R&D and productivity growth: evidence from firm-level data for the Netherlands

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1. Introduction

This article presents evidence on the links between R&D and productivity for manufacturing firms in the Netherlands. The study provides estimates of the output elasticity of the R&D stock and of the private rate of return to R&D. The article applies the methodology used by Hall and Mairesse (1995) to a panel dataset of R&D performing firms in the Netherlands, with some minor modifications. First, a correction for sample selection bias is used in an attempt to adjust the results for possible bias arising when the basic methodology is applied to the R&D survey for the Netherlands. Next, more complete adjustment is made to the resource input data to correct for the 'double counting' of R&D inputs. Lastly, an attempt is made to correct for heteroskedasticity in the error term of the basic model. The study makes use of linked files of the R&D surveys and the annual production statistics collected by Statistics Netherlands for the years 1985, 1989, and 1993.

Most previous work on the link between R&D and productivity in the Netherlands has been based on aggregate or industry data. Den Butter and Wollmer (1992) report a significantly negative estimate for private returns to R&D, whereas the cross-country study of Coe and Helpman (1993) shows a positive contribution of private R&D to total factor productivity growth for the Netherlands. These inconclusive results are a likely reason that Verspagen (1995) omits the Netherlands from his broad-based survey article on R&D and productivity growth. The ambiguous estimates probably derive from the very skewed distribution of firm size and R&D expenditure in the Netherlands. R&D expenditure in Dutch manufacturing is highly concentrated in five multinational companies. These companies spend a disproportionate – albeit decreasing – part of their worldwide R&D in the Netherlands, whereas their production is to a large extent located outside the Netherlands. The recent dramatic decrease of domestic R&D expenditure of these companies can be held responsible for the decline in aggregate manufacturing R&D from 1989 onwards.

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The use of micro-data enables us to estimate the effect of R&D on productivity growth free from aggregation bias. However, the use of firm-level data does not solve all econometric problems. Measurement errors, simultaneity and selectivity can continue to cloud results (see e.g. Grilliches and Mairesse, 1995). The data allow robustness checks of the results with respect to measurement of capital stocks, double counting of R&D inputs, creation of initial R&D knowledge stocks, and different measures of output. We correct for simultaneity bias by estimating a production function in 'long-difference' form and by using a partial TFP approach. Selectivity may be a problem in our sample: indeed the probability of exiting the sample is negatively related to the level of R&D intensity. The problem appears to be more severe in the period 1989–1993, when R&D expenditure was declining, on average. In our estimation procedure an attempt is made to correct for the selectivity problem by using a Tobit model.

Our findings are very similar to the results recently published by Hall and Mairesse (1995). It is found that the elasticity for the stock of R&D capital is about 0.06 for gross output and 0.08 for value added and the private gross rate of return to R&D varies between 12 percent for gross output and about 30 percent for value added. Because the Hall and Mairesse estimates were derived from a panel with considerably more observations in the time dimension, this is a surprising result.

2. The data

The dataset used in this study contains linked firm-level information from the annual production surveys and the extended R&D surveys of 1985, 1989 and 1993, conducted by Statistics Netherlands [1)]. The production surveys provide data for each firm on sales, gross output, value added, payroll, number of employees, materials, electricity use and capital consumption allowances (depreciation costs). The R&D surveys give information on R&D full-time equivalents and other staff, and expenditure on in-house R&D and outsourced R&D. The R&D expenditure is further disaggregated into staff costs, material costs and R&D plant and equipment investments. Other disaggregations split expenditure by type of research (basic and applied) and by process and product research.

A distinct advantage of this dataset is that the R&D expenditures can be separated from the other operating expenses of the firm, avoiding the biases in estimation caused by 'double counting' resource inputs (see Schankerman, 1981). In the production function estimations, material and labour input variables can be adjusted for the amounts used in R&D endeavour. This adjustment is not attempted for the capital input because the R&D investments account for only 10 percent of total R&D expenditure and we have only two observations of R&D expenditure for each panel (1985–1989 and 1989–1993). So the best we can do is to solve the double counting problem for 90 percent.

The nominal variables in the dataset are all deflated into constant 1985 guilders. Output and materials are deflated by applying 3-digit SIC [2)] product and material prices to all firms within the corresponding industry. R&D expenditure is deflated by a Divisia index of changes in wages of R&D staff and material prices. The price changes for R&D staff were computed for industry groups as the change in average hourly compensation for R&D employees between 1985 and 1989 and between 1989 and 1993 [3)]. Using firm-specific labour and material expenditure shares, the appropriate wage change was averaged with the material price change to construct R&D expenditure deflators.

The capital input measure required to estimate the production functions is proxied by the consumption allowances, available in the production statistics. This financial measure is related to the capital stock but does not directly reflect the capital service flow. Tax laws, vintage and type distribution of the assets, and cyclical capital utilisation all cause differences between the depreciation data and the desired measure of capital real capital input. When the production function is estimated in first difference form, changes in the capital inputs are proxied by changes in electricity use. This measure should correct for fluctuations in capital utilisation, but may misrepresent the growth of capital inputs if firms adopt energy saving technologies. Given the fall of electricity prices in the period of observation, it is unlikely that large scale substitution between energy and capital has taken place.

Tables 1A, 1B and 2 give some summary statistics for the linked datasets. In table 1A descriptive statistics for three cross-sections of linked data are presented. In total 382, 436 and 347 R&D firms could be linked to the production statistics of 1985, 1989 and 1993 respectively. These firms contribute to between 90 and 95 percent of Dutch manufacturing R&D. The major R&D performing firms are included in all years, ensuring that coverage remains high. The top five firms alone account for approximately 70%, 65% and 60% of manufacturing R&D in 1985, 1989 and 1993 respectively. Smaller firms – as measured by their contribution to manufacturing R&D – have a higher probability of exiting the panel due to incidental R&D performance. In fact the four-yearly extended R&D surveys reflect to some extent a rotating design, because small firms have higher probability to be replaced by other firms. Firms may also exit the sample owing to merging or liquidation. Because of the considerable drop out of the smaller R&D performing firms no attempt was made to construct a panel over the full period of three years. Instead two different panels are used in the estimation procedures, labelled PS-RD8589 and PS-RD8993. The nature of the balanced panels may introduce a selectivity bias in the estimated R&D coefficients. An attempt is made to correct for this problem by including a selectivity equation in the models.

Table 1A. Summary Statistics for yearly cross-sections

Year	1985		1989		1993	
	Mean	Q1–Q3[a]	Mean	Q1–Q3	Mean	Q1–Q3
Number of employees	757	100–430	686	102–368	619	85–317
Gross output[b]	252	22–128	226	21–131	232	20–102
Value added[b]	71	8– 35	66	7– 36	68	6– 31
Capital per employee[c]	10	5– 13	13	6– 16	16	7– 19
Labour productivity[d]	87	60– 96	92	59– 06	94	57–107
R&D to sales ratio (%)	2.0	0.3–2.7	2.4	0.5–2.9	2.7	0.6–3.1
Number of observations	382		436		347	

[a] IQ: inter-quartile range: first and third quartile boundary;
[b] In million guilders of 1985;
[c] Depreciation charges per employee in thousand guilders;
[d] Value added per employee in 1985 prices in thousand guilders.

Table 1B. Summary Statistics for balanced data

Period	1985–1989[a]				1989–1993[a]			
Year	1985		1989		1989		1993	
	Mean	Q1–Q3[b]	Mean	Q1–Q3	Mean	Q1–Q3	Mean	Q1–Q3
Number of employees	1,169	124–581	1,158	146–589	1,347	119–589	1,084	119–480
Gross output	380	32–167	393	38–190	414	30–165	348	31–195
Value added	110	10– 55	119	12– 54	133	10– 49	111	9– 63
Capital per employee	11	5– 14	15	7– 17	13	6– 17	16	8– 20
Labour productivity	92	66– 99	106	65–116	103	73–115	114	70–129
R&D to sales ratio (%)	2.6	0.4–3.3	2.7	0.6–3.1	3.1	0.7–3.6	3.4	0.8–4.0

[a] Number of observations for 1985–1989: 209, for 1989–1993: 159. All amounts in constant 1985 guilders;
[b] IQ: inter-quartile range: first and third quartile boundary.

Table 2. Growth in balanced panels[a]

Period	1985–1989[b]					1989–1993[b]				
	Mean	Median	Q1–Q3[c]	Min	Max	Mean	Median	Q1–Q3	Min	Max
Employment	0.2	1.4	–2.6– 4.9	–45	24	–0.5	–0.7	–2.8– 2.5	–23	26
Labour productivity	2.0	1.5	–2.3 –6.8	–65	64	0.5	–0.2	–5.1– 5.5	–36	33
Total factor productivity	0.6	0.1	–1.3– 2.1	–10	26	0.2	–0.2	–1.9– 2.3	–7	11
R&D capital δ[d] = 0.05	6.3	5.0	3.7– 7.6	–4	48	5.8	4.4	2.7– 7.3	–3	56
R&D capital δ = 0.15	6.9	5.0	2.8– 9.5	–13	61	5.7	4.0	0.7– 9.2	12	71
R&D capital δ = 0.25	7.0	5.0	1.9–11.0	–24	69	5.4	3.7	1.1–10.6	–21	79
R&D expenditures	4.7	3.4	–2.6–14.0	–100	90	1.2	0.9	–8.8–13.3	–90	101

[a] Average growth (%) per year (in constant 1985 prices);
[b] Number of observations for 1985 1989: 209, for 1989 1993: 159;
[c] IQ: interquartile-range: boundary of the first and third quartile;
[d] δ = depreciation rate.

As can be seen from the means and inter-quartile ranges for the balanced panels (table 1B) and the 1985 cross-section, as presented in table 1A, the datasets consist of relatively large firms. Average firm size in the panel is much larger than the average firm size for total manufacturing for two reasons: the R&D survey only covers firms with more than 50 employees and the probability of performing own R&D increases with firm size. Further, the size distributions within our dataset are very skew, with means for employment, gross output and value added substantially larger than the third quartile. The distribution of R&D expenditure is even more skew than for output and employment. For example the average R&D-sales ratios presented in tables 1A and 1B are unweighted averages. On a weighted base these ratios are considerably larger: respectively 4.6%, 6.6% and 6.7% for 1985, 1989 and 1993. This reflects the dominance of the 'top five' enterprises, which spend a disproportionately large share of their worldwide R&D in the Netherlands compared with the domestic share of their production. The extreme size of these enterprises together with their inordinate share of R&D indicates why estimates of the return from R&D from industry-level data reveal little about the effects of R&D for the average firm [4)]. Idiosyncratic movements in their research expenditure, such as moving research labs overseas, may greatly affect the aggregate R&D measure, while not affecting domestic production.

From table 1B it can also be inferred that the two periods are rather different. Employment, gross output and value added dropped significantly in the second period. The turn of the business cycle is more manifest in our dataset because of the impact of the chemical industry. Chemical firms are overrepresented in our R&D panels. Due to severe price competition gross output and value added of relatively few but very large firms producing basic chemicals show a dramatic decrease in the period 1989–1993. Together with the downsizing of other large R&D performing companies this explains the picture of aggregate R&D in the second period. A better impression of the dynamics can be obtained by looking at the distribution of growth rates in both periods. From table 2 it can be inferred that the distributions for R&D expenditure and productivity growth rates are shifted to the left in 1989–1993. Average labour productivity growth dropped from 2.0 in 1985–1989 to 0.5 in 1989–1993. Similar patterns are observed for the decreases of total factor productivity and R&D expenditure. We also have listed growth rates for R&D capital using different depreciation rates (δ). As can be seen the different depreciation assumptions have a substantial impact on the shape of the R&D capital growth rates distributions, but the means and medians remain relatively stable between the alternatives presented.

3. Methodology

The empirical framework for this article will be a production function with R&D knowledge stock, or R&D intensity, as an additional input. This is a commonly used specification to estimate the effects of R&D on productivity (see e.g. Mairesse and Sassenou, 1991). Starting point is the Cobb-Douglas production function:

(1) $q_{it} = \alpha_{it} + \gamma k_{it} + \Sigma_j \beta_j x_{jit} + \varepsilon_{it}$

where q_{it} is the log of real production of firm i in year t, α_{it} is a firm and time specific indicator of the level of technology, k_{it} is the (log of) R&D stock of knowledge and the x's are the (log) traditional factor inputs belonging to set S, and ε is a normally distributed error term with mean zero and variance σ^2. The summation in (1) runs over factor inputs, $j \in S$. If production is measured by value added then S = {C, L}, capital and labour, and if it is measured by real gross output then the input set is augmented by materials: S = {C, L, M}. The β's and γ are output elasticity parameters to be estimated. In its present form, equation (1) is not identified and further assumptions regarding the disembodied technology parameter α_{it}, are needed. For example, if $\alpha_{it} = \alpha_i + \lambda t$, and if a full panel of firm data over time were available, then a fixed effect estimator of differenced data, a 'within' estimator, would provide consistent estimates of the output elasticities.

Given that data are only available for 1985, 1989 and 1993, 'within' estimation is not possible. The first possibility is to estimate the elasticities from equation (1) under the assumption that there is a different constant term in each year ($\alpha_{it} = \lambda_t$). The restriction that the output elasticities are constant over time can also be dropped. The resulting estimation procedure is then equivalent to estimating a separate cross-sectional equation for 1985, 1989 and 1993. Using the matched panel, firm-level fixed effects of the form $\alpha_{it} = \alpha_i + \lambda t$ cannot be estimated from (1), but can be eliminated by estimating the production function in 'long-difference' form. Taking 'long-differences' has the additional advantage that it preserves more variance for the identification of the parameters than other data transformations (see Griliches and Mairesse, 1995, pp 13). The long difference form is

(2) $\Delta_4 q_{it} = \lambda + \gamma \Delta_4 k_{it} + \Sigma \beta_j \Delta_4 x_{jit} + \mu_{it}$

where $\Delta_4 z_{it} = z_{i,89} - z_{i,85}$ or $z_{i,93} - z_{i,89}$ and μ_{it} is a newly defined disturbance term ($= \Delta_4 \varepsilon_{it}$). Equation (2) is used in various forms to get estimates of the output elasticities. A number of alternatives will be discussed in section 4. The issue of how to measure the relevant R&D variable is explained below.

R&D knowledge stock

Two related methods have been widely used to assess the effects of R&D on productivity. The first assumes that R&D expenditure accumulates into a stock of knowledge, similar to the formation of capital through investment. This assumption implies that past R&D continues to have spillover effects on production in the present, although the effect may diminish over time through depreciation. In estimating this specification, it is assumed that all firms have the same output elasticity of the knowledge stock. The alternative specification assumes that there is no depreciation of the knowledge stock, and in estimating assumes that the rate of return to the R&D knowledge stock is the same for all firms.

The first method calculates the R&D stock using the perpetual inventory method (PIM):

$$(3) \qquad K_{it} = R_{it} + (1-\delta)K_{it-1}$$

where K_{it} is the R&D knowledge stock of firm i in year t, R_{it} represents real R&D expenditures and δ is the rate of depreciation. The depreciation is supposed to reflect, for example, the obsolescence of ideas and the reduced profitability of old products as new ones are created. The magnitude of the depreciation rate is usually chosen in the 15 to 20 percent range (see e.g. Hall and Mairesse, 1995).

Two problems arise in implementing this method with the available data: R&D expenditure is observed only in 1985, 1989 and 1993, and no initial R&D knowledge stock measure is available. Real R&D expenditure for the intervening years is interpolated using the observed growth rate for each firm. Initial stocks of knowledge, $K_{i,85}$ for the first wave and $K_{i,89}$ for the second wave, are created by assuming a pre-sample R&D expenditure growth rate, g, constant across firms. Then, following Hall and Mairesse (1995), the initial knowledge stock can be written as:

$$(4) \qquad K_{i0} = \frac{R_{i0}}{(g+\delta)}$$

Combining this expression into the PIM framework yields the knowledge stock growth equation:

$$(5) \qquad \Delta_4 k_i = 1\text{n}\left(\frac{(1-\delta)^4}{(g+\delta)} + \sum_{s=1}^{4}(1+r_i)^s(1-\delta)^{4-s}\right) + 1\text{n}(g+\delta)$$

with r_i the growth rate of real R&D expenditure for firm i in the period 1985–1989 or 1989–1993. A range of parameter values for g and δ will be used in order to assess the sensitivity of the estimated R&D elasticities to different assumptions pertaining to depreciation and initial stocks.

R&D intensity

The alternative method for estimating the effect of R&D on productivity is the intensity method, where the rate of return to R&D is assumed to be constant across firms. Assuming no depreciation ($\delta = 0$), the change in the R&D knowledge stock can be written as:

$$(6) \qquad \Delta_4 K_{it} = \sum_{s=1}^{4} R_{io}(1 + r_i)^s.$$

Using the fact that the marginal product of the R&D stock, ρ, is equal to its output elasticity times the ratio of output to the R&D stock:

$$(7) \qquad \rho \equiv \frac{\partial Q_{it}}{\partial Q_{it}} = \gamma \frac{Q_{it}}{K_{it}},$$

Now we can rewrite equation (2) as:

$$(8) \qquad \Delta_4 q_{it} = \lambda + \gamma \frac{Q_{i0}}{K_{i0}} \frac{\Delta_4 K_{it}}{Q_{i0}} + \sum_{j \in s} \beta_j x_{jit} + \mu_{it} = \lambda + \rho \frac{\Delta_4 K_{it}}{Q_{i0}} + \sum_{j \in s} \beta_j x_{jit} + \mu_{it}.$$

In this specification, the R&D intensity variable is computed as the sum of R&D expenditure from 1986 to 1989 and from 1990 to 1993 divided by output in 1985 and 1989 respectively. The interpretation of ρ is that of the marginal product of a unit of knowledge stock, which in the absence of depreciation, is the amount by which output increases with an increase in real R&D expenditure. Although being a different model than (2) we also estimated equation (8) for two reasons: its ease of interpretation and because this specification has been frequently applied in related empirical research.

4. Estimation of R&D contribution

Cross-sectional estimates

As a starting point estimates are presented for the output elasticities using a log-linear Cobb-Douglas production function with R&D capital (equation 1). In this level specification R&D-capital is proportional to the R&D expenditures (see equation 4). Both gross output and value added are used as output measures and estimates are presented for specifications with and without the adjustment for ’double-counting’, the latter with labour and material inputs containing non-R&D inputs, and value added measured as gross output minus non-R&D materials. In estimating, all R&D firms that could be linked to the production surveys in either year are used and sectoral dummy intercepts are included.

Table 3A. Cross-sectional estimates 'log-level' specification not adjusted for double-counting

Dependent variable	Gross output			Value added		
Year	1985	1989	1993	1985	1989	1993
Coefficient of						
Labour	.136	.145	.189	.570	.626	.755
	(.013)	(.014)	(.019)	(.036)	(.042)	(.067)
Material inputs	.769	.750	.727			
	(.010)	(.010)	(.013)			
Capital	.080	.103	.085	.365	.352	.253
	(.009)	(.010)	(.013)	(.025)	(.031)	(.049)
R&D	.009	.003	.012	.041	.026	.035
	(.006)	(.005)	(.006)	(.018)	(.018)	(.026)
SIC dummies[a]	yes	yes	yes	yes	yes	yes
N of observations	382	436	347	382	436	347
R^2	.992	.990	.990	.911	.882	.826

[a] SIC-dummies for four groups: 1) food, beverages and tobacco, 2) petroleum, chemical industry and allied, 3) metal industries and 4) other industries (textiles, wearing apparel, paper and paper products and manufacture of building materials).

The sectoral dummies distinguish between four sectors: 1) food, beverages and tobacco, 2) petroleum, chemical industry and allied, 3) metal industries and 4) other industries (textiles, wearing apparel, paper and paper products and manufacture of building materials). These groups will be used throughout.

In estimating the production function in log-levels with panel data, much of the identification comes from cross sectional variation. Biases in coefficient estimates may arise owing to fixed effects or endogeneity of inputs, i.e., better firms have elevated outputs and inputs. Even so, the estimates presented in Table 3A for the traditional factor elasticities are close to the corresponding factor shares as these should be under the maintained hypothesis of perfect competition. Further the elasticities add up to about unity in most cases and constant returns to scale cannot be rejected [5)]. Contrary to the results for traditional factor inputs, the estimate for the R&D elasticity does not differ significantly from zero in the majority of cases. However, the adjustment for 'double counting' (see Table 3B) produces some important differences. When the traditional inputs are adjusted for double counting, the R&D elasticities become significant. This result confirms predictions by Schankerman (1981) that double counting factor inputs gives lower estimates of R&D output elasticities. The interpretation for this, on the assumption that the estimates are accurate, is that total returns to R&D are significantly positive, but R&D did not provide increases in output above and beyond that predicted by the traditional factors, i.e. no excess returns.

Table 3B Cross-sectional estimates 'log-level' specification adjusted for double-counting

Dependent variable	Gross output			Value added		
Year	1985	1989	1993	1985	1989	1993
Coefficient of						
Labour	.134	.142	.174	.552	.602	.700
	(.012)	(.013)	(.013)	(.035)	(.039)	(.063)
Material inputs	.763	.740	.723			
	(.010)	(.010)	(.013)			
Capital	.081	.105	.090	.362	.347	.269
	(.010)	(.010)	(.013)	(.025)	(.030)	(.048)
R&D	.018	.015	.024	.068	.059	.076
	(.006)	(.005)	(.006)	(.017)	(.017)	(.025)
SIC dummies[a]	yes	yes	yes	yes	yes	yes
N of observations	382	436	347	382	436	347
R^2	.992	.990	.990	.914	.889	.833

[a] SIC-dummies for four groups: [1] food, beverages and tobacco, [2] petroleum, chemical industry and allied, [3] metal industries and [4] other industries (textiles, wearing apparel, paper and paper products and manufacture of building materials).

'Long difference' estimates

A disadvantage of estimating 'log-level' specifications is that they have not been controlled for fixed effects. If these effects are correlated with other explanatory variables, then the cross-sectional estimates are not consistent. This problem can be solved by using differenced series. However, by differencing the data measurements errors are exacerbated. This pitfall can be circumvented by estimating 'long difference' equations, which relate growth of output to growth of factor inputs over some years. The introduction of the time dimension may, however, worsen the simultaneity problem. Before treating this issue further, we first present several variants of 'long-difference' growth equations.

R&D knowledge stock approach

Estimates for the 'long difference' equations are presented in Table 4. All firms for which two adjacent observations were available in the four-yearly R&D surveys are included. The growth of the R&D knowledge stock is calculated according to (5), using a pre-sample R&D growth of 5% and a depreciation rate of 15%. Estimates are presented for the two panels separately and for the pooled data. In the pooled estimates an extra dummy intercept is included. This time dummy represents a mixture of time and population effects. The data are adjusted for double-counted R&D inputs. Further, we distinguish between estimates for the gross output and the value added specification.

Table 4. Estimates R&D contribution for 'long-difference' specifications

Dependent variable	Gross output			Value added		
Year	85–89	89–93	Pooled	85–89	89–93	Pooled
Coefficient of						
Labour	.196	.222	.205	.780	.700	.752
	(.037)	(.052)	(.030)	(.125)	(.139)	(.092)
Material inputs	.718	.689	.705			
	(.025)	(.032)	(.019)			
Capital	.024	.031	.030	.083	.105	.095
	(.019)	(.027)	(.015)	(.069)	(.083)	(.052)
R&D capital	.074	.028	.051	.247	.104	.179
	(.023)	(.026)	(.017)	(.083)	(.080)	(.057)
Period dummy			.123			–.764
SIC dummies	yes	yes	yes	yes	yes	yes
N of observations	209	159	368	209	159	368
R^2	.903	.867	.890	.329	.227	.299

The results show two major differences from the 'log-level' specifications of Tables 3A and 3B. First, the output elasticities for labour increase at the expense of the capital output elasticities. With the exception of the pooled estimates the capital elasticity even becomes insignificant. Secondly, the elasticity of the R&D knowledge stock is more than doubled when one controls for 'permanent' differences across firms. The results suggest that both the traditional and the R&D capital variable are strongly correlated with firm effects. Further, Table 4 shows that the estimates for R&D stock elasticities for 1989–1993 are insignificant.

R&D intensity approach

Next estimates are made of the rate of return to R&D under the assumption of zero depreciation of the R&D knowledge stock and a marginal rate of return to R&D common to all firms. Here, as mentioned above, we replace $\Delta_4 k_i$ by the appropriate R&D intensity by estimating equation (8). The coefficient of the R&D intensity variable can be interpreted as the gross marginal private rate of return to R&D. The results are presented in Table 5. As can be seen from a comparison with Table 4, imposing the constraint $\delta = 0$ has only minor effects on the pattern of parameter estimates for the traditional inputs. According to these estimates the gross rate of return to R&D is insignificantly different from zero in the gross output specification and about 20 percent in the value added specification. The 1989–1993 period has a lower rate of return than the earlier period, although the differences are not statistically significant.

Table 5. Estimates R&D intensity equations

Dependent variable	Gross output			Value added		
Year	85–89	89–93	Pooled	85–89	89–93	Pooled
Coefficient of						
Labour	.216	.223	.215	.838	.677	.771
	(.038)	(.052)	(.030)	(.124)	(.139)	(.091)
Material inputs	.719	.693	.707			
	(.027)	(.032)	(.020)			
Capital	.024	.032	.030	.069	.101	.085
	(.020)	(.027)	(.015)	(.069)	(.083)	(.052)
R&D intensity	.052	–.004	.030	.218	.173	.192
	(.061)	(.079)	(.048)	(.085)	(.082)	(.059)
Period dummy			.083			–1.032
			(.032)			(1.088)
SIC dummies	yes	yes	yes	yes	yes	yes
N of observations	209	159	368	209	159	368
R^2	.898	.866	.990	.321	.241	.301

5. Robustness tests

A striking difference between the estimates for the ’log-level’ specifications of table 3B and the estimates for the ’long-difference’ equations (Table 4) is that the coefficients for the R&D variables are higher in the ’long difference’ estimates than in the ’log-level’ estimates, whereas the opposite applies to the elasticity estimates for the traditional inputs. There are several possible candidates for explaining the observed change in the patterns of the parameter estimates when switching from the cross-sectional to the time series dimension of the data. Plausible candidates are the measurement related issues such as the assumptions underlying the construction of the R&D knowledge stocks and the selectivity of the R&D data set. Furthermore, our data show heteroskedasticity in the error terms related to the R&D variables used in the equations. Also the simultaneity problem may be more manifest when estimating ’long difference’ equations. In this section we pay attention to the robustness of the results, to the assumptions underlying the calculation of the growth of the R&D knowledge stock variable, to selectivity and to the problems of heteroskedasticity and simultaneity. We first discuss the way in which several sources of biases were dealt with and lastly we present the results of the robustness tests, focusing on the estimates of the R&D variables and the elasticity of traditional capital inputs.

Depreciation and pre-sample growth for the R&D knowledge stock

With respect to the measurement related problems we first look at the construction of the R&D knowledge stock. A robustness test was performed by applying various assumptions for the depreciation parameter and the R&D pre-sample growth rate. The results of similar previous studies suggest that the estimates for the output elasticities of the R&D stock are rather robust to different assumptions concerning the rate of depreciation, δ. However, these results are based on balanced firm-level time series data with longer R&D histories. Given that the construction of data on the growth of the R&D stock – in essence – rests on only two observations for R&D expenditure, the elasticities presented in Tables 3 to 5 may be dependent on the choice of δ and the pre-sample growth g in formula 5. For this reason equation (2) is re-estimated using three alternative assumptions for δ (0.10, 0.15 and 0.20) and three assumptions for pre-sample R&D growth, g (0.03, 0.05, 0.07). The results of this robustness test show that the R&D output elasticities only slightly decline with increasing δ and with increasing g. Overall, the output elasticities seem to be rather robust to different assumptions with respect δ and g. For this reason and for reasons of space we shall not present the estimates for this robustness test (see Bartelsman et al. (1996) for more details).

Selectivity

In section 2 it was shown that in constructing the panel data, sample attrition was a possible cause of selectivity biases in regression results. Some elements of selectivity are inherent in the use of the R&D surveys, because the probability of exit decreases with the R&D intensity, which is our variable of interest. For this reason, the estimated R&D contribution to productivity growth could be biased. Selectivity can be taken into account by extending our models with a selection equation which models the probability of continuing in the sample. Several approaches are possible to capture the effects of selectivity. We could follow Heckman’s two-step method by including a correction term in the regression equations. A more efficient estimate can be obtained with the so-called Tobit model. Assuming that the probability of being selected in the sample depends on the level of the R&D intensity in the first year, the Tobit model reads as:

(9A) $\Delta_4 q_{it} = \lambda + \gamma\Delta_4 k_{it} + \Sigma_{j\in s}\beta_j\Delta_4 x_{jit} + \mu_{it}$

or

$$\Delta_4 q_{it} = \lambda + \rho\,\frac{\Delta_4 K_{it}}{Q_{i0}} + \sum_{j\in s}\beta_j\Delta_4 x_{jit} + \mu_{it} \qquad \text{if } D = 1$$

(9B) $\Delta_4 q_{it}$ not observed if $D = 0$,

with selection equations

(10A) $D = 1$ if $c + \alpha \frac{R_{i0}}{Q_{i0}} + \eta_{it} > 0$

(10B) $D = 0$ if $c + \alpha \frac{R_{i0}}{Q_{i0}} + \eta_{it} \leq 0$,

where $\frac{R_{i0}}{Q_{i0}}$ is the R&D intensity in the starting year, c a constant term and η_{it} a Gaussian disturbance term.

In using the Tobit model the number of observations differ from those given for the matching specifications in tables 4 and 5, because firms which are in production survey samples but not in the R&D dataset in the end year are also included in the analysis.

Heteroskedasticty and simultaneity

Other possible biases in the ’long difference’ estimates can arise due to heteroskedasticity and simultaneity. Indeed, the Goldfeld-Quandt test for heteroskedasticity indicates a significantly higher residual variance for firms with the lowest growth rates in the R&D stock than for firms with the highest growth rates[6)]. In the robustness tests we corrected for heteroskedasticity by applying weighted least squares with weights equal to the square root of the R&D variables. The possible biases due to simultaneity caused by the producers’ joint decisions on inputs and outputs was investigated by using the Partial Total Productivity (labelled P-TFP) form for the productivity equation (see Bartelsman et al. (1996) for a detailed explanation of this approach).

Results of the robustness tests

The results for the different robustness tests applied to the pooled data are presented in Tables 6 and 7. Table 6 gives the elasticity estimates for R&D and traditional capital for the specifications with the growth of the R&D knowledge stock as the explanatory R&D variable. Table 7 gives the same estimates for the R&D intensity specifications, using the pooled results of Table 5 as a reference. The base case of Table 6 is represented by the pooled estimates of Table 4. WLS estimates are not given for the gross output specification because the relevant Goldfeld-Quandt statistics did not indicate heteroskedasticity for this specification.

Table 6. Robustness tests R&D stock approach on pooled data

Dependent variable	Gross output		Value added	
Coefficient of	R&D capital	Ordinary Capital	R&D capital	Ordinary Capital
Base LD	.051 (0.17)	.030 (0.15)	.179 (0.57)	.095 (0.52)
Selectivity LD	.061 (.022)	.038 (0.17)	.226 (.080)	.095 (.045)
Simultaneity LD	x	x	.190 (.064)	.098 (.043)
Heteroskedasticity LD	x	x	.070 (.039)	.269 (.054)
Heteroskedasticity + Simultaneity LD	x	x	.077 (.039)	.304 (.045)

Further P-TFP estimates are not presented for the gross output specification because the P-TFP approach starts from a value added specification.

Two conclusion can be drawn from Table 6. First when relating output growth to the growth of the R&D knowledge stock, the selectivity and the simultaneity bias seem to be rather small. Correcting for selectivity raises the R&D output elasticity for both specifications, but the difference compared with the base case is statistically insignificant. Secondly, simultaneity seems not to be an important source of bias for this specification either: the elasticity estimate for the P-TFP variant also does not differ very much from the base case estimate. However, correcting for heteroskedasticity makes quite a difference. Applying WLS reduces the estimates of the R&D capital elasticities and also restores the pattern of the two capital elasticity estimates found for the 'log-level' specifications of Table 3B, with the elasticity of the traditional capital input higher than that for the R&D capital input.

Lastly, Table 7 presents the results of the robustness test for the estimates of the rates of return to R&D, with the base case represented by the estimates of Table 5. Again the comparisons aim at assessing the importance of biases due to selectivity (both for the gross output and value added specifications) and heteroskedasticity (for the value added specification) [7)]. However, the pattern of results differ from that presented in Table 6. Selectivity seems to be an equally important bias as heteroskedasticity. Modelling the presence in the sample being dependent on the level of R&D doubles the rate of return for the gross output specification and also increases the rate of return to R&D in case of the value added specification by more than ten percent. The latter result is also obtained after correcting the base case estimates for heteroskedasticity in the R&D intensity measure, leading to an estimate for the gross rate of return to R&D close to 0.30.

Table 7 Robustness tests R&D intensity approach on pooled data

Dependent variable	Gross output		Value added	
Coefficient of	R/Q	Ordinary Capital	R/Y	Ordinary Capital
Base LD	.030 (0.48)	.030 (0.15)	.192 (0.59)	.085 (0.52)
Selectivity LD	.124 (.058)	.025 (0.17)	.314 (.078)	.085 (.060)
Heteroskedasticity LD	x	x	.348 (.154)	.276 (.041)

6. Summary and conclusions

In a first attempt to estimate the contribution of R&D to productivity growth using firm-level data for the Netherlands, several variants of production functions with R&D as a separate input have been analysed. The main objective was to estimate the private returns to R&D and output elasticities of the stock of R&D knowledge capital. The data derive from the four-yearly extended R&D surveys for 1985, 1989 and 1993. These surveys were linked to the production surveys. In using firm-level data it became possible to circumvent the specific problems which arise when using aggregated R&D data for the Dutch manufacturing industry. These problems are related to the very skew distribution of manufacturing R&D due to the dominance of few multinational enterprises. The variants of the basic R&D augmented production functions were made along different dimensions. First corrections were made for double- counting of R&D inputs. This correction increased the R&D output elasticity estimate for the 'log-level' value added specification by about 5 percentage points. Next 'long-difference' estimates were presented, both for output elasticities and rates of return to R&D. The 'long-difference' specifications correct for biases from firm fixed effects. Subsequently, the 'long-difference' specifications of the R&D augmented production function were used as a base case to assess the importance of other sources of biases in the R&D estimates. The R&D elasticities appeared to be relatively insensitive to different assumptions concerning the depreciation rate and pre-sample growth in R&D expenditure and also to simultaneity due to the joint decision on inputs and outputs. Selectivity appeared to be an important source of bias for the estimation of the gross rate of return to R&D, but not so when estimating elasticities of R&D capital. In both cases heteroskedasticity of the error terms related to the R&D measures seems to be an equally important source of bias. Cutting through all the specifications the output elasticity for R&D capital is about 6 percent for gross output and about 8 percent for value added, while the private rate of return to R&D varies between 12 percent for gross output and 30 percent for value added.

Notes

1) R&D surveys were also conducted for the intervening years, but only for the largest R&D performing firms. The 1985, 1989 and 1993 surveys are more representative, and provide a more adequate sample size after linking with the production statistics.
2) SIC: Standard Industrial Classification of Statistics Netherlands; the 3-digit-level allocates industrial firms to 122 groups.
3) The industry groups are: food, beverages and tobacco (SIC 20,21), chemical industry and allied (SIC 28–31), metal industry (SIC 33–38) and other manufacturing (SIC 22–27, 32 and 39).
4) For instance in 1989 the 'top five' firms had 15 percent of their employees working in R&D but their labour productivity was about the same as the rest of the firms in the panel.
5) At the 90% significance level the hypothesis of constant returns to scale is rejected in favour of slightly increasing returns to scale for the 1993 value added specifications.
6) The Goldfeld-Quandt test statistics is computed based on residual variances for the first and forth quartiles of firms for the distribution of the R&D stock growth. For instance for $\delta = 0.15$ the test statistics were 3.151 for 1985–1989 at a critical value of 1.60.
7) The Goldfeld-Quandt test also indicates that heteroskedasticity is absent for the gross output R&D intensity specification. Furthermore simultaneity appears to be an insignificant source of bias for the value added specification, also when using the R&D intensity measure as the explanatory R&D variable.

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