NBER WORKING PAPERS SERIES

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Working Paper No. 3956

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
January 1992

NBER Working Paper #3956
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ABSTRACT

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 growth at the firm level during the 1970s. The focus of the paper is on the use of a single dataset to evaluate the robustness of the methods commonly used to measure the private returns to R&D. We investigate the consequences of varying specifications and estimations, and in particular that of using different measures of R&D (knowledge) capital and of double counting corrections.

Our main findings are the following: first, having a longer history of R&D expenditures helps in predicting the productivity growth of firms, but the choice of depreciation rate for R&D capital makes little difference to the results. Second, the correction for double counting of R&D expenditures in capital and labor is important and converts a measured "excess" rate of returns to a total rate of return to R&D. Third, we show that the direct production function approach to measuring the returns to R&D capital is preferred on several grounds over the rate of returns variation which has been used in the past. Finally, the productivity of knowledge capital in the production function is uniformly positive, fairly robust, and correlated with permanent firm or industry effects.

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December 1991

EXPLORING THE RELATIONSHIP BETWEEN R&D AND PRODUCTIVITY AT THE FIRM LEVEL IN FRENCH MANUFACTURING

Bronwyn H. Hall and Jacques Mairesse[1]

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 (1989). These studies, along with most other studies using individual firm data for the United States and Japan, have been surveyed by Mairesse and Sassenou (1991). 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 differences 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.

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[1]University of California at Berkeley and the National Bureau of Economic Research, and ENSAE-CREST and The National Bureau of Economic Research, respectively. This paper was written while the first author was visiting INSEE. We are grateful to Bruno Crepon for supplying us with the new dataset on the R&D of French firms, and to Jean-Marie Chanut for helping us resurrect the 1970s dataset. Comments by Zvi Griliches on an earlier draft are gratefully acknowledged.

A justification for the present study is the fact that the new dataset[2] 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. 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 (Schankerman 1981).[3] 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, which impose a particular functional form on the production function.

Another justification for our study is that the period of the 1970s, on which the previous studies were based, was not a "normal" 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 over-all growth, the variance in the right hand side variables of the regression is dominated by such

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[2] The data on research and development expenditures used in this paper come from the Enquete annuelle sur les moyens consacrés à la recherche et au developpement dans les entreprises conducted by the French Ministry of Research and Technology. This has been augmented with data on value added, sales, investment, capital, employment, and other variables from the Enquete annuelle d'entreprises at INSEE.

[3] A useful discussion of the biases introduced by such "double-counting" and an evaluation of their effects on estimates with French data may be found in the Appendix to Cuneo and Mairesse (1984).

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 moving to a period of more stable growth rates, we hope to achieve more real dispersion in our regressors, and hence better estimates.

We begin by describing our new dataset and then outline the production function framework within which we are working and the measurement issues which it raises, particularly 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 productionfunction. 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.

The raw dataset consists of approximately 350 French manufacturing firms in a slightly unbalanced panel from 1980 to 1987, among which approximately 210 of them had R&D information available back to 1971 from the previous studies. 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. Appendix A gives more detail on the data cleaning process.

Table 1 shows the sectoral breakdown of the firms in the two different samples, while 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 stock of the firm, the knowledge or R&D capital, and the number of employees. All variables (except employment) are deflated; the deflators are output deflators at the 10-sector 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 and more R&D intensive (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 and 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 the labor growth rate is substantially negative over the whole period, implying an average increase in the capital-labor ratio of about three and one half percent per annum.

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 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 fifty

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

percent of the total. We also required that our long panel be balanced with good data for all eight years from 1980 to 1987.

The results in the next several sections are based primarily on this balanced panel, consisting of 197 firms. We also give the results of estimating our preferred specifications for the largest possible sample of firms, which is cleaned but slightly unbalanced. This sample consists of 2670 observations on 340 firms corresponding to the 197 firms in the balanced long panel, and 143 firms with shorter or incomplete histories.

3. The Production Function Framework and the Measurement of R&D Capital.

In this section of the paper, we use our longer balanced sample to explore the consequences of using differing methods of measuring the stock of R&D capital in the enterprise. The issues to be addressed are: 1) The importance of the length of time over which the stock is constructed. 2) The choice of depreciation rate and pre-sample growth rate applied to the R&D investment series when constructing the stock of knowledge capital. 3) The effect on the coefficient estimates of correcting capital, labor, and value added for the double counting induced by the fact that components of the R&D expenditures are included in them.

Before we discuss these measurement issues, we remind the reader of the by now familiar theoretical framework in which we are working. 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:

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

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

To implement the estimation of the parameters of this function, which include the parameter of interest (the elasticity of value added with respect to R&D capital γ) we take logarithms and obtain the following equation (where lower case letters denote the logarithms of variables):

$$(2) \quad y_{it} = a + \lambda t + \alpha c_{it} + \beta l_{it} + \gamma k_{it} + \varepsilon_{it}$$

Under constant returns to scale with respect to the three inputs, the sum of α, β, and γ will be unity. For interpretive reasons, we prefer to rewrite equation (2) so that the deviation from constant returns is measured explicitly, by subtracting labor from both sides of the equation:

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

The coefficient of the logarithm of labor ($\mu = \alpha + \beta + \gamma$) 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 beginning of period input measures, 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[5] and this will introduce a "firm effect" in our disturbance. 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,[6] they also include any errors in the price deflators common across firms, or other macro influences which may affect measured outputs and inputs. Although our model as written in equations (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

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

[6]Our 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 there was a time component to the disturbance, while a deterministic trend does not <u>necessarily</u> imply one.

[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 6 are 4.46, 3.69, 6.22, and 5.38 respectively, with denominator degrees of freedom equal to 2643, 1633, 2644, and 1634.

perpetual inventory method like that commonly used for physical capital.[8] The equation defining knowledge capital K is the following:

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

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 pre-sample. 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 been used previously in this type of estimation: we assume a depreciation rate of 15 percent, a pre-sample growth rate of 5 percent in real R&D expenditures,[9] and we start the perpetual inventory accumulation process with the earliest year of R&D data available (1971 for our long history sample). That is, if our R&D series starts in year t=1, and the presample accumulation of knowledge capital is given by equation (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:

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[8]This method has been discussed by Griliches (1979).

[9]This 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.

$$(5)\quad K_1 = R_0 + (1-\delta)R_{-1} + (1-\delta)^2 R_{-2} + \ldots\ldots$$

$$= \sum_{s=0}^{\infty} R_{-s}(1-\delta)^s = R_0 \sum_{s=0}^{\infty} \left[\frac{1-\delta}{1+g}\right]^s = \frac{R_1}{g+\delta}$$

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 which 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 current year's R&D expenditures are the best indicator of the quality of its knowledge capital; here we scale these expenditures up by the sum of a depreciation rate of 15 percent and a growth rate of 5 percent so that they are comparable in magnitude to the other measures (KR). In other words, we are not 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. The next section discusses the results which we obtained using these different measures of R&D capital.

4. Productivity Growth and R&D during the 1980s.

In this section we present our basic production function results for both samples of firms. First we present a complete set of estimates for the long balanced panel and then selected estimates for the larger sample. Table 3 shows the results obtained for the production function estimates when constant returns to scale is not imposed, using our balanced long history sample of 197 firms, different assumptions for calculating knowledge capital, and different estimation techniques. 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 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 one 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 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

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[10]See Griliches and Hausman (1986).

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

zero in the totals.[12] These results are consistent with the observation that the average double counting adjustment to labor is four times that to capital (four percent of the total as compared with one percent).

Contrary to the results in Cuneo and Mairesse (1984), the bias in the estimated marginal product 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 are 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, it is clear that a more precise estimate of the initial knowledge capital starting point helps in estimating the true growth rate of R&D capital at the firm-specific level, and hence provides 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

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[12] As Schankerman (1981) as shown, the interpretation and prediction of the effects of the double counting bias on the productivity regression are not simple, and depend in subtle ways on the actual pattern of covariances across the regressors. The only firm prediction one can make is that, under the reasonable assumption that the R&D capital and R&D labor corrections are positively correlated with the measured R&D capital itself, the coefficient on R&D capital will be biased downward if uncorrected data are used.

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 previous year's level of R&D expenditures (a depreciation rate of 100 percent) gave approximately the same coefficients as K71 in all specifications with lower standard errors of estimate, but a worse fit in the within and first-differenced dimensions. Thus it appears extremely difficult to disentangle the appropriate depreciation rate using the production function approach.

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), 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), Griliches and Mairesse (1984), and Griliches (1986), 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 to estimates using our large slightly unbalanced sample of firms. In the absence of compelling evidence to the contrary, we use our base measure of R&D capital (K71), which is constructed with a depreciation rate of 15 percent and a pre-sample growth rate of 5 percent when estimating using this sample. We also use as much history of R&D expenditures as is available in constructing K71; that is, for the 143 additional firms, the R&D history will begin in about 1978, rather than 1971.

The results of selected estimations using the larger sample are shown in columns 1 and 3 of Table 5; in columns 2 and 4 we repeat the estimates using the long sample for comparison. The most striking difference between the large sample and the long sample is that in the total estimates (as well as the long-differenced estimates without constant returns imposed) the R&D capital coefficient is higher by 0.05 for the firms with longer history than for the sample as a whole, and the coefficient for labor (derived from the scale coefficient) is correspondingly lower. This is not accounted for by differences 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.

Since the differences in the R&D capital coefficient are much smaller (or negative) in the within dimension, the most likely cause of the change is differences across firms which are correlated with R&D intensity rather than differences in the actual productivity of R&D within firms. This hypothesis is suggested by inspection of the difference in industrial composition in the two samples shown in Table 1. 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 have a smaller technological base than the other industries.

To test the hypothesis that the differences in the total estimates were due to industrial composition changes, we re-estimated the equations in columns 1 and 2, excluding firms in the first two sectors of Table 1. The R&D coefficients in the totals were 0.255(.009) and 0.237(.007) respectively, confirming that the difference between the two sets of estimates was due to the changing industrial composition of the sample, not to the fact that the larger sample contains younger firms.

This last fact highlights one of the more robust results in these and other production data: The pattern of estimates usually yields an R&D capital elasticity in the cross section dimension which is statistically significant, usually large, and even of the same order of magnitude as the elasticity of ordinary capital, whereas the estimates 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 industry which are correlated with the presence of knowledge 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 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 higher productivity growth which can be achieved by R&D through the shifting industrial composition which might be induced by an R&D subsidy.

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 which is not observable to us as econometricians. 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. There is an alternative solution available, however, which involves attempting to measure "partial" factor productivity by removing labor's share from our value-added measure. If done correctly, this leaves only the capital measures on the right hand side of the equation and these are more likely than labor input to be predetermined with respect to output the following period.

To implement this method, we begin with equation (2) and add the assumption of perfect competition (price-taking in both labor and output markets), which implies that

β can be estimated by the share of labor in value-added, without appealing to the regression framework. If we have such an estimate, denoted $\hat{\beta}$, then equation (2) becomes

$$(6) \quad y_{it}-\hat{\beta}l_{it} = a + \lambda t + \alpha c_{it} + \gamma k_{it} + \varepsilon_{it} + (\beta-\hat{\beta})l_{it}$$

If all firms were alike we would expect $(\beta-\hat{\beta})$ to be vanishingly small, which implies that estimates of α and γ which are uncontaminated by simultaneity bias could be obtained by regressing $y-\hat{\beta}l$ on c and k.

Note that in deriving equation (6) we made no assumption about the fixity of the choices for capital c_{it} and k_{it} other than assuming that they were not correlated with the disturbance ε_{it}. If we assume that the two stocks of capital are fixed in the shortrun, equation (6) can be derived in a slightly different way directly from the production function by assuming that the firm chooses labor and output in any period to maximize short-run variable profits, taking the two capitals and all prices as given. This approach, called "semi-reduced form" by Griliches and Mairesse (1984), yields the following two equations:

$$(7) \quad l_{it} = \text{const} + (1-\beta)^{-1}\ [\lambda_l t + \alpha c_{it} + \gamma k_{it}] + u_{it}$$
$$y_{it} = \text{const} + (1-\beta)^{-1}\ [\lambda_y t + \alpha c_{it} + \gamma k_{it}] + v_{it}$$

If we multiply the first equation by $\hat{\beta}$ and subtract from the second, we obtain the following:

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

Now, if we have a consistent estimate of β, then $(1-\hat{\beta})/(1-\beta)$ converges to one and clearly equation (8) will yield the same consistent estimates of α and γ as equation (6). The advantage of this method of derivation is that it clarifies the fact that under the assumptions which allowed us to derive equation (6), the semi-reduced form version of the model in equations (7) should yield the same estimates for the capital coefficients. This is far from being the case, as we will show later in this section. First, however, for the sake of comparability with earlier studies, we focus on the partial TFP estimates.

We present two sets of estimates for equations (6) or (8) 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 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 $\hat{\beta}_i$ 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, but they do not appear to imply that a large simultaneity bias was present in the estimates of the R&D coefficient in Tables 3 through 5, except in the totals where the bias was negative, and the first-differenced estimates, where the bias was small and positive. Both long-differenced and within estimates show a fairly strong positive relationship between the growth of both kinds of capital and labor productivity growth; this relationship does <u>not</u> exist in the first-differenced estimates. These latter 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. But this is just what we would expect if capital is only adjustable in the long run as we have assumed in deriving equation (8): 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 equations (7), but before doing so, we expand the model slightly to include the possibility of imperfect competition in the output market.[13] We assume a constant elasticity of demand function:

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

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 equation (1), and the stocks of ordinary capital C and knowledge capital K. This set of assumptions yields the following variation of equations (7):

$$(10)\quad l_{it} = \text{const} + (1-\beta\varepsilon)^{-1}\,\varepsilon\,[\lambda_{l} t + \alpha c_{it} + \gamma k_{it}] + u_{it}$$
$$y_{it} = \text{const} + (1-\beta\varepsilon)^{-1}\,[\lambda_{y} t + \alpha c_{it} + \gamma k_{it}] + v_{it}$$

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 capital stocks than output does. Note also that when $\hat{\beta} = \beta$ (the true coefficient), equation (6) is still implied by equations (10).

In Table 7, we explore the estimation of equations (10) for our data using

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[13]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 capital to shift the demand curve, which removes the proportionality between the output and labor equations, implying no overidentifying restrictions on the model.

nonlinear seemingly unrelated regression to estimate both equations simultaneously. The first column repeats the estimates of equation (6) for comparison. The next two columns give the unconstrained estimates of equations (10), where proportionality has not been imposed across either the year effects or the capital coefficients.[14] The final two columns give the estimates when proportionality has been imposed as in equations (10), 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.

The primary result of this set of estimates is that the proportionality constraint, which is required to justify the partial TFP estimates, does not hold for the totals and first differenced estimates, but does hold for the estimates in the within and long differenced dimension.[15] This result can be seen easily by comparing the coefficient estimates in columns 2 and 3 with those in column 1. An implication of the derivation of equation (8) is that the estimates in column 1 are just a linear transformation of those in columns 2 and 3.[16] If the proportionality holds, this will guarantee that equation (6) or (8) and equations (7) 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

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[14] In order to make these columns comparable to the estimates in column 1, the model has been estimated with an explicit $(1-\beta)^{-1}$, with β set to 0.67. This means that the 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.

[15] The test statistics are $\chi^2(2)=291.2$, $\chi^2(2)=0.8$, $\chi^2(2)=1.8$, and $\chi^2(2)=16.2$ for the totals, within, long differenced, and first differenced specifications respectively.

[16] The transformation vector is $[(1-\hat{\beta})^{-1},\ -\hat{\beta}(1-\hat{\beta})^{-1}]$.

partial TFP 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.

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 15 with an approximate standard error of 2.[17] 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, equation (10) for y_{it} would be identical to equation (10) for l_{it} and we would be unable to separately identify the demand elasticity and the scale coefficient 1-β. 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.

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

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

firms, the estimated R&D elasticity is 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.[18] 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 equation (2) as

$$(11)\quad \Delta y_{it} = \lambda + \alpha\Delta c_{it} + \beta\Delta l_{it} + \rho(\dot{K}_{it}/Y_{it}) + \eta_{it}$$

where η_{it} is a new disturbance containing approximation errors in addition to the differenced ε_{it} and $\dot{K}_{it}$ is the change in R&D capital over time. In discrete time and if R&D capital does not depreciate, we could approximate ΔK_{it} by the flow of R&D expenditures during the period, which implies that the relevant right hand side variable is the R&D to value added intensity, which is easily measured.

There are at least two problems 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

[18] See also the survey by Mairesse and Sassenou (1991).

hand side of the equation. The second problem is that the relevant concept for ΔK is the net R&D expenditure rather than the gross, but to do this we have to make an assumption about the measurement of R&D capital, so we have not really avoided the problem of measurement.

The results of estimating equation (11) with both gross and net R&D expenditures are shown in Table 8, which is parallel in format to Tables 3 and 4. We measure the gross rate of expenditure by the lagged R&D to value added ratio, and the net rate of by the same ratio less replacement expenditures, which are defined to be δ times the ratio of lagged R&D capital to value added.[19] Using a depreciation rate of 15 percent, the resulting mean R&D intensities are 9.3 percent and 2.1 percent respectively.[20]

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. 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

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[19]Note that the estimates which are based on the gross rate of R&D expenditure only differ slightly because all that is changing across these estimates is the double counting adjustment to physical capital, which is affected by the choice of depreciation rate for the R&D capital correction.

[20]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 will be equal to $(g/(g+\delta))R_t$; this is roughly consistent with these numbers for g=0.05 and δ=0.15, which implies that net R&D is one quarter of gross. This is not independent information, just a check on our calculations.

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 constant of four, we would expect its coefficient to be <u>lower</u>, not higher, and by a factor of four (see footnote 19). Which interpretation is correct depends on which parameter (gross rate of return, net rate of return, or elasticity) is constant across firms, but neither interpretation implies that the coefficients should be nearly equal.

A second difference between these estimates 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 confidence in the robustness of our conclusions, although those who favor other approaches to the measurement of R&D productivity may be more skeptical.

Our first set of conclusions concerns the measurement of the relationship between productivity and R&D. The 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, even holding the sample of firms constant. The 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 is not very new; it has been observed by almost every researcher who has experimented with this specification, and it arises from the basic fact that the time series of R&D expenditure within firm does not vary all that much.

A third measurement result 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 consistent with an interpretation which says that results based on uncorrected data are basically measuring an excess rate of return for R&D, rather than the total private rate of return. This fact may allow one to interpret results reported by researchers who do not have the data available for performing the 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 so 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. We base this conclusion on the frequent inconsistency between these results and the long differenced results, which in principle ought to be quite similar, and on the widely varying parameter estimates and large standard errors which we observe using these estimates. For this reason, the remainder of this concluding section largely ignores the first differenced 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, since 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. Additionally, the primary argument in favor of this specification, which is the desire to avoid measuring R&D capital, or to proxy it by expenditures, does not really hold rigorously. A final problem with this method of measurement is the question of the timing or R&D and the output which it affects, which can be seen to have a large impact on our results when we compare long differenced and first differenced estimates. For these several reasons, we prefer the production function approach discussed in the first several sections of the paper, unless the rate of return model is improved.

Turning to the substantive results in the paper, we find that the coefficient of knowledge capital in the production function is uniformly positive in different specifications, and fairly robust to the specification of the model. Most of the estimates are consistent with those of previous studies; in some cases they are much higher. We also find that the productivity of knowledge capital is correlated with permanent firm or industry effects (in particular, the overall level of knowledge capital in the industry), which implies substantially higher coefficients in the cross section dimension than in the time series (within firm) dimension.

However, when we correct for the estimation bias which might arise from the simultaneous choice of labor and output levels, this difference between total and within firm estimates falls substantially, from about 0.2 to 0.06; the simultaneity bias itself appears to affect total and long differenced estimates of the R&D capital coefficient, but not the within or first differenced estimates. 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. This 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.

TABLE 1

INDUSTRIAL SECTOR BREAKDOWN

Sector	Number of Firms		Number of Obs.		R&D to Output*		R&D to Sales Ratio**	
	Large Sample	Long Sample	Large Sample	Long Sample	Large Sample	Long Sample	(France)	(U.S.)
1 Food & Agriculture	32	2	252	16	0.5	0.5		0.6
2 Textiles, Apparel, Leather, & Wood	40	15	313	120	3.9	5.5		0.8
3 Chemicals	13	9	104	72	3.3	3.4		2.7
4 Const. Materials & Glass	18	12	141	96	0.5	0.6		1.2
5 Metals & Fabrication	31	17	246	136	1.3	1.3		0.8
6 Non-elec. Machinery	56	36	441	288	2.3	1.8		2.3
7 Elec. Machinery	33	25	261	200	4.0	4.0		3.7
8 Autos, Aircraft	28	20	212	160	5.1	4.6		2.8
9 Pharmaceuticals	56	36	441	288	4.5	5.1		5.5
10 Electronics	33	25	259	200	7.1	6.3		5.2
TOTAL	340	197	2670	1576	4.2	4.2		2.8

* This is the <u>industry</u> R&D to sales ratio (in percent), not the average of individual firm ratios. It is computed for the year 1982.

** These are the corresponding pecentage ratios for the United States publicly traded manufacturing sector in 1982, taken from Table 3 of Hall (1990). They represent over 90 percent of the industrial R&D performed in the United States. The numbers for France come from the OECD (1990).

TABLE 2

STATISTICS ON THE VARIABLES

(After Cleaning and Deflation)
1980-1987

Variable	Name	Large Sample Median	Large Sample IQ Range[*]	Long Sample Median	Long Sample IQ Range	Large Sample Minimum	Large Sample Maximum
Number of Observations		2670		1576		2670	
Value added (MM of 1980 FF)	VA	146.2	76,358	198.8	85,458	8.06	15,174.
VA adj. for R&D (MM of 1980 FF)	VADJ	150.6	77,369	202.5	89,465	8.31	15,642.
Net capital stock (MM of 1980 FF)	C	305.0	115,816	395.0	125,1189	10.01	44,902.
Cap stk adj for R&D (MM of 1980 FF)	CADJ	300.7	110,806	385.4	122,1135	9.26	43,881.
Knowledge capital[**] (MM of 1980 FF)	K71	40.7	14,113	64.7	23,154	1.06	17,916.
Knowledge capital[**] (MM of 1980 FF)	KH71	26.8	9,72	40.7	16,100	0.68	11,908.
Knowledge capital[**] (MM of 1980 FF)	KS78	38.7	14,110	61.0	23,148	1.06	17,390.
R&D expenditures (MM of 1980 FF)	R	7.3	2.5,20.3	11.1	4.7,29.8	0.17	3,535.
Number of employees (beg. of year)	L	964.	533,2304	1251.	584,2957	68.	106,740.
No. emp. adj for R&D (beg. of year)	LADJ	924.	499,2193	1134.	524,2817	65.	103,042.
VA Growth Rate[***]	(percent)	1.17	-6.5,9.46	.009	-6.7,8.95	-81.	226.
C Growth Rate[***]	(percent)	2.76	0.38,5.73	2.79	0.28,5.06	-22.	92.
L Growth Rate[***]	(percent)	-0.99	-4.6,2.02	-1.21	-4.8,1.73	-44.	189.
K Growth Rate[***]	(percent)	3.96	0.15,8.57	3.97	0.07,8.63	-13.	159.

See the next page for notes to the table.

TABLE 2 (CONTINUED)

Notes:

*The IQ Range is the interquartile range, the value of the variable at the 25 percent and 75 percent level of the univariate distribution.

**The three types of knowledge capital are calculated as described in Section 3 of the paper.

***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).

TABLE 3

PRODUCTION FUNCTION ESTIMATES - LONG SAMPLE

1980-1987: 197 FIRMS (1576 OBS.)

DEPENDENT VARIABLE: LOG (VALUE ADDED/EMPLOYEE)
CONSTANT RETURNS TO SCALE NOT IMPOSED

	Unadj. K71	Adjusted K71	Adjusted KH71	Adjusted KR	Adjusted KS78
			Totals		
log (C/L)	.207(.013)	.199(.013)	.214(.013)	.217(.012)	.207(.013)
log (K/L)	.180(.009)	.252(.008)	.254(.008)	.248(.008)	.246(.008)
log L	-.030(.007)	-.035(.007)	-.035(.007)	-.037(.007)	-.035(.008)
R^2(st.err.)	.996(.336)	.996(.344)	.996(.338)	.996(.335)	.996(.345)
			Within		
log (C/L)	.121(.059)	.174(.057)	.178(.058)	.102(.036)	.187(.057)
log (K/L)	-.001(.036)	.069(.035)	.050(.028)	.051(.016)	.004(.031)
log L	-.095(.052)	-.055(.053)	-.070(.051)	-.132(.042)	-.090(.053)
R^2(st.err.)	.075(.188)	.103(.186)	.103(.186)	.104(.185)	.101(.186)
			Long Differences		
log (C/L)	.137(.137)	.199(.133)	.202(.133)	.164(.084)	.209(.132)
log (K/L)	.064(.085)	.129(.029)	.122(.069)	.122(.049)	.086(.077)
log L	.131(.115)	.165(.116)	.150(.112)	.095(.097)	.149(.118)
R^2(st.err.)	.011(.0510)	.030(.0507)	.034(.0506)	.050(.0502)	.022(.0509)
			First Differences		
log (C/L)	.203(.096)	.233(.092)	.239(.092)	.071(.040)	.234(.092)
log (K/L)	.045(.072)	.051(.070)	.034(.051)	.022(.019)	.025(.065)
log L	-.607(.099)	-.600(.098)	-.611(.091)	-.754(.060)	-.621(.098)
R^2(st.err.)	.157(.197)	.183(.193)	.183(.193)	.181(.193)	.183(.193)

See the notes to the next table for variable definitions.

TABLE 4

PRODUCTION FUNCTION ESTIMATES - LONG SAMPLE

1980-1987: 197 FIRMS (1576 OBS.)

DEPENDENT VARIABLE: LOG (VALUE ADDED/EMPLOYEE)
CONSTANT RETURNS TO SCALE IMPOSED

	Unadj K71	Adjusted K71	Adjusted KH71	Adjusted KR	Adjusted KS78
			Totals		
log (C/L)	.190(.012)	.179(.012)	.193(.012)	.195(.012)	.187(.012)
log (K/L)	.176(.009)	.251(.008)	.253(.008)	.247(.008)	.245(.008)
R^2(st.err.)	.996(.338)	.996(.346)	.996(.341)	.996(.337)	.996(.347)
			Within		
log (C/L)	.181(.04()	.209(.047)	.229(.044)	.161(.031)	.246(.045)
log (K/L)	.032(.035)	.080(.033)	.057(.028)	.056(.016)	.022(.030)
R^2(st.err.)	.074(.188)	.103(.186)	.102(.186)	.099(.186)	.099(.186)
			Long Differences		
log (C/L)	.058(.119)	.103(.159)	.103(.110)	.127(.075)	.121(.113)
log (K/L)	.038(.082)	.093(.079)	.105(.068)	.117(.048)	.053(.072)
R^2(st.err.)	.004(.0511)	.019(.0509)	.025(.0507)	.045(.0502)	.014(.0510)
			First Differences		
log (C/L)	.558(.077)	.575(.073)	.674(.067)	.324(.036)	.611(.071)
log (K/L)	.252(.065)	.266(.061)	.156(.049)	.075(.020)	.227(.057)
R^2(st.err.)	.134(.199)	.161(.195)	.157(.196)	.088(.204)	.159(.195)

Variable Definitions:

K71 -- Knowledge capital constructed with δ=.15, using R&D history to 1971.
KH71 -- Knowledge capital constructed with δ=.25, using R&D history to 1971.
KR -- Knowledge capital = R_{-1} divided by δ=.15.
KS78 -- Knowledge capital constructed with δ=.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*
		Totals		
log (C/L)	.167(.010)	.199(.013)	.156(.010)	.179(.012)
log (K/L)**	.198(.006)	.252(.008)	.198(.006)	.251(.008)
log L	-.080(.006)	-.035(.007)	-	-
R^2(st.err.)	.995(.368)	.996(.344)	.995(.369)	.996(.346)
		Within		
log (C/L)	.183(.037)	.169(.057)	.258(.032)	.209(.047)
log (K/L)	.070(.024)	.055(.035)	.105(.023)	.080(.033)
log L	-.138(.034)	-.055(.053)	-	-
R^2(st.err.)	.123(.177)	.103(.186)	.118(.178)	.103(.186)
		Long Differences		
log (C/L)	.113(.080)	.199(.133)	.126(.073)	.103(.115)
log (K/L)	.077(.056)	.129(.082)	.086(.052)	.093(.679)
log L	-.032(.073)	.165(.116)	-	-
R^2(st.err.)	.026(.0490)	.030(.0507)	.025(.0489)	.019(.0509)
		First Differences		
log (C/L)	.225(.053)	.233(.092)	.476(.047)	.575(.073)
log (K/L)	.067(.047)	.051(.070)	.320(.039)	.266(.061)
log L	-.594(.065)	-.600(.098)	-	-
R^2(st.err.)	.196(.185)	.183(.193)	.161(.188)	.161(.195)

*The long sample contains 1576 observations and 197 firms. The large sample contains 2670 observations and 340 firms.

**The knowledge capital K is calculated using all of the history available for each firm, and a depreciation rate of 15 percent (K71).

TABLE 6

PARTIAL TFP ESTIMATES: LONG SAMPLE[*]
1980-1987: 196 FIRMS (1568 OBS.)

Dep. Var.[**]	Unadjusted LogY-.76·LogL	Unadjusted LogY-$\hat{\beta}$·LogL	Adjusted LogY-.67·LogL	Adjusted LogY-$\hat{\beta}$·LogL
		Totals		
log C	.115(.007)	.227(.024)	.112(.007)	-.053(.024)
log K[***]	.134(.007)	.055(.024)	.216(.007)	.485(.024)
Scale	.004	.037	-.002	.099
R^2(st.err.)	.998(.341)	.971(1.193)	.998(.347)	.974(1.234)
		Within		
log C	.129(.051)	.111(.051)	.190(.050)	.165(.050)
log K	.018(.035)	.010(.035)	.075(.034)	.056(.034)
Scale	-.098	-.124	-.065	-.126
R^2(st.err.)	.051(.186)	.056(.155)	.066(.184)	.071(.182)
		Long Differences		
log C	.247(.115)	.224(.115)	.301(.113)	.272(.112)
log K	.093(.082)	.081(.082)	.154(.081)	.126(.080)
Scale	.095	.060	.108	.065
R^2(st.err.)	.046(.0508)	.037(.0507)	.079(.0506)	.062(.0503)
		First Differences		
log C	-.177(.091)	-.180(.091)	-.121(.087)	-.121(.087)
log K	-.058(.075)	-.059(.074)	-.025(.071)	-.037(.071)
Scale	-.480	-.484	-.476	-.491
R^2(st.err.)	.072(.203)	.023(.204)	.017(.199)	.023(.199)

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

[**] 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.

[***] The knowledge capital K is calculated using all of the history available for each firm, and a depreciation rate of 15 percent.

TABLE 7

SEMI-REDUCED FORM ESTIMATES

1980-1987: 196 FIRMS (1568 OBS.)*

Dep. Var.	LogY-.67·LogL	LogY	LogL	LogY, LogL	LogY, LogL
			Totals		
log C	.112(.007)***	.158(.003)	.181(.003)	.168(.002)	.193(.005)
log K	.216(.007)	.121(.003)	.075(.003)	.101(.002)	.121(.003)
Demand ε**	1.0	-	-	1.0	.934(.009)
Log Likelihood			-1447.2	-1592.8	-1565.7
			Within		
log C	.190(.050)	.203(.020)	.209(.017)	.209(.016)	.215(.048)
log K	.075(.034)	.053(.013)	.042(.008)	.043(.008)	.045(.013)
Demand ε	1.0	-	-	1.0	.989(.077)
Log Likelihood			1659.1	1658.7	1658.7
			Long Differences		
log C	.301(.113)	.240(.044)	.211(.034)	.213(.034)	.359(.091)
log K	.154(.081)	.082(.029)	.047(.019)	.050(.018)	.088(.036)
Demand ε	1.0	-	-	1.0	.806(.087)
Log Likelihood			647.6	645.8	647.2
			First Differences		
log C	-.121(.087)	.099(.039)	.208(.031)	.189(.026)	-.118(.127)
log K	-.025(.071)	.026(.021)	.050(.017)	.046(.015)	-.029(.031)
Demand ε	1.0	-	-	1.0	2.07(.81)
Log Likelihood			1644.2	1636.1	1644.2

*One firm whose labor share was larger than unity has been deleted from the sample.

**$\varepsilon = 1-1/\eta$ where η is the demand elasticity.

***Heteroskedastic-consistent estimates of the standard errors are shown in parentheses.

TABLE 8

RATES OF RETURN IN MANUFACTURING

1980-1987: 197 FIRMS+

	Long Sample				Large Sample***
	Unadjusted	Adj. K71	Adj. KH71	Adj. KS78	Adj. K71
	First Differences: Dep. Var. = ΔlogVA				
Δlog C	.148(.095)	.179(.091)	.181(.092)	.177(.091)	.181(.061)
Δlog L	.132(.060)	.107(.055)	.107(.055)	.108(.055)	.107(.041)
Gross R^*_{-1}	.231(.053)	.273(.059)	.273(.059)	.274(.059)	.222(.046)
R^2(s.e.)	.042(.195)	.044(.191)	.044(.191)	.044(.191)	.037(.184)
Δlog C	.162(.097)	.201(.092)	.213(.093)	.197(.092)	.203(.061)
Δlog L	.137(.060)	.111(.056)	.111(.056)	.110(.056)	.103(.042)
Net R^*_{-1}	.293(.128)	.310(.136)	.304(.161)	.341(.133)	.259(.110)
R^2(s.e.)	.032(.196)	.033(.192)	.031(.192)	.033(.192)	.030(.184)
	Long Differences: Dep. Var. = Δ^6logVA				
Δlog C	.027(.139)	.101(.136)	.109(.137)	.101(.136)	.155(.099)
Δlog L	.954(.123)	.876(.106)	.873(.166)	.876(.106)	.789(.074)
Gross R^{**}_{-1}	.036(.053)	.065(.060)	.064(.060)	.066(.060)	.104(.048)
R^2(s.e.)	.387(.0611)	.383(.0607)	.384(.0607)	.383(.0607)	.372(.0587)
Δlog C	.048(.145)	.101(.142)	.120(.143)	.103(.140)	.154(.103)
Δlog L	.954(.112)	.876(.106)	.871(.106)	.876(.106)	.723(.078)
Net R^{**}_{-1}	-.013(.147)	.126(.160)	.116(.215)	.124(.156)	.205(.135)
R^2(s.e.)	.386(.0612)	.382(.0608)	.381(.0608)	.382(.0608)	.367(.0590)

The notes to the table are on the following page.

TABLE 8 (CONTINUED)

Notes:

+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.

*Gross R&D is R_{-1}/VA_{-2} and net R&D is $(R_{-1}-.15K_{-1})/VA_{-2}$, 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.

**In the long differenced version, the mean of each variable is computed over the 7 years 1980-1986, and the ratios are then computed.

***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.

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APPENDIX A

Construction of the Data Samples

This Appendix provides some detail on how we constructed and cleaned our dataset. Table A1 shows the number of firms available in each year, and also the number left after observations with bad data (as defined below) are removed. There were approximately 400 firms in the original cleaned R&D surveys for 1980 through 1987. We deleted 49 firms which were not in the manufacturing sector by the conventional definitions. The firms deleted included firms in the energy industries (14 firms in petroleum refining, natural gas production and distribution, electricity production and distribution), construction industries (10 firms), wholesale and retail trade (7 firms), and business services (15 firms). We chose to delete these firms because of our focus on the contribution of R&D to the growth of total factor productivity in manufacturing, which is also the topic of the previous studies to which we compare our results. It is also true that TFP itself is 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 inter-quartile range (the 75 percent value minus the 25 percent value) above or below the median.[1] 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 be 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.[2]

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)

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[1]For a normally distributed variable, this would remove all observations which are outside of 4 standard deviations away from the mean (less than 0.01 percent of the observations).

[2]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.

because some observations clearly had a wrong datum (number of employees too low by a factor of 10 in one year, for example) and thus caused them to be removed for several reasons simultaneously.

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 in the within dimension (the primary coefficient of interest) 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.[3] We 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.

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

TABLE A1

FRENCH MANUFACTURING SECTOR - R&D SAMPLE

1980-1987

Year	Number in R&D File	No. of Firms (Manufacturing)	No. of Firms (After Cleaning) Large Sample	Long Sample
1980	393	347	326	200
1981	393	347	332	202
1982	393	347	336	203
1983	393	347	336	205
1984	394	347	334	205
1985	394	347	336	206
1986	393	347	336	206
1987	392	347	334	205
Total	3145	2776	2670	1632
Number of Firms	399	351	340	206

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 B1.

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 productivity by 5 or 9 percent with a standard error of 2-3 percent, depending on which cutoff is chosen. It also reduces the 7 year growth rate of productivity by an average of 2-3 percent per year; once again, the first differenced results are insignificantly difference from zero. About half the result in levels goes away when industry dummies at the 10 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 about 10 percent, and the growth rate effect is 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.

TABLE B1

PRODUCTION FUNCTION ESTIMATES
WITH BASIC AND GOVERNMENT FUNDED R&D

1980-1987: 197 FIRMS (1576 OBS.)

	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)	.202(.013)	.204(.013)	.181(.012)	.181(.012)
log (K/L)	.255(.009)	.243(.009)	.256(.009)	.244(.009)
log L	-.034(.007)	-.039(.007)	-	-
D(Basic)	-.052(.020)	-.092(.027)	-.052(.020)	-.090(.027)
D(Govt.)	-.018(.020)	.117(.033)	-.028(.020)	.093(.033)
R^2(st.err.)	.996(.343)	.996(.341)	.996(.345)	.996(.344)
		Long Differences		
log (C/L)	.230(.133)	.204(.129)	.130(.115)	.125(.112)
log (K/L)	.106(.082)	.096(.081)	.070(.079)	.066(.077)
log L	.169(.114)	.136(.113)	-	-
D(Basic)	-.021(.009)	-.029(.012)	-.020(.009)	-.029(.012)
D(Govt.)	-.001(.009)	.033(.013)	-.000(.009)	.034(.013)
R^2(st.err.)	.057(.0503)	.089(.0494)	.046(.0504)	.082(.0495)
		First Differences		
log (C/L)	.217(.080)	.223(.080)	.507(.066)	.514(.066)
log (K/L)	.128(.064)	.126(.064)	.330(.056)	.331(.055)
log L	-.549(.088)	-.554(.088)	-	-
D(Basic)	.000(.011)	-.011(.015)	-.001(.011)	-.012(.015)
D(Govt.)	.019(.010)	.060(.017)	.013(.010)	.054(.017)
R^2(st.err.)	.190(.189)	.195(.189)	.170(.192)	.175(.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.