D capital coefficient is lower by 0.05 in the large sample, and the coefficient for labor (derived from the scale coefficient) is correspondingly higher.[14] Since the

[13] The fit using *KR* was typically as good as or better than estimates using the other measures, with lower standard errors on the R&D coefficient in the within and first-differenced dimensions. This can be explained by the fact that in these dimensions we are comparing regressions based on the growth of R&D spending (*KR*) with those based on the growth of R&D capital (*K71*, etc.). The former variable has higher variance than the latter, leading to a more precise estimate of the coefficient.

[14] The difference is not accounted for by difference in the share of R&D capital across the two samples, since the long sample has only a slightly higher R&D to ordinary capital ratio (0.17 as compared with 0.14) than the large sample. Nor is it explained by the fact that R&D capital is better measured for the long sample, since it occurs in the total estimates also, where the measurement made almost no difference in Tables 4 and 5.

R&D capital coefficients are much closer in the within dimension, the most likely cause of such a discrepancy is differences across firms which are correlated with R&D intensity rather than differences in the actual productivity of R&D within firms. The simple comparison of the industrial composition of the two samples shown in Table 1 seems to support this view. Many (about 40 percent) of the firms added in the larger sample are in the first two sectors of Table 1: the Food, Textile, Apparel, Leather, and Wood industries, which are less R&D-intensive than the other industries. We re-estimated the equations in columns 1 and 2, excluding firms in the first two sectors of Table 1, and the R&D coefficients in the totals were 0.255 (0.009) and 0.237 (0.007) respectively, confirming that the difference between the two sets of estimates was indeed due to the changing industrial composition of the sample.

This last fact highlights once again perhaps the most robust result in this and other previous studies (Mairesse and Sassenou, 1991) which we have already pointed out: the pattern of estimates usually yields an R&D capital elasticity in the cross-section dimension which is statistically significant, usually large, and even possibly of the same order of magnitude as the elasticity of ordinary capital, whereas the estimates in the time dimension, which control for permanent differences across firms, whether within, long-differenced, or first-differenced, typically have an R&D capital elasticity which is much smaller, about one third or half that of ordinary capital, and often statistically insignificant. One can interpret this fact as arising from differences across industries and firms which are correlated with the presence of R&D capital, and regard the within-firm estimates as yielding the 'true' parameters, but it is possible to argue that this too yields biased estimates of the R&D capital elasticity. One reason all firms in the electronics industry, for example, may have higher productivity growth is their higher investment in R&D, which is perhaps induced by higher technological opportunity in this industry; this fact will be properly captured only in the totals estimates. In the absence of the meaningless experiment, where we observe 'textile' producers in the electronics industry or 'aircraft' producers in the food industry, the answer to this conundrum is unknowable, but also not very interesting. A better way to summarize the results is to say that there is more than one measure of the elasticity of output with respect to R&D capital: which one is preferred depends on the purpose to which it is to be put. For example, from a policy perspective one could argue both that the within-firm measure is a better indicator of what happens when a given firm invests in R&D, but also that the between-firm measure gives a better idea of the economy-wide productivity gains which might be induced by R&D subsidies. That is, nontargeted R&D subsidies would encourage R&D more in those industries where it is more productive and profitable, thus both increasing its magnitude and changing its industrial composition.

5. Simultaneity and the partial productivity approach

As we alluded to earlier in the paper, a possible problem with the production function approach to measuring the productivity of knowledge capital is that the right-hand-side variables in the equation are under the control of the firms and may be chosen simultaneously with the output level by a firm acting on information not observable to the econometrician. In general, this implies correlation between the inputs and the disturbance in the equation. We have tried to minimize such a simultaneity bias by using beginning-of-period measures of the inputs, but this is an imperfect solution. In this section we relax the assumption that labor input is predetermined, and derive the appropriate reduced form equations for output and labor for the case where only the two types of capital are predetermined. This model allows us to use the partial productivity approach to estimating the productivity growth equation, and also to investigate whether there is any evidence that the firm faces a downward-sloping curve (rather than the vertical demand curve assumed by perfect competition).

We first present our model under the perfect competition assumption, and then show how to relax that assumption. We assume that the firm chooses labor and output in any period to maximize short-run variable profits, taking the two capitals and output and factor prices as given. This approach, called 'semi-reduced form' by Griliches and Mairesse (1984), yields the following two equations:

$$l_{it} = \text{const} + (1-\beta)^{-1}[\phi_t + \alpha c_{it} + \gamma k_{it}] + u_{it}, \tag{6}$$

$$y_{it} = \text{const} + (1-\beta)^{-1}[\theta_t + \alpha c_{it} + \gamma k_{it}] + v_{it}, \tag{7}$$

where the unobserved prices are included in the time dummies ϕ_t and θ_t and the error terms u and v. We can use these two equations to estimate α and γ simultaneously, or more precisely, their relative magnitudes, imposing the cross-equation proportionality constraint. If we multiply Eq. (6) by $\hat{\beta}$ and subtract it from Eq. (7), we obtain the following:

$$y_{it} - \hat{\beta} l_{it} = \text{const} + \zeta_t + \frac{(1-\hat{\beta})}{(1-\beta)}[\alpha c_{it} + \gamma k_{it}] + v_{it} - \hat{\beta} u_{it}, \tag{8}$$

where $\xi_t = (\theta_t - \hat{\beta}\phi_t)/(1-\beta)$. Now, if we have a consistent estimate of β, then $(1-\hat{\beta})/(1-\beta)$ converges to one and clearly Eq. (8) will also yield consistent estimates of α and γ. This is the partial productivity approach found in the literature.

The advantage of this method of derivation is that it clarifies the fact that under the assumptions which allowed us to derive Eqs. (6) and (7), the semi-reduced form version of the model should yield the same estimates as Eq. (8) for the capital coefficients. On the other hand, Eq. (8) will remain valid even if β is different for each firm (and $\hat{\beta}$ is the corresponding within-firm estimate), while the semi-reduced form estimates will no longer be consistent if β varies across firms. We first focus on the partial productivity estimates and then compare them to the semi-reduced form estimates as a kind of specification test of our procedure.

Two sets of partial productivity estimates are presented in Table 6. The first uses the average labor share (measured as total labor costs divided by value added) for the sample of firms as an estimate of $\hat{\beta}$. Since it may be more realistic

Table 6
Partial TFP estimates, long sample, 1980–1987; 196 firms[a](1568 observations)

Dependent variable[b]	Unadjusted		Adjusted	
	$\log Y - 0.76 \cdot \log L$	$\log Y - \hat{\beta} \cdot \log L$	$\log Y - 0.67 \cdot \log L$	$\log Y - \hat{\beta} \cdot \log L$
Totals				
$\log C$	0.115 (0.007)	0.227 (0.024)	0.112 (0.007)	− 0.053 (0.024)
$\log K$[c]	0.134 (0.007)	0.055 (0.024)	0.216 (0.007)	0.485 (0.024)
Scale	0.004	0.037	− 0.002	0.099
R^2 (s.e.)	0.998 (0.341)	0.971 (1.193)	0.998 (0.347)	0.974 (1.234)
Within				
$\log C$	0.129 (0.051)	0.111 (0.051)	0.190 (0.050)	0.165 (0.050)
$\log K$	0.018 (0.035)	0.010 (0.035)	0.075 (0.034)	0.056 (0.034)
Scale	− 0.098	− 0.124	− 0.065	− 0.126
R^2 (s.e.)	0.051 (0.186)	0.056 (0.155)	0.066 (0.184)	0.071 (0.182)
Long differences				
$\log C$	0.247 (0.115)	0.224 (0.115)	0.301 (0.113)	0.272 (0.112)
$\log K$	0.093 (0.082)	0.081 (0.082)	0.154 (0.081)	0.126 (0.080)
Scale	0.095	0.060	0.108	0.065
R^2 (s.e.)	0.046 (0.0508)	0.037 (0.0507)	0.079 (0.0506)	0.062 (0.0503)
First differences				
$\log C$	− 0.177 (0.091)	− 0.180 (0.091)	− 0.121 (0.087)	− 0.121 (0.087)
$\log K$	− 0.058 (0.075)	− 0.059 (0.074)	− 0.025 (0.071)	− 0.037 (0.071)
Scale	− 0.480	− 0.484	− 0.476	− 0.491
R^2 (s.e.)	0.072 (0.203)	0.023 (0.204)	0.017 (0.199)	0.023 (0.199)

[a]One firm whose labor share was larger than unity was deleted from the sample.

[b]The first dependent variable is labor productivity calculated using a single labor share for all the firms; the second uses a firm-specific labor share calculated by averaging over eight years for each firm.

[c]The R&D capital K is calculated using all of the history available for each firm and a depreciation rate of 15 percent.

not to assume that all firms have an identical production function, in the second set of estimates, we use a variable coefficient version of this model, and estimate β_i at the firm level, assuming it is constant over the time period. There do not seem to be systematic differences between these sets of estimates, except in the totals, where we are not controlling for firm effects.

The results are a bit difficult to interpret. They do not appear to imply that large simultaneity biases were present in the within and differenced estimates of the R&D and physical capital coefficients in Table 3, while the biases in the total estimates tend to be negative, contrary to what would be *a priori* expected. Both long-differenced and within estimates confirm a fairly strong positive relationship between the growth of both kinds of capital and labor productivity growth. However, in first differences this relationship, which was already at best marginal, seems now to have disappeared completely. These estimates appear to be swamped by random year-to year noise in the growth rates, which yield very substantial decreasing returns and leave no room for either capital in explaining value added growth after we remove labor growth. In fact this is just what one would expect if capital is only adjustable in the long run: it would be quite surprising to find a strong effect from last year's growth rate while maintaining that nothing can be done this year to adjust the capital in current production.

We now turn to the semi-reduced form estimates of the model in Eq. (7), but before doing so, we expand the model slightly to include the possibility of imperfect competition in the output market.[15] We assume a constant elasticity of demand function:

$$P \sim Y^{(-1/\eta)}, \tag{9}$$

where P is the output price and η is the elasticity of demand. Now the firm maximizes variable profit each period, subject to this demand curve, the production function in Eq. (1), and the stocks of ordinary capital C and knowledge capital K. This set of assumptions yields the following variation of Eq. (7):

$$l_{it} = \text{const} + (1-\beta\varepsilon)^{-1}\varepsilon[\phi_t + \alpha c_{it} + \gamma k_{it}] + u_{it}, \tag{10}$$

$$y_{it} = \text{const} + (1-\beta\varepsilon)^{-1}[\theta_t + \alpha c_{it} + \gamma k_{it}] + v_{it}, \tag{11}$$

where $\varepsilon = 1-(1/\eta)$. Clearly when η is infinite (perfect competition), ε is unity, and we have the previous model. For reasonable values of η, say $\eta > 1$ (elastic demand), ε is positive and less than unity, and labor responds less to changes in

[15] The idea here is in Griliches and Mairesse (1984), although they do not present a full set of estimates or tests of the specification. They also allow the R&D coefficient to shift the demand curve, which removes the proportionality between the output and labor equations, implying no overidentifying restrictions on the model.

capital stocks than output does. Note also that when $\hat{\beta} = \beta$ (the true coefficient), Eq. (8) is still implied by Eqs. (10) and (11).

In Table 7, we explore the estimation of Eqs. (10) and (11) for our data using nonlinear seemingly unrelated regression to estimate both equations simultaneously. The first column repeats the estimates of Eq. (8) for comparison. The next two columns give the unconstrained estimates of Eqs. (10) and (11), where proportionality has not been imposed across the capital coefficients.[16] The final two columns give the estimates when proportionality has been imposed as in Eqs. (10) and (11), with $\varepsilon \equiv 1$ (perfect competition) and then with ε free. The statistic labelled 'log-likelihood' may be used to perform likelihood ratio tests across the specifications, under the assumption that the disturbances are identically distributed as multivariate normal random variables.[17]

The primary result of this set of estimates is that the proportionality constraint, which is required to justify the partial productivity estimates with constant β, does not hold for the totals and first-differenced estimates, but does hold for the estimates in the within and long-differenced dimension.[18] This result can be seen easily by comparing the coefficient estimates in columns 2 and 3 with those in column 1.[19] A possible implication of this result is that the total estimates in column 1 are inconsistent because of the correlation of the capital measures with permanent differences across firms in output–labor ratios, while the within-firm estimates are not contaminated by this firm effect, and therefore they can be estimated using either Eqs. (6) and (7) or Eq. (8).

Can we learn anything about the perfect competition assumption from these data? The results in column 5 say that the demand elasticity is consistent with perfect competition, except in the totals, where the measured elasticity is about

[16] In order to make these columns comparable to the estimates in column 1, they have been estimated with an explicit $(1-\beta)^{-1}$, with β set to 0.67. This means that estimates for the capital coefficients in all columns are estimates of α and γ themselves, under the assumption that labor's share is two-thirds.

[17] Note also that the standard error estimates shown in this table are consistent in the presence of heteroskedasticity across firms and time, unlike those in the earlier tables.

[18] The test statistics are $\chi^2(2) = 29.2$, $\chi^2(2) + 0.8$, $\chi^2(2) = 1.8$, and $\chi^2(2) = 16.2$ for the totals, within, long-differenced, and first-differenced specifications respectively.

[19] An implication of the derivation of Eq. (8) is that the estimates in column 1 are just a linear transformation of those in columns 2 and 3 with transformation vector $[(1-\hat{\beta})^{-1}, -\hat{\beta}(1-\hat{\beta})^{-1}]$. If the proportionality holds, this will guarantee that Eqs. (6) or (7) and Eq. (8) give the same answer for the capital coefficients. However, when proportionality does not hold (i.e., there is linear independence between the two sets of coefficients), we can get differing answers for estimation using the partial productivity approach, just by our choice of $\hat{\beta}$. For example, for a reasonable range of values in these data, 0.5 to 0.8, the range of estimated capital coefficients in the totals would be 0.14 to 0.07 for ordinary capital, and 0.17 to 0.30 for knowledge capital.

Table 7

Semi-reduced form estimates, 1980–1987, 196 firms[a] (1568 observations)

Dependent variable	$\log Y - 0.67{\cdot}\log L$	$\log Y$	$\log L$	$\log Y$, $\log L$	$\log Y$, $\log L$
Totals					
$\log C$	0.112(0.007)[c]	0.158(0.003)	0.181(0.003)	0.168(0.002)	0.193(0.005)
$\log K$	0.216(0.007)	0.121(0.003)	0.075(0.003)	0.101(0.002)	0.121(0.003)
Demand ε[b]	1.0	–	–	1.0	0.934(0.009)
Log-likelihood		− 1447.2		− 1592.8	− 1565.7
Within					
$\log C$	0.190(0.050)	0.203(0.020)	0.209(0.017)	0.209(0.016)	0.215(0.048)
$\log K$	0.075(0.34)	0.053(0.013)	0.042(0.008)	0.043(0.008)	0.045(0.013)
Demand ε	1.0	–	–	1.0	0.989(0.077)
Log-likelihood		1659.1		1658.7	1658.7
Long differences					
$\log C$	0.301(0.113)	0.240(0.044)	0.211(0.034)	0.213(0.034)	0.359(0.091)
$\log K$	0.154(0.081)	0.082(0.029)	0.047(0.019)	0.050(0.018)	0.088(0.036)
Demand ε	1.0	–	–	1.0	0.806(0.087)
Log-likelihood		647.6		645.8	647.2
First differences					
$\log C$	− 0.121(0.087)	0.099(0.039)	0.208(0.031)	0.189(0.026)	− 0.118(0.127)
$\log K$	− 0.025(0.071)	0.026(0.021)	0.050(0.017)	0.046(0.015)	− 0.029(0.031)
Demand ε	1.0	–	–	1.0	2.07 (0.81)
Log-likelihood		1644.2		1636.1	1644.2

[a] One firm whose labor share was larger than unity was deleted from the sample.

[b] $\varepsilon = 1 - 1/\eta$ where η is the demand elasticity.

[c] Heteroskedastic-consistent estimates of the standard errors are shown in parentheses.

Value added, capital, and labor have been corrected for R&D double-counting in all cases.

15 with an approximate standard error of 2.[20] Unfortunately, another interpretation of these estimates is that the output measure we are using, value added deflated by a fairly coarse industry deflator, is not truly an output measure, but closer to a revenue measure (quantity times price). It is easy to show that if this is the case, Eq. (11) for y_{it} would be identical to Eq. (10) for l_{it} and we would be unable to identify the demand elasticity. Since imperfect competition or market power at the firm level is surely associated with firm-specific prices, which we do not observe, it is hardly surprising that we are unable to measure it using a revenue measure.[21]

The conclusion from Table 7 is that using a semi-reduced form approach to estimating the production function reduces the coefficient of R&D capital by a factor of two in the totals and possibly the long differences, and hardly at all in the within-firm and first-differenced estimates. The physical capital coefficient is relatively unaffected in all the estimates. This implies that the simultaneity bias due to the presence of labor on the right-hand side of the production function hits R&D harder than physical capital; more importantly, once we control for permanent differences across firms, the estimated R&D elasticity is apparently not biased by the endogenous choice of labor by the firm.

6. The rate of return to R&D expenditures

Because of the difficulty of measuring R&D capital, an alternative approach to estimating the productivity of R&D is often used which tries to avoid this problem, although somewhat unsuccessfully, as we shall see.[22] This method begins by assuming that the parameter which is assumed to be constant is ρ, the rate of return to R&D capital $\partial Y/\partial K$, rather than $\gamma = (K/Y)(\partial Y/\partial K)$, the elasticity of output with respect to such capital. With this definition, we can rewrite the differenced (growth rate) version of Eq. (2) as

$$\Delta y_{it} = \lambda + \alpha \Delta c_{it} + \beta \Delta l_{it} + \rho(\Delta K_{it}/Y_{it}) + \eta_{it}, \qquad (12)$$

where η is a new disturbance containing approximation errors in addition to the differenced ε and ΔK is the change in R&D capital over time. In discrete time and if R&D capital does not depreciate, one can also approximate ΔK by the

[20] The first-differenced estimates in column 5 are even more bizarre than usual, with negative capital coefficients and an implied negative demand elasticity.

[21] In the future we may have price indices available at the firm level, and we plan to investigate the extent to which the aggregate deflators are the cause of the finding here.

[22] See also the survey by Mairesse and Sassenou (1991b). For work using this methodology, see Mansfield (1965) and Griliches (1986).

flow of R&D expenditures during the period, which implies that the relevant right-hand-side variable is simply the R&D to value added intensity, which is easily measured.

There are at least two difficulties with this method of estimation. First, it is not obvious what the relevant timing for the R&D variable is; we have used R&D to value added lagged one period, both to be consistent with our production function estimates, where beginning of period stock is used, and because of the measurement error simultaneity which would be induced by using contemporaneous value added on the right-hand side of the equation.[23] The second difficulty is that the relevant concept for ΔK is the net R&D expenditure rather than the gross, unless we make the extreme assumption of no depreciation. But if we want to use net R&D expenditures, we have to make an explicit assumption about the depreciation of R&D capital, so we have not completely avoided the problem of measurement.

The results of estimating Eq. (12) both in first and long differences and with both gross and net R&D expenditures are shown in Table 8, similar in format to Tables 3 through 5 with the different columns corresponding to alternative measures of the variables for the long sample or the large sample. We measure the gross rate of expenditure by the lagged R&D to value added ratio, and the net rate by the same ratio less the ratio of replacement expenditures, which are defined to be δ times the ratio of lagged R&D capital to value added.[24] Using a depreciation rate of 15 percent, the resulting mean R&D intensities are 9.3 percent and 2.1 percent respectively.[25]

Although the coefficient estimates in Table 8 display some similarities with those in the earlier tables, they are also quite puzzling in some respects. Beginning with the similarities, adjusting the data for double-counting raises the rate of return to R&D by about 3 to 4 percent in both first and long differences, in most cases decreasing the labor coefficient by about the same amount.

[23] We experimented with the timing of both R&D and value added and confirmed that the R&D intensity coefficient did indeed seem to be biased upward when contemporaneous values were used. This can occur both because of simultaneity between R&D investment and value added during the period and because of measurement error bias arising from the presence of the dependent variable in the denominator of R&D intensity; both biases are expected to have the same (positive) sign. We also tried using averages of R&D lagged over the preceding two periods, with little change to the results.

[24] Note that estimates that are based on the gross rate of R&D expenditures differ only slightly from each other. This is because all that is changing across these estimates is the R&D double-counting adjustment to physical capital, which is affected by the choice of depreciation rate for the R&D capital.

[25] If real R&D expenditures have been growing at g percent per year from the infinite past, then R&D capital $K_t = R_t/(g + \delta)$. This implies that net R&D expenditure is equal to $(g/(g + \delta))R_t$; this is roughly consistent with these numbers for $g = 0.05$ and $\delta = 0.15$, which implies that net R&D is one quarter of gross. This is not independent information, just a check on our calculations.

Table 8

Rates of return in manufacturing, 1980–1987, 197 firms

	Long sample				Large sample
	Unadjusted	Adjusted *K71*	Adjusted *KH71*	Adjusted *KS78*	Adjusted *K71*
First differences:[d] Dependent variable = $\Delta \log VA$					
$\Delta \log C$	0.148 (0.095)	0.179 (0.091)	0.181 (0.092)	0.177 (0.091)	0.181 (0.061)
$\Delta \log L$	0.132 (0.060)	0.107 (0.055)	0.107 (0.055)	0.108 (0.055)	0.107 (0.041)
Gross R_{-1}[a]	0.231 (0.053)	0.273 (0.059)	0.273 (0.059)	0.274 (0.059)	0.222 (0.046)
R^2(s.e.)	0.042 (0.195)	0.044 (0.191)	0.044 (0.191)	0.044 (0.191)	0.037 (0.184)
$\Delta \log C$	0.162 (0.097)	0.201 (0.092)	0.213 (0.093)	0.197 (0.092)	0.203 (0.061)
$\Delta \log L$	0.137 (0.060)	0.111 (0.056)	0.111 (0.056)	0.110 (0.056)	0.103 (0.042)
Net R_{-1}[a]	0.293 (0.128)	0.310 (0.136)	0.304 (0.161)	0.341 (0.133)	0.259 (0.110)
R^2(s.e.)	0.032 (0.196)	0.033 (0.192)	0.031 (0.192)	0.033 (0.192)	0.030 (0.184)
Long differences: Dependent variable = $\Delta^6 \log VA$					
$\Delta \log C$	0.027 (0.139)	0.101 (0.136)	0.109 (0.137)	0.101 (0.136)	0.155 (0.099)
$\Delta \log L$	0.954 (0.123)	0.876 (0.106)	0.873 (0.166)	0.876 (0.106)	0.789 (0.074)
Gross R_{-1}[b]	0.036 (0.053)	0.065 (0.060)	0.064 (0.060)	0.066 (0.060)	0.104 (0.048)
R^2(s.e.)	0.387 (0.0611)	0.383 (0.0607)	0.384 (0.0607)	0.383 (0.0607)	0.372 (0.0587)
$\Delta \log C$	0.048 (0.145)	0.101 (0.142)	0.120 (0.143)	0.103 (0.140)	0.154 (0.103)
$\Delta \log L$	0.954 (0.112)	0.876 (0.106)	0.871 (0.106)	0.876 (0.106)	0.723 (0.078)
Net R_{-1}[b]	− 0.013 (0.147)	0.126 (0.160)	0.116 (0.215)	0.124 (0.156)	0.205 (0.135)
R^2(s.e.)	0.386 (0.0612)	0.382 (0.0608)	0.381 (0.0608)	0.382 (0.0608)	0.367 (0.0590)

[a]Gross R&D is R_{-1}/VA_{-2} and net R&D is $(R_{-1} - 0.15K_{-1})/VA_{-2}$, as described in the text. Lag 2 value added is used to avoid measurement error bias due to the presence of the value added growth rate on the left-hand side.

[b]In the long-differenced version, the mean of each variable is computed over the seven years 1980–1986, and the ratios are then computed.

[c]The large sample consists of 2306 observations on 322 firms. The samples are not identical to those in the earlier tables because we have used VA_{-2} in order to avoid measurement error bias and this variable is not available in 1978.

[d]The first-differenced estimates use six log value-added differences per firm, from 1981–82 to 1986–87, for a total of 1182 observations. The long-differenced estimates use the difference in log value added from 1981 to 1986, for a total of 197 observations.

Second, in long differences, the labor coefficient is substantially larger than in first differences, which is consistent with the implied labor coefficients in Tables 3 and 5, when constant returns to scale is not imposed. Third, the overall explanatory power of the regressions is negligible for the first-differenced estimates, which appear to be dominated by random year-to-year movements in the data.

The puzzling aspect of these estimates is the small size of the difference between the gross and net R&D coefficients. We can provide arguments as to why the difference in these coefficients should be either quite positive or quite negative, but neither argument predicts that they will be nearly equal. The conventional interpretation of this equation sees the coefficient of gross R&D expenditures as a gross rate of return and that for net as a net rate of return. This would imply that the difference between gross and net should be positive and of the order of the depreciation rate, about 0.15. On the other hand, the derivation of this equation from the Cobb–Douglas production function implies that the 'correct' right-hand-side variable is net R&D expenditure. Since gross R&D expenditure is typically proportional to net with a proportionality factor of an order of magnitude of about four, we would expect its coefficient to be *lower*, not higher, and by such a factor (see footnote 20). Which interpretation is right depends on which parameter (gross rate of return, net rate of return, or elasticity) is more constant across firms, but neither interpretation implies that the coefficients should be nearly equal.

A second difference between the estimates here and the earlier ones is that the R&D coefficients tend to be lower in long differences than in first differences, whereas in the production function estimates they were almost always higher, except when constant returns to scale was imposed. In fact, in long differences, the standard errors on both kinds of capital are so large that the estimates are consistent with a model where long-term growth in value added is simply proportional to growth in the number of employees, with nothing left over for ordinary capital or R&D intensity.

7. Conclusions

The results presented in this paper allow us to draw several conclusions, both about the measurement of R&D capital and about its productivity. Within the production function and representative firm framework in which we are operating, we have fairly good confidence in most of them, although those who think that this approach to the measurement of R&D productivity is much too simple (or even simplistic) may remain more skeptical.

Our first set of conclusions concerns the measurement of the relationship between productivity and R&D. A first finding is that having a longer history of R&D expenditures clearly helps in the sense that an R&D variable thus measured is a more potent predictor of productivity growth. A second finding is that the choice of depreciation rate in constructing R&D capital does not make much difference to the coefficient estimates, particularly in the within-firm dimension, although it does change the average level of measured R&D capital greatly, of course. This result has already been observed in a number of previous studies and arises from the basic fact that the time series of R&D expenditures *within firm* does not vary all that much.

A third measurement result, which is also not very new, is that the correction for the double-counting of R&D expenditures in capital and labor is quite important in either the production function or rate of return framework, and seems in general more or less consistent with an interpretation which says that results based on uncorrected data are measuring an excess private rate of return for R&D, rather than the total private rate of return. Such interpretation may allow one to assess better the meaning of the results reported by researchers who do not have the data available for performing the R&D double-counting correction, and must therefore rely on uncorrected data.

Fourth, the set of results given in this paper for different econometric specifications, as in many other papers, cast doubt on the utility of first-differenced estimates of production function parameters, unless they can be supplemented with other information, such as the imposition of constant returns to scale. This is clear from their large standard errors and their widely ranging values across specifications, and also from their frequent inconsistency with the long-differenced estimates, which in principle ought to be quite similar. For this reason, we tend to disregard the first-differenced estimates when we assess the results.

Finally, we have highlighted the fact that the previous interpretations of the rate of return method of estimating the productivity of R&D are somewhat problematical. The primary argument in favor of this specification, which is to avoid measuring R&D capital and use only R&D investment intensity ratios, can be very misleading. Neither the model nor the estimates imply that the rate of return to gross R&D measured by such a regression should exceed the rate of return to net R&D; in fact, it is the other way around. An additional problem with this method of measurement is the question of the timing of R&D and the output which it affects, which has a fairly large impact on our estimates. For these several reasons, we have a preference for trying to measure R&D capital and relying on the usual production function approach as in the first sections of this paper.

Turning to the substantive results in the paper, we find that the coefficient of R&D capital in the production function is uniformly positive for the different specifications and the different types of estimates (except some of the first-differenced ones) that we experimented with. Most of the estimates are consistent with those of previous studies; in some cases they are much higher. We also find that the level of R&D capital is correlated with permanent firm or industry effects, which implies substantially higher coefficients in the cross-section dimension than in the time-series dimension. This is also true for physical capital, but less strongly so.

However, when we try to correct for the estimation bias which might arise from the simultaneous choice of labor and output levels, such discrepancy between the cross-sectional and time-series estimates falls substantially. The simultaneity bias itself appears to affect the total estimates of the R&D capital coefficient greatly, but the within and long-differenced (and first-differenced) estimates only slightly. The fact that the R&D capital coefficient is reduced in the totals, both by the inclusion of firm effects and by correction for the simultaneity of labor and output, is consistent with the following explanation: in firms and industries where 'true' productivity is higher than the norm, possibly because of previous investments in technological innovation, labor input is permanently lower. Such an explanation accounts both for the correlation of cross-sectional R&D effects with industry and for the upward bias on the R&D coefficient when labor is (incorrectly) treated as predetermined.

Appendix A

Construction of the data samples

This appendix provides some detail on how we constructed and cleaned our dataset. We started with a sample of 351 manufacturing firms in a slightly unbalanced panel from 1980 to 1987, deleting those which were not in the manufacturing sector by conventional definitions, i.e., excluding energy, construction, wholesale and retail trade, and business services. We chose to focus on the contribution of R&D to the growth of total factor productivity in manufacturing, since it is the topic of the previous studies to which we compare our results. It is also true that both labor productivity and total factor productivity are far better measured and more meaningful in the manufacturing sector than in these other sectors.

When performing a comparative measurement analysis such as ours, it is important that the sample of data with which one is working be held fixed, so that any differences in estimates can be attributed to the change in measurement techniques rather than a slight change in sample. Accordingly, we defined at the outset our 'clean' sample according to the following criterion:

1) We removed any observations for which value added or value added lagged was zero or negative, since this creates obvious problems for our logarithmic specification. There are 52 such observations (2.0 percent of the sample).

2) For the remaining firms, we removed any *observations* (but not the entire eight years of data) for which the value added per worker, capital stock per worker, or R&D capital per worker was outside of three times the interquartile

range (the 75 percent value minus the 25 percent value) above or below the median.[26] This removed 16 observations (about 0.6 percent).

3) We removed any observations for which the growth rate of value added was less than minus 90 percent or greater than 300 percent, or for which the growth rates of labor, capital, or R&D capital were less than minus 50 percent or greater than 200 percent. This removed 19 observations (0.7 percent).

4) We required that the R&D double-counting corrections to value added, capital, and labor or less than 50 percent of the total. This removed 16 observations (0.6 percent), most of which were for two firms whose primary activity was apparently research and development, and therefore did not really belong in the manufacturing sector.[27]

5) Finally, we removed any firms which had fewer than three years of data along with the first half of the data for five firms which had gaps in their data around the years 1982–1984 (see below for a fuller discussion). This removed 12 observations.

In total, 106 observations (approximately 3.8 percent of the total) were removed by these cuts; the number is less than the sum of 1) through 5) because some observations clearly had a wrong datum (number of employees too low by a factor of ten in one year, for example) and caused them to be removed for several reasons simultaneously. Thus we were left with a large slightly unbalanced panel of 340 firms (and 2670 observations over the study period 1980–1987), among which 206 firms had R&D information going back to 1971.

Preliminary experimentation with the long sample of 206 firms produced results which differed substantially according to whether we insisted that the cleaned panel be balanced (have eight years of data per firm) or not. The omission of the nine firms which had less than eight years of data reduced the R&D coefficients of the production function estimated in the within dimension by a factor of two or more. Investigation revealed that this large change in coefficient estimates was caused in fact by five firms who experienced substantial jumps in one or more series following a gap in the data, presumably because of divestiture or acquisition. Although the regression results are not spurious, it is not appropriate to maintain that these firms are drawn from the same probability distribution which generated the majority of our data; the result is intriguing, but unfortunately the sample is too small for drawing firm conclusions.[28] We

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[26] For a normally distributed variable, this would remove all observations which are outside of four standard deviations away from the mean (less than 0.01 percent of the observations).

[27] The obvious question arises, where is their R&D going? Since the survey provides data on R&D performed outside the enterprises and paid for by them as well as on R&D performed for others, this question could be explored in future work.

[28] A similar finding is reported in Griliches and Mairesse (1984) and investigated there to some extent.

therefore removed these five firms as well as the four other firms with less than eight years of good data from our long sample, leaving us with a balanced long panel of 197 firms for eight years from 1980 to 1987 (and $1576 = 197 \times 8$ observations).

Appendix B

The returns to basic and government-funded research

In this Appendix, we give some hint of the potential for using the more detailed information provided by the French survey of R&D expenditures to investigate the compositional effects of R&D, in particular the role of basic research and government funded research. To our knowledge, the only prior (large-scale) empirical studies of these compositional effects are those of Mansfield (1980), Griliches (1986), and Cuneo (1982) for basic research, and Griliches (1980) and Griliches and Lichtenberg (1984) for government-funded research. Our approach is quite simple: we start with the basic production function specification of Tables 3 through 5, with data adjusted for double-counting, knowledge capital *K71*, and the long history sample of 197 firms. To this specification we add two dummies, one for firms which report that a sizable fraction of their research is basic (as opposed to applied or development) and one for firms which report that a sizable fraction of their research and development expenditure is government financed. This choice of specification is based on the fact that the distribution of these shares is extremely skewed, and a continuous variable such as a share does not seem appropriate in this context. We also found that these variables were largely orthogonal in their effects, so that we report only regressions which include both variables in Table 9.

The remaining problem of specification is how to choose the cutoff for the two dummy variables: we chose two sets of cutoffs, the first set slightly below the mean shares (but well above the medians) and the second set well above them. For our first set of cutoffs (2 percent for basic research and 5 percent for government-funded research), we obtained 22 percent and 23 percent of the observations respectively. For the second set (8 percent for basic and 20 percent for government), these figures were 10 percent and 8 percent of the observations. Most firms either had a dummy equal to one or zero for all eight years, although some firms switched, particularly those with government funding. In the growth rate estimations (long and first differences) as well as in the level estimations we used this "level" variable as a regressor. In the growth rate versions, the dummies are being allowed to affect the growth rates of productivity, as opposed to the levels.

The results are quite suggestive and consistent across levels and growth rates for basic research: the fraction of R&D devoted to basic research reduces overall

Table 9
Production function estimates with basic and government-funded R&D, 1980–1987, 197 firms (1576 observations)

	CRS not imposed		CRS imposed	
	Basic > 2% Govt. > 5%	Basic > 8% Govt. > 20%	Basic > 2% Govt. > 5%	Basic > 8% Govt. > 20%
Totals				
log(C/L)	0.202 (0.013)	0.204 (0.013)	0.181 (0.012)	0.181 (0.012)
log(K/L)	0.255 (0.009)	0.243 (0.009)	0.256 (0.009)	0.244 (0.009)
log*L*	− 0.034 (0.007)	− 0.039 (0.007)	–	–
D (basic)	− 0.052 (0.020)	− 0.092 (0.027)	− 0.052 (0.020)	− 0.090 (0.027)
D (govt.)	− 0.018 (0.020)	− 0.117 (0.033)	− 0.028 (0.020)	− 0.093 (0.033)
R^2(s.e.)	0.996 (0.343)	0.996 (0.341)	0.996 (0.345)	0.996 (0.344)
Long differences				
log(C/L)	0.230 (0.133)	0.204 (0.129)	0.130 (0.115)	0.125 (0.112)
log(K/L)	0.106 (0.082)	0.096 (0.081)	0.070 (0.079)	0.066 (0.077)
log*L*	0.169 (0.114)	0.136 (0.113)	–	–
D (basic)	− 0.021 (0.009)	− 0.029 (0.012)	− 0.020 (0.009)	− 0.029 (0.012)
D (govt.)	− 0.001 (0.009)	0.033 (0.013)	− 0.000 (0.009)	0.034 (0.013)
R^2(s.e.)	0.057 (0.0503)	0.089 (0.0494)	0.046 (0.0504)	0.082 (0.0495)
First differences				
log(C/L)	0.217 (0.080)	0.223 (0.080)	0.507 (0.066)	0.514 (0.066)
log(K/L)	0.128 (0.064)	0.126 (0.064)	0.330 (0.056)	0.331 (0.055)
log*L*	− 0.549 (0.088)	− 0.554 (0.088)	–	–
D (basic)	0.000 (0.011)	− 0.011 (0.015)	− 0.001 (0.011)	− 0.012 (0.015)
D (govt.)	0.019 (0.010)	0.060 (0.017)	0.013 (0.010)	0.054 (0.017)
R^2(s.e.)	0.190 (0.189)	0.195 (0.189)	0.170 (0.192)	0.175 (0.191)

The regression and variables in this table are the same as those in Tables 3 to 5 of the paper, except for the addition of the basic and government-funded dummies.

productivity by 5 or 9 percent with a standard error of 2–3 percent, depending on which cutoff is chosen. It also reduces the seven-year growth rate of productivity by an average of 2–3 percent per year; once again, the first-differenced results are insignificantly different from zero. About half the result in levels goes away when industry dummies at the ten-sector breakdown of Table 1 are included (not shown), implying that some of the effect is due to permanent differences across industries both in the propensity to do basic research and in their productivity growth.

Government funding for R&D, on the other hand, does not seem to have much effect until it rises to over 20 percent of the firm's R&D budget. At this point, the overall productivity effect is positive and about 10 percent and the growth rate effect is also positive and anywhere from 3 to 6 percent. In contrast to basic research, the addition of the industry dummy variables had no effect on this estimate, in spite of the fact that 60 percent of the firms whose R&D funding comes from the government are in only two industries: Motor Vehicles and Aircraft, and Electronics.

References

Cuneo, Philippe, 1982, Recherche dévelopment et productivité: une étude économetrique sur données de panel, Thése de 3éme cycle (Ecole des Hautes Etudes en Sciences Sociales, Paris).

Cuneo, Philippe and Jacques Mairesse, 1984, Productivity and R&D at the firm level in French manufacturing, in: Z. Griliches, ed., R&D, patents, and productivity (University of Chicago Press, Chicago, IL) 393–416.

Griliches, Zvi, 1979, Issues in assessing the contribution of R&D to productivity growth, Bell Journal of Economics 10, 92–116.

Griliches, Zvi, 1980, Returns to research and development expenditures in the private sector, in: J. Kendrick and B. Vaccara, eds., New developments in productivity measurement and analysis (University of Chicago Press, Chicago, IL) 419–462.

Griliches, Zvi, 1986, Productivity, R&D, and basic research at the firm level in the 1970s, American Economic Review 76, 141–154.

Griliches, Zvi and J.A. Hausman, 1986, Errors in variables in panel data, Journal of Econometrics 31, 93–118.

Griliches, Zvi and Frank Lichtenberg, 1984, R&D and productivity growth at the industry level: Is there still a relationship?, in: Z. Griliches, ed., R&D, patents, and productivity (University of Chicago Press, Chicago, IL) 465–502.

Griliches, Zvi and Jacques Mairesse, 1983, Comparing productivity growth: An exploration of French and US industrial and firm data, European Economic Review 21, 89–119.

Griliches, Zvi and Jacques Mairesse, 1984, Productivity and R&D at the firm level, in: Z. Griliches, ed., R&D, patents and productivity (University of Chicago Press, Chicago, IL).

Hall, Bronwyn H., 1988, The market value of intangible corporate assets: an empirical study of the components of Tobin's *Q*, Photocopied (NBER and University of California, Berkeley, CA).

Hall, Bronwyn H., Zvi Griliches, and Jerry A. Hausman, 1986, Is there a second (technological opportunity) factor ?, International Economic Review 27, 265–283.

Mairesse, Jacques, 1988, Les lois de la production ne sont plus ce qu'elles étaient: Une introduction à l'économetrie des panels, Revue Economique 39, 225–271.

Mairesse, Jacques, 1990, Times-series and cross-national estimates on panel data: Why are they different and why should they be equal?, in: J. Hartog, G. Ridder, and J. Theeuwes, eds,. Panel data and labor market studies (North-Holland, Amsterdam) 81–95.

Mairesse, J. and P. Cuneo, 1985, Recherche, dévelopement et performances des entreprises: Une étude économetrique sur données individuelles, Revue Economique 36, 1001–1042.

Mairesse, Jacques and Zvi Griliches, 1990, Heterogeneity in panel data: Are there stable production functions?, in P. Champsaur et al., eds., Essays in honor of Edmund Malinvaud (MIT Press, Cambridge, MA).

Mairesse, J. and M. Sassenou, 1991a, Les facteurs qualitatifs de la productivité: Un essai d'évaluation, Economie et Prévision 91, 35–42.

Mairesse, J. and M. Sassenou, 1991b, R&D and productivity: A survey of econometric studies at the firm level, Science–Technology–Industry Review 8 (OECD, Paris) 317–348.

Mansfield, Edwin, 1965, Rates of return from industrial research and development, American Economic Review 55, 310–322.

Mansfield, Edwin, 1980, Basic research and productivity increase in manufacturing, American Economic Review 70, 863–873.

Ministére de la Recherche et de l'Enseignement Supérieur, Government of France, 1985, La recherche dans les entreprises (La Documentation Française, Paris).

Pakes, Ariel and Mark Schankerman, 1984, Rates of obsolescence of knowledge, research gestation lags, and the private rate of return to research resources, in: Z. Griliches, ed., R&D, patents, and productivity (Univeristy of Chicago Press, Chicago, IL).

Schankerman, Mark, 1981, The effect of double counting and expensing on the measured returns to R&D, Review of Economics and Statistics 63, 454–458.