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Capital, Labour, Materials and Additional R&D Investment in Japan: The Issue of Double-Counting

Marga PEETERS, Paul GHIJSEN *

ABSTRACT. – R&D components are investigated in dynamic factor demand models using pooled Japanese data. Models without R&D, with R&D (double or) wrongly counted and (once or) correctly counted are compared by means of GMM estimates, (non-)nested GMM tests and residual analyses. The results indicate that R&D contributes significantly to the explanation of capital, labour, energy and materials demand in the Japanese manufacturing industry. Double-counted R&D is even preferred to not incorporating R&D as a separate production factor. After including R&D as a production factor and correcting for double-counting, there is however no unambiguous answer to the question which model utilizes the information of R&D best.

Capital, travail, matières premières et investissement en R&D au Japon

RÉSUMÉ. – Les composantes de la recherche et développement (R&D) sont analysées dans des modèles dynamiques de demande de facteurs à partir des données japonaises. Des modèles sans R&D, avec R&D mesurée avec erreur ou non sont comparés à travers des tests d'hypothèses (non)-emboîtées basés sur l'estimation des GMM et l'analyse des résidus. Les résultats montrent que la R&D intervient significativement pour expliquer les demandes en capital, travail, énergie et matières premières des entreprises manufacturières japonaises. Les modèles incorporant des doubles-comptes de la R&D semblent même dominer des modèles où celle-ci n'est pas prise en compte. Néanmoins, après une prise en compte correcte de la R&D comme un facteur de production, il n'y a pas de réponse claire quant au choix du modèle qui utilise au mieux l'apport informationnel de la R&D.

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* M. PEETERS: Econometric Research and Special Studies Department, De Nederlandsche Bank; P. GHIJSEN: Department of General Economics, Faculty of Economics and Business Administration, University of Maastricht.
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1 Introduction

Research and Development investment contributes to productivity growth for which reason accounting for R&D in econometric modelling seems important. Modelling the role of R&D in the production process is however not straightforward.

One of the difficulties of R&D, the double-counting of its components, was already discussed by SCHANKERMAN [1981]. R&D investment consists of investment in physical capital, labour, materials and possibly other items. These components are included in the "*regular*" production factors in traditional models. SCHANKERMAN argues that in order to correctly measure R&D productivity, the production factors capital, labour and materials should be purified by subtracting the R&D shares from these factors.

In econometric modelling the high collinearity of R&D investment with linear deterministic trends and the physical capital stock is also problematic. R&D capital is non-stationary, highly persistent and very similar to deterministic trends that are often used in order to account for non-stationarities in production. This in particular holds for Japan, a country in which R&D investment has risen during the past decades.

This study focusses on the underlying components of R&D investment: capital, labour, materials and additional expenditures. The additional expenditures concern communication costs, patent costs etc.[1]

The adopted modelling framework is a neoclassical one where an entrepreneur is assumed to minimize his production costs. Existing studies are extended in two directions: 1) dynamics for capital, labour and R&D are specified and 2) a pooled data set is used to estimate the model. In contrast to other R&D studies like SCHANKERMAN [1981] and CUNEO and MAIRESSE [1984], *intertemporal* features are accounted for by the assumption of capital, labour and R&D adjustment costs. In contrast to many Japanese and non-Japanese factor demand studies in the field, a pooled data set of annual time series (1960-1985) of five Japanese sectors is used here. An advantage of pooling is that estimation results are more reliable than the ones obtained with highly aggregate samples often used in R&D studies. The heterogeneity among sectors is also taken into account. Fixed sector effects are eliminated by differencing first order conditions. This rules out non-stationarity problems and, moreover, multi-collinearity of R&D-series and deterministic trends or capital (see above) cannot occur.

A first question to be answered is whether *incorporating information on R&D in econometric models is important*. Other studies have shown that R&D is difficult to measure, correlates strongly with the capital stock (see, for example, CUNEO and MAIRESSE [1984]) and is well described by deterministic trends. The answer to this question might hence not be affirmative. Although all kinds of evidence indicate that R&D and production are closely

1. Another look at R&D is to distinguish between basic, applied and development R&D investment. Although this distinction is also interesting no attention is paid to it here. In the sixth chapter of the dissertation of the second author, this distinction is used to determine regions that are less or more attractive in the technological sense.

related (see, for example, GRILICHES [1994]), doubts are raised about the importance of a separate R&D component in factor demand models here.

Another question is to what extent *a model that neglects R&D is better or worse than a model that "wrongly" accounts for R&D*. SCHANKERMAN [1981] calculates biases of a model with a Cobb-Douglas production function, thus with constant factor substitutability, assuming that a model where corrections for double-counting are made is "*correct*". But not accounting for R&D can lead to lower biases than a wrongly, double-counting of R&D. A generalized McFadden cost function with factor interrelations is adopted in the analyses to test this.

The last question we intend to answer is *what the optimal model specification is which includes information on R&D*. If R&D is a production factor of importance, how should it be specified? Two alternative specifications are directly available to correct for double-counting. On one hand, one can subtract the R&D shares from the total production factor shares, yielding a "*net*" production factor share for "*ordinary*" capital, labour energy and materials and a total R&D factor, that incorporates information on R&D capital, labour, energy and materials as well as additional R&D investment. SCHANKERMAN [1981], CUNEO and MAIRESSE [1984] and HALL and MAIRESSE [1993] use this specification. On the other hand, it is possible to leave the production factors untouched and to incorporate only the additional or "*rest*" R&D production factor in the specification. Tests are used to found our conclusions.

In order to answer these three questions, an econometric model is specified where R&D is treated in four different ways. These four alternatives are compared and the pre-mentioned questions are answered using information obtained from results of these applications.

The outline is as follows. Section 2 gives descriptive statistics of the Japanese R&D data. Section 3 specifies the econometric model and discusses the incorporation of R&D in this model. Section 4 presents GMM estimation results and comparison tests for the different models. Section 5 summarizes the conclusions.

2 Descriptive Statistics on R&D in Japanese Sectors

The data are annual time-series for 1960-1985 from eight Japanese sectors: the agricultural, materials, fabricated products (light manufacturing), chemical materials, metal materials, fabricated products (heavy manufacturing), construction and public utilities sector. For each sector information on production and five production factors along with their nominal prices are considered. The factors are real gross investment in physical capital stock, labour measured as the total number of hours worked (corrected for the labour quality), the volume of energy, the volume of materials and real gross R&D investment. The R&D investment consists of investment in R&D capital, R&D labour, R&D materials and additional R&D expenditures. The additional R&D investment concerns communication costs, patent costs but also energy costs [2] etc. The data are described in detail in the appendix.

Table 1a presents the annual averages (in percentages) of the four underlying components of R&D investment for each sector. It follows that the major part of the total R&D investment, about 70 %, concerns investment in labour. The additional R&D expenditures are quite important as they constitute 7 %-10 % of total R&D expenditures.

Table 1b presents the annual averages (in percentages) of the R&D-share in physical capital investment, labour and materials. For the chemical materials sector more than one quarter of labour is addressed to research and/or development. For the (heavy) fabricated products sector about 19 % of the materials are R&D-materials. Also in most other sectors the R&D inputs turn

TABLE 1a
Descriptive Statistics R&D Investment 1960-1985

	Components of R&D Investment (sample average, in percentages)			
Sector	capital	labour	materials	additional
Agriculture	8	78	7	7
Materials	12	75	6	7
Fabricated products *(Light manufacturing)*	10	77	6	7
Chemical materials	11	75	5	9
Metal materials	13	70	8	9
Fabricated products *(Heavy manufacturing)*	11	70	11	8
Construction	14	70	6	10
Public utilities	24	55	11	10

TABLE 1b
Descriptive Statistics R&D Investment 1960-1985

Sector	R&D capital/ Total capital	R&D labour/ Total labour	R&D materials/ Total materials
Agriculture	0.01	0.1	0.1
Materials	1.5	4.3	0.7
Fabricated products *(Light manufacturing)*	0.7	4.2	2.5
Chemical materials	2.8	28.2	2.2
Metal materials	1.1	5.6	0.1
Fabricated products *(Heavy manufacturing)*	5.2	11.4	18.8
Construction	4.5	5.3	4.8
Public utilities	0.4	0.9	0.6

2. Unfortunately, energy costs are not observed separately.

out to be a non-negligible part of the total factor inputs, with a remarkable 28 % R&D labour cost share in the chemical materials industry.

To summarize, R&D investment consists for the major part of labour expenditures and the shares of R&D investment in capital, labour and materials are substantial, though differ over the sectors. To what extent these shares, usually double-counted in neoclassical factor demand models, lead to misleading results will be investigated next.

3 A Neoclassical Factor Demand Model with R&D

This section presents a neoclassical factor demand model and its first order conditions. Four different possibilities to include R&D as a production factor in the model are then discussed. These four models are further investigated in the next section.

3.1 The Econometric Model and the Model Solution

An entrepreneur is assumed to be a representative of all firms within the industry and rational, *i.e.* to use all information available when making decisions. The entrepreneur needs a physical capital stock, labour, energy, materials, and a R&D capital stock in the production process. Some production inputs incur adjustment costs. Energy and materials can always be acquired without any delay, at least within one time period *i.e.* one year, and without additional costs besides their factor price. On the contrary, capital, labour and R&D are quasi-fixed: they can only be acquired when additional costs, called adjustment costs, are paid. The objective function that the entrepreneur aims to minimize, is specified as

(1)

$$E\left\{\sum_{\tau=0}^{\infty}\beta_{t+\tau}[RC_{t+\tau}+p_{K,t+\tau}I^{K}_{t+\tau}+p_{L,t+\tau}L_{t+\tau}+p_{R,t+\tau}I^{R}_{t+\tau}]\,\middle|\,\Omega_t\right\}$$

where subscript t is the time index and

E is the rational expectations sign;

Ω_t is the information set containing all variables until period t;

$RC_t = RC(p_{E,t}, p_{M,t}, Q_t, K_t, L_t, R_t, I_t^K, \Delta L_t, I_t^R)$ is the restricted cost function;

Q_t is the production;

K_t, L_t, E_t, M_t, R_t is the physical capital stock (in volumes), the number of hours worked, energy (in volumes), materials (in volumes) and the R&D stock;

I_t^K, I_t^R are the gross investment (in volumes) in capital stock and R&D respectively;

$p_{X,t}$ where $x = K, L, E, M, R$ is the nominal price of investment in capital stock, the nominal wage rate, the nominal price of energy and materials, the nominal price of investment in R&D respectively, at period *t*;

$$\beta_{t+\tau} \equiv \prod_{i=0}^{\tau} \frac{1}{1 + r_{t+i}}$$ where is the r_t nominal interest rate at period *t*.

Costs in each period consist of the variable costs of energy and materials (specified in the restricted cost function) and the expenditures on physical capital stock ($p_{K,t} I_t^K$), wages ($p_{L,t} L_t$) and R&D stock ($p_{R,t} I_t^R$). Function (1) represents therefore the discounted costs stream over an infinite horizon. The entrepreneur minimizes this function with respect to K_t, L_t, E_t, M_t, R_t, given the factor prices and the output level Q_t.

The restricted cost function is assumed to be of the symmetric Generalized McFadden type with the functional form

(2) $$RC_t = Q_t^{\rho} \left[\frac{\alpha_{p_E, p_M} p_{M,t} p_{E,t} + 0.5\alpha_{p_M, p_M} p_{M,t}^2 + 0.5\alpha_{p_E, p_E} p_{E,t}^2}{\overline{p_t}} + \alpha_{p_E, Q} p_E + \alpha_{p_M, Q} p_M \right]$$

$$+ (\alpha_{p_{E,K}} \; p_{E,t} + \alpha_{p_{M,K}} p_{M,b}) K_t + (\alpha_{p_{E,L}} p_{E,t} + \alpha_{p_{M,L}} p_{M,t}) L_t + (\alpha_{p_{E,R}} p_{E,t} + \alpha_{p_{M,R}} p_{M,t}) R_t$$

$$+ 0.5 \overline{p_t} Q^{-\rho} \left[\alpha_{K,K} (I_t^K)^2 + \alpha_{L,L} (\Delta L_t)^2 + \alpha_{R,R} (I_t^R)^2 + 2\alpha_{K,L} I_t^K \Delta L_t + 2\alpha_{K,R} I_t^K I_t^R + 2\alpha_{L,R} \Delta L_t I_t^p \right]$$

where $\overline{p_t} \equiv \dfrac{p_{E,t} p_{E,1960} E_{1960} + p_{M,t} p_{M,1960} M_{1960}}{p_{E,1960} E_{1960} + p_{M,1960} M_{1960}}$. Parameters to be estimated are $\alpha_{i,j}$ where $i, j \in \{p_E, p_M, K, L, R\}$. The parameter ρ can represent a heteroskedasticity correction of the variables. Interrelated adjustments costs of capital, labour and R&D capital are specified in the latter part of the restricted costs function. The matrix $A = \{\alpha_{i,j}\}, \quad i, j \in \{K, L, R\}$ should be semi-negative definite according to the theory, as the demand for production factor decreases if its relative price rises. This specified restricted cost function (2) is flexible in the DIEWERT and WALES' [1987] sense. Regularity conditions such as linear homogeneity and concavity in factor prices and convexity in output were verified. The function is symmetric in the prices of the variable inputs, being energy and materials. This is a consequence of the inclusion of $\overline{p_t}$ (where 1960 is the first sample period year). For more information on the cost function, see, for example, DIEWERT and WALES [1987] who consider several types of static cost functions (*i.e.* without adjustment costs).

The entrepreneur accumulates the physical capital and R&D capital, respectively, as

(3a) $$K_t = I_t^K + (1 - \delta^K) K_{t-1}$$

and

(3b) $$I_t^R + (1 - \delta^R) R_{t-1}$$

δ^K, δ^R are the constant depreciation rates. [3]

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3. For a detailed description of the series, see the appendix.

In order to minimize (1) subject to (3a)-(3b) the first order conditions need to be satisfied. The first order conditions concerning the quasi-fixed production factors, being $X_f \in \{K, L, R\}$, are given by

(4a,4b,4e)

$$\beta_t \left[\frac{\partial RC_t}{\partial X_{f,t}} + p_{X_{f,t}} \right] + E \left\{ \beta_{t+1} \left[\frac{\partial RC_{t+1}}{\partial X_{f,t}} + (\delta^{X_f} - 1) p_{X_f, t+1} \right] \mid \Omega_t \right\} = 0$$

where $\delta^L = 1$. The first order conditions of the variable production factors, energy and materials, follow from the Shephard's lemma, *i.e.*

(4c,4d) $$E_t = \frac{\partial RC_t}{\partial p_{E,t}} \text{ and } M_t = \frac{\partial RC_t}{\partial p_{M,t}}.$$

Several estimation methods can be applied. The five-variate system (4) can be estimated directly. In this case the non-observed variables in (4a,4b,4e) at period *t*, resulting from the adjustment costs specification, are to be substituted by their realisations. The resulting disturbance term, being the forecast error, is a moving average of order one. [4] An instrumental variables method like the General Method of Moments (GMM, see HANSEN [1982]) is to be used as the disturbance is not independent of the (contemporaneous and one period lagged) explanatory variables. Alternatively, if assumptions are made concerning the stochastic prices in (4a,4b,4e), a "*closed form*" solution can be derived and estimated by a Full Information Maximum Likelihood method. In this case statistically efficient estimates are obtained if the statistical assumptions are true but the structural parameters are computationally more cumbersome to derive (see, for example, MOHNEN, NADIRI and ROSEN [1986]). In comparison with this method GMM estimates are robust and structural parameters are obtained directly. For these reasons GMM is applied here.

3.2 The Incorporation of Information about R&D Investment

As described in the previous section, R&D investment comprises expenditures on capital stock, labour, materials and additional R&D, *i.e.*

(5) R&D investment $$= I_t^{RK} + I_t^{RL} + I_t^{RM} + I_t^{RR}.$$

Focussing on R&D, three types of factor demand models can be distinguished as discussed below. Model A is the first type in which the R&D factor is measured only in an indirect manner. The second type is presented as model two which incorporates a R&D production factor, but without corrections for double-counting. These types are complemented by a third type in which the

4. Define $u_{t+1} \equiv \beta_{t+1} \left[\frac{\partial RC_{t+1}}{\partial X_{f,t}} + (\partial^{X_t} - 1) p_{x_f, t+1} \right]$ by which the disturbance is $\varepsilon_{t+1} \equiv E\{u_{t+1} \mid \Omega_t\} - u_{t+1}$. This is a MA(1) process because $E\{\varepsilon_{t+1}\varepsilon_t\} \neq 0$ and $E\{\varepsilon_{t+1}\varepsilon_{t-s}\} = 0$ if $s > 0$.

double-counting is taken care off and an R&D production factor is applied in two different ways, yielding models C and D which will be explained shortly.

Model A: R&D investment unobserved

If R_t in (1) is not included as a *separate* production factor, contributions of R&D to productivity are neglected. R&D investment in capital, labour and materials, however, is accounted for by the production factors K_t, L_t and M_t. In this case, the R&D investment not included in the other production factors is contained in the disturbance term. If R&D is important the residuals thus contain information on technological developments. Examples of factor demand studies that do not explicitly take into account information on R_t are PINDYCK and ROTEMBERG [1983] and NAKAMURA [1992].

Model B: R&D investment observed but double-counted

If R_t is included as a variable, the contribution of R&D to production and its interrelations with physical capital stock, labour, energy and materials can be estimated. The inclusion of R&D in this way gives however rise to a double-counting. R&D investment is already a part of the traditional capital stock, labour and materials because R&D investment contains capital (I_t^{RK}), labour (I_t^{RL}) and materials investment (I_t^{RM}). These shares can be quite large, as shown in Table 1b for the Japanese sectors, by which estimation results will be biased. A factor demand study that includes R&D without corrections are for instance SOETE and PATEL [1985].

Models C and D: R&D observed without double-counting

If R&D is included as a production factor and corrections are made for the double-counting of capital, labour and materials, "*correct*" estimation results can be obtained. In this way, the productivity of R&D, and interrelations with other production factors are specified. R&D double-counting can be avoided in two different ways.

For example, the R&D capital, labour and materials components can be subtracted from the respective capital investment, labour and materials variables. That is,

(6a) $$I_t^K \equiv I_t^{K+} - I_t^{RK}\ , \quad L_t \equiv L_t^+ - I_t^{RL}\ , \quad M_t \equiv M_t^+ - I_t^{RM}$$

and $$I^R \equiv I_t^{RK} + I_t^{RL} + I_t^{RM} + I_t^{RR}$$

where I_t^{K+}, L_t^+, M_t^+ is the total (R&D and non-R&D) capital investment, (R&D and non-R&D) labour and (R&D and non-R&D) materials. We will refer to this as model C.

Alternatively, the R&D factor contains only the R&D additional expenditures, *i.e.* (model D)

(6b) $$I_t^R = I_t^{RR}.$$

The major difference between model C and D is that in model C (see (6a)) it is assumed that productivity contributions of R&D capital (R&D labour, R&D materials) differ from the productivity contributions of non-R&D capital (non-R&D labour, non-R&D materials). On the contrary, in (6b) both non-R&D and R&D capital (labour, materials) are comprised as capital (labour, materials). In this specification only additional R&D investment is assumed to be a production factor having a productivity contribution that may differ from the productivity of all capital, as well as the productivity of all labour and all materials.

Factor demand models with corrections for both R&D capital and R&D labour are analysed by SCHANKERMAN [1981], MOHNEN and NADIRI [1985], CUNEO and MAIRESSE [1984] and HALL and MAIRESSE [1993]. The study of MOHNEN and NADIRI corrects for R&D energy while the other studies correct for R&D materials. MOHNEN and NADIRI estimate a slightly different version of (dynamic) model (1) with (6a) imposed. The other three studies compare a static Cobb-Douglas production function using a similar model as model B with United States or French firm data.

To the best of our knowledge, model D has never been investigated, but seems appropriate. Neither are comparisons of model C with model A, and comparisons of model A and model B known to us.

From an econometric point of view models A and B are not "*correct*" if R&D is important. Model A renders statistically inefficient and possibly inconsistent estimates since information on R&D is neglected. Model B is misspecified because of the double-counting by which biased estimates will be obtained. Both model C and D seem to be preferred to model A and B. Whether model C or D is better depends on the differences in productivity and cost characteristics between regular capital (labour, materials) on one side, and R&D capital (R&D labour, R&D materials) on the other side.

From a comparison of model A and C or model A and D follows that parameter estimates only differ if R&D is not fully separable from the other production factors. In this case, the parameter estimates for model C and D are more efficient than those for model A. Model A is furthermore a special case of model B. Similarly, model A is nested in model D. The models are however not easy to compare by simple tests. This is a consequence of the fact that model A has four first order conditions whereas both model B, C and D have five first order conditions. [5]

4 Estimation Results

This section presents estimation results for each of the four models. First, the methodology of the estimating system (4) is discussed. Second, GMM parameter estimates are presented. Third, the four models are compared by means of several statistics.

4.1 Methodology

The data are pooled because of the large number of parameters and the small sample for each sector by the use of annual data 1960-1985. This pooling occurs in the most simple way, *i.e.* by stacking the observations of the

5. This is further discussed in section 4.3.

sectors (first all observations of sector 1, then all observations of sector 2, etc.). First differences of the Euler equations (see system (4)) are taken by which possible fixed sector effects are eliminated. Advantages of pooling are many observations (originally 8*26 = 208), parameter estimates are less sensitive to slight changes and the account of sectoral differences in factor demand.

An advantage of taking first differences is that stationarity of the estimated relationships is assured. The original series, in particular the capital stock and R&D capital series, are highly trending. As the GMM does not only require orthogonality conditions to be fulfilled but also stationary disturbances, detrending the original series is necessary.

In the econometric analyses the data of only five Japanese sectors, being the manufacturing industry sectors 2-6 mentioned in Table 1a, are used. The agricultural, construction and public utilities sectors are disregarded as these sectors do not invest much in R&D. Moreover, estimation experiments with the model using the whole sample of eight sectors showed that imposing the same cost structure, *i.e.* the same structural parameters for each sector, is rejected by the data.

Instruments taken in all estimations are a constant, and the first differenced production, capital stock, labour, energy, materials and the R&D capital. They are lagged two periods because taking first differences of equations (4a,4b,4e) implies that a moving average of two period holds. [6]

4.2 GMM Estimates [7]

Table 2 contains the GMM-results. The first panel presents the second stage GMM-parameter estimates of for each model and the parameters associated with the energy and materials prices, the second panel the parameter estimates associated with the quasi-fixed production factors – *i.e.* the adjustment cost parameters – and the third panel the parameters a_i (where $i = K, L, E, M, R$). These latter are associated with the constant in each equation. This constant is included to account for a possible trend in the original model.

Estimations of the original model with quasi-differencing instead of first differencing and including sector dummies, rendered a highly significant (quasi-differencing) parameter estimate close to 1. This is a justification of taking first differences. Furthermore, the restriction

$$\alpha_{p_E, p_M} = -\alpha_{p_M, p_M} = -\alpha_{p_E, p_E}$$

was imposed. The parameter α_{p_E, p_M} turned out to be close to zero, even tended to become negative in some cases. For this reason, its value was fixed

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6. If ε_{t+1} is a MA(1), $\varepsilon_{t+1} - \varepsilon_t$ is a MA(2). Denoting as instrument,

$$E\{(\varepsilon_{t+1} - \varepsilon_t)(X_{t-2} - X_{t-3})\} = 0.$$

7. GMM-results are obtained with TSP. The moving average of second order is accounted for by using the Bartlett kernel, corrections for heteroskedasticity are made, a criterium tolerance of 0.001 is imposed and the maximum number of iterations over the weighting matrix in each iteration is 3. The fact that heteroskedasticity corrections are not possible in small samples, which is the case when the model is applied to one sector, was one of the reasons for us to pool the five sector samples. Heteroskedasticity corrections turn out to be very important, in particular in the energy equation.

TABLE 2
GMM-estimates System (4a-e) in First Differences

	Model A No R&D	Model B Double-counting	Model C $I_t^R = I_t^{RK} + I_t^{RL} + I_t^{RM} + I_t^{RR}$	Model D $I_t^R = I_t^{RR}$
ρ	1.07**	1.12**	1.59**	1.85**
$\alpha_{p_E,Q}$	2.54*	2.14**	0.98*	0.75*
$\alpha_{p_M,Q}$	1.32**	1.47**	0.79*	0.51*
$\alpha_{p_E,K}$	– 0.09	– 0.10	– 0.24	– 0.30*
$\alpha_{p_E,L}$	-0.57*	0.08	-– 0.02	– 0.01
$\alpha_{p_E,R}$		– 0.63*	– 0.80*	– 0.52*
$\alpha_{p_M,K}$	– 0.31**	– 0.22	– 0.11	– 0.01
$\alpha_{p_M,L}$	– 0.31	– 1.40*	– 2.01*	– 1.52*
$\alpha_{p_M,R}$		1.62*	2.23*	0.32
$\alpha_{K,K}$	2.29*	0.09	0.04	0.28
$\alpha_{L,L}$	0.34	– 2.25*	– 0.30	0.84
$\alpha_{R,R}$		– 9.93	5.30	– 0.22
$\alpha_{K,L}$	1.65*	– 0.18	– 0.73*	– 0.22
$\alpha_{K,R}$		0.55	1.95*	0.53
$\alpha_{L,R}$		– 2.49	2.56	0.59
a_K	– 0.02	– 0.01	0.01	– 0.01
a_L	– 0.07**	– 0.07**	– 0.06*	– 0.05**
a_E	0.06	0.05	– 0.04	– 0.03
a_M	– 0.02	0.04	– 0.01	– 0.11*
a_R		– 0.02	0.03	– 0.01
J	15.59 [0.34]	16.26 [0.36]	13.24 [0.58]	12.91 [0.61]

* Absolute t-value larger than 2
** Absolute t-value larger than 4
The number of observations is 110 (= 5 (industries) *22).
J is the Sargan test statistic of over identifying restriction, distributed χ^2 with 14 degrees of freedom for model A and 15 for models B,C,D.
The number in square brackets is the p-value.

at zero. This restriction guarantees the convexity in prices of the cost function (2) if and only if $\alpha_{p_E,p_M} \geqslant 0$ and is suggested in DIEWERT and WALES [1987]. It facilitates estimation considerably.

At the bottom part of Table 2, the test statistic of overidentifying restrictions is given. This test is a necessary condition for the model to be correctly specified. For none of the models this test is rejected (even at the 20 % level), as indicated by the *p*-values given in square brackets. Consequently, the hypothesis that the model is correctly specified cannot be rejected. On the basis of this statistic, models C or D are not better or worse than models A or B.

The first panel in Table 2, shows the parameter ρ to be significant in all models (the *t*-value even exceeds 4). This indicates that the scaling of the cost function by the production, see (2), is important. A value of ρ larger than one, guarantees the convexity of the cost function in production. The higher ρ, the stricter the convexity. This has also an effect on the adjustment cost part.

Also, from the first panel follows further that many parameters associated with the cross terms of energy (materials) prices with output are significant.

The adjustment cost parameters are rarely significant, as follows from the second panel. This might indicate that other dynamic factor demand studies, like MOHNEN *et al.* [1985] where highly aggregated time series are used in very small samples, find significant dynamics because of the fact that their data are not detrended before estimation. The impact of discussed above, should also be considered. In the model of MOHNEN *et al.*, like in most models with restricted cost functions, the restriction $\rho = 1$ is imposed. The Japanese data used here clearly indicate that production costs are not linear in production – associated with prices –, but strictly convex. If $\rho = 1$ is imposed in our models, the parameter estimates for $\alpha_{p_M,Q}$ and $\alpha_{p_E,Q}$ are higher and their t-values are higher than in Table 2. For all models the hypothesis $\rho = 1$ is rejected.

The last panel presents the estimates of time trends. Negative linear trends in the labour equation and (in model D) in the materials equation are found.

4.3 Comparison of the Models

As already discussed in section 3.2, from a theoretical point of view models C and D are preferred to models A and B. Assuming that model C is the true model the difference between the parameter estimates (the "*bias*") can be calculated. The results are presented in the left columns of Table 3. The parameter "*biases*" presented in the right columns of Table 3, assume that model D is the "*correct*" model. The second column of Table 3, *i.e.* a comparison of the double-counting model B with model C is comparable with the calculations of SCHANKERMAN [1981]. Though SCHANKERMAN uses a Cobb-Douglas production function in growth rates instead of a Generalized McFadden.

The main result of SCHANKERMAN is that the bias of the R&D – parameters in the R&D double-counting model is negative which implies that the productivity growth generated by the normal production factors is too high. This is under the assumption that the correct model is comparable with model C, hence the four components of R&D are treated as one homogeneous production factor. SCHANKERMAN finds furthermore more efficient R&D parameter estimates in the "*correctly*" specified model. These results are confirmed by HALL and MAIRESSE [1993] who apply the same model as SCHANKERMAN to French firm data.

It is very interesting to see that these findings are confirmed by our results here. From the second column of parameter estimates follows that the biases of the parameters associated with R&D are all negative indeed. A comparison of the standard errors does also show slightly more efficient estimates in model C than in model B. So, despite the difference in model specification and degree of aggregation of data, the conclusions that the model with double-counting renders negative "*biases*" and less efficient parameter estimates are the same for the United States, France and Japan.

Further conclusions can be drawn from Table 3. A comparison of the biases of model A and model B, both in case of model C (compare column 1-2) as well as model D as the "*correct*" model (compare column 4-5), shows a slight preference of model B to model A. Model A has, after all, in most cases a higher bias. A comparison of models B and D (compare column 2-3) and

TABLE 3
Comparisons

	Comparison with Model C			Comparison with Model D		
	Model A No R&D	Model B Double-counting	Model D $I_t^R = I_t^{RR}$	Model A No R&D	Model B Double-counting	Model C
ρ	– 0.3*	– 0.3*	0.2*	– 0.4*	– 0.4*	– 0.1*
$\alpha_{p_E,Q}$	1.6*	1.2*	– 0.2*	2.4*	1.9*	0.3*
$\alpha_{p_M,Q}$	0.7*	0.9*	– 0.4*	1.6*	1.9*	0.6*
$\alpha_{p_E,K}$	– 0.6	– 0.6	0.3	– 0.7*	– 0.7*	– 0.2*
$\alpha_{p_E,L}$	27.5	– 5	– 0.5	56	– 9	1
$\alpha_{p_E,R}$		– 0.2*	– 0.4*		0.2*	0.5*
$\alpha_{p_M,K}$	1.8	1	– 0.9	30	21	10
$\alpha_{p_M,L}$	– 0.9*	– 0.3*	– 0.2*	– 0.8*	– 0.1*	0.3*
$\alpha_{p_M,R}$		– 0.3*	– 0.9*		4.1	6
$\alpha_{K,K}$	56.3	1.3	6	7.2	– 0.7	– 0.9
$\alpha_{L,L}$	– 2.1	6.5	– 0.8	– 7.8	44	5
$\alpha_{R,R}$		– 2.9	– 1		44.2	– 25.1
$\alpha_{K,L}$	– 3.3*	– 0.8*	– 0.7*	– 8.9	– 0.1	2.5
$\alpha_{K,R}$		– 0.7*	– 0.7*		0	2.7
$\alpha_{L,R}$		– 2	– 0.8		– 5.2	3.3
a_K	1	0	0	1	0	0
a_L	0.2*	0.2*	– 0.2*	0.4*	0.4*	0.2*
a_E	– 2.5	– 2	– 0.3	– 3	– 2.2	0.3
a_M	1	– 6	10	– 0.8*	– 1.5*	– 0.9*
a_R		– 1.7	– 1.3		1	– 4

The bias is calculated by taking the ratio of the parameters of model A, B, D (or C) and model C (or D), under the assumption that model C (or D) is correct. The correlation between the parameters is not taken into account. Figures with superscript * are significant parameter estimates at the 5 %-level in model C or D.

TABLE 4
Non-nested GMM Tests

H_1 / H_0	Model B Double-counting	Model C $I_t^R = I_t^{KR} + I_t^{LR} + I_t^{LR} + I_t^{RR}$	Model D $I_t^R = I_t^{RR}$
Model B Double-counting		0.03 [0.86]	0.05 [0.81]
Model C $I_t^R = I_t^{KR} + I_t^{LR} + I_t^{LR} + I_t^{RR}$	0.52 [0.47]		2.13 [0.14]
Model D $I_t^R = I_t^{RR}$	0.33 [0.57]	0.16 [0.69]	

The figures are according SINGLETON [1985], equation (35) page 406. They are distributed with one degree of freedom. Statistics are scaled by which heteroskedasticity corrections are made (see, SINGLETON [1985]). The values in square brackets are *p*-values.

models B and C (compare column 5-6) shows that the biases of the latter models are smaller. Model C and D are thus closest to one another.

Despite the preference of models C and D to models A and B from a theoretical point of view, a good to bad ranking of the four models is not easy to give. It is certainly not possible from Table 3, since in this table it is assumed that both models C and D, respectively, are "*correct*". Nor are statistics for comparisons easy to provide.

TABLE 5
OLS-Results with Euler Residuals and R&D

Sector R&D	Materials					(*Light*) Fabricated Products					Chemical Materials				
cap		– 13.2	– 4.4	2.2	0.01		– 3.6	– 0.5	0.6	0.01		2.4	1.1	0.4	0.01
lab	– 2.1*		– 0.9	5.2*	0.07	0.7		– 0.7	– 0.8	0.01	0.8*		2.7*	– 0.7	0.13
ene	1.2	5.9	– 2.1	– 2.0	0.06	– 0.6	– 1.5	2.6	0.4	0.01	0.3	8.5*	1.1	0.5	0.30
mat	0.1	0.4		– 0.2	0.01	– 0.1	0.2		0.1	0.01	– 0.2*	– 0.5		– 0.05	0.12
	Metal Materials					(*Heavy*) Fabricated Products									
cap		– 4.6	– 0.3	– 0.2	0.01		– 1.7	-1.1	1.0	0.02					
lab	– 2.1*		0.4	1.8	0.13	– 1.2*		– 0.7	2.0	0.02					
ene	1.5	2.9	– 2.5	– 0.9	0.01	1.6*	10.5*	– 3.9*	– 0.3	0.20					
mat	0.2	– 0.1		– 0.3	0.01	0.1	– 0.7		– 0.1	0.02					
R&D	cap	lab	mat	add	R^2	cap	lab	mat	add	R^2	cap	lab	mat	add	R^2

Each line gives the OLS estimates from a regression of the residual, whose names are indicated in the first column, on a constant and the (first differenced) R&D capital components, indicated in the last line. For instance, the "*residual*" of the capital equation is regressed on R&D-labour, R&D-materials and R&D additional and renders coefficients -13.2, -4.4 and 2.2. for the materials sector. The "*residual*" is the white noise part of an IMA (1,1) estimation for the capital GMM-residuals. The figures with a superscript * are significant at the 5 %-level. Estimates of the constants are not reported.

TABLE 6
Importance of R&D in Restricted Models

H_0: No R&D (Model A)	H_1: R&D (Model B)	H_1: R&D (Model D)
Manufacturing industry (5 sectors)	24.0* [0.00]	22.2* [0.00]
Materials	14.8* [0.01]	27.9* [0.00]
(*Light*) Fabricated products	1.8 [0.87]	7.1 [0.22]
Chemical products	7.2 [0.21]	15.3* [0.01]
Metal materials	1.2 [0.94]	5.9 [0.31]
(*Heavy*) Fabricated products	8.5 [0.13]	15.5* [0.01]

The figures in square brackets are p-values. The figures with a superscript * are significant at the 5 %-level.

Comparing model C and model A for example, is a comparison of a model where 5 and 4 equations are estimated respectively. The number of moment conditions of these two models, being 35 = 5*7 and 28 = 4*7 (*i.e.* equations times instruments), thus differs. Beside this, models C and A measure variables differently. The same holds for models C and B and for models D and B.

The only nested pair of models are A-B and A-D since only R&D (measured in different ways) is additionally incorporated. A direct comparison is however not possible since model B and model D have an additional equation, being the R&D equation, in comparison with model A. So, despite the fact that these models are nested they are statistically not comparable. This can be seen by assuming that R&D is zero in which case the variance of the residual in the R&D equation is not zero since the (observed) price of R&D investment appears.

At first sight, the J-statistic presented in Table 2 might indicate that model D is slightly preferred to the other models. This model has the highest p-value. The model without R&D (model A) has the lowest p-value, which is still more than 0.3.

As more formal tests are necessary to make comparisons, non-nested GMM tests are carried out as presented in SINGLETON [1985]. These tests allow for serially correlated and heteroskedastic error terms that appear in our models. As in most non-nested tests, SINGLETON's test is only able to verify whether the H_0 hypothesis is rejected or not against the model under the H_1 hypothesis. SINGLETON's test is further applicable provided that the number of moment conditions under both hypotheses is equal. As this is the case for the models B, C and D, these models can be compared.

The results are presented in Table 4. The conclusion from these statistics is that in all cases the H_0 hypothesis is not rejected. For example, the test H_0: "*model C is correct*" against H_1: "*model D is correct*" has the statistics 2.13 with a p-value of 0.14. The H_0-hypothesis is thus not rejected. The reverse hypothesis, though, also does not reject the H_0: "*model D is correct*". This implies that there is not enough evidence that model C is better than D or *vice versa*. The same holds for the tests with model B. So, the main conclusion from these tests is that a clear-cut ranking of models B,C,D cannot be made since the three models seem to be very close to one another. Attention will now be paid to comparisons with model A.

A direct testing of model B (or C or D) against model A is not possible, but the residuals of the latter model can be investigated. If R&D is important, the residuals of model A contain information on R&D. According to the theoretical model the residuals of model A are first differenced moving averages of order one in the capital and labour equations and first differenced in the energy and materials equation. In order to do simple tests the residuals are needed. These residuals are obtained here by estimating univariately an IMA(1,1) process for the capital and labour equations, for each industrial sector. [8] For each sector, the four residuals are hereafter each regressed on a constant and the four (first differenced) R&D capital components. In each equation, the R&D component that is already present in the model is not

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8. See also, DAVIDSON and MCKINNON [1981] who perform similar tests.

included in the regression. For example R&D capital is omitted in the capital equation if the residual is regressed on the other remaining components etc. The univariate regression results are presented in Table 5.

The first row presents the estimation results of the capital residual regressed on the R&D components. It follows that a very poor fit holds for all equations. This indicates that the capital demand equation (4a) cannot be improved by the inclusion of R&D. For the labour demand equation, R&D is an important explanatory variable of the residual in three sectors. In the chemical materials sector, R&D explains 13 % of the labour residual. In this sector, the energy residual (third line) can even be explained for 30 % by R&D. As should be reminded, in this sector the R&D labour share is the largest (see Table 1). In the sector of (heavy) fabricated products energy can be explained for 20 % by R&D. In the materials sector R&D seems not to play an important role in the description of capital, labour, energy and materials demand.

The fact that some of the (sector) residuals correlate significantly with R&D components does however not imply that the inclusion of R&D is overall significant. In order to gain information on this, model B and model D are re-estimated without the R&D equation. Because of interrelation effects, the R&D parameters in the capital, labour, energy and materials equations are still identified. These restricted models B and D nest thus model A and, more important, the same number of moment restrictions exist. Model A can thus be tested against model B and against model D by Wald statistics. The results are given in Table 6.

The results for the five industrial sectors show that Wald statistics are 24.0 and 22.2 for model B and D respectively. H_0 is rejected at the 5 %-level, indicating the importance of R&D.

From the sectoral tests in the subsequent rows different conclusions result. Having model D as alternative hypothesis, R&D is significant in three of five industries, being the materials, the chemical materials and the (heavy) fabricated products sector. Having model B as an alternative, R&D is significant in only one out of five sectors. We therefore conclude that model D better describes the effect of R&D on labour and investment demand 10. These findings are remarkably similar to the findings in Table.[9]

5 Conclusions

The aim of this article is to answer four questions concerning the so-called R&D double-counting issue. Double-counting occurs if R&D is included in a factor demand model as a separate production factor without correcting for the overlapping production factor shares. The R&D factor is in fact a composite factor of R&D-capital, R&D-labour, R&D-energy, R&D-materials and a miscellaneous R&D factor, that incorporates for instance patent costs etc.

9. Notice that model B was already theoretically rejected against model D since it counts R&D double.

The first of the four interrelated questions is: Is incorporating information in econometric models important or not? Second question and in line with the first one, is a model that neglects R&D better or worse than a model in which R&D is misspecified? Third, what is the best specification of a model if double-counting is corrected for?

These issues are investigated by the use of different specifications that can be applied to the intertemporal interrelated factor demand model of the generalized McFadden type. Pooled data from five Japanese manufacturing sectors for the years 1960 to 1985 are applied using GMM estimation to yield results that are tested. The results presented below are in line with other studies such as SCHANKERMAN [1981] and HALL and MAIRESSE [1993], although in their models the production is exogenous, both their functions are static and firm data were used instead of the pooled data set we prefer.

An indication for the answer to the first questions is found in Table 1 which shows a relatively large R&D share in the traditional production factors capital, labour, energy and materials, foremost for the manufacturing sectors which are well-known for their product and process innovations. Thus R&D seems relevant indeed.

An answer to the second question is given by comparing two types of models. Model A does not have an explicit incorporation of an R&D factor, while model B has, but the double-counting is not corrected for. The bias prevalent in the parameters of model A is higher than that of model B, so model B is less wrong than model A. In other words, the double-counting of R&D is less wrong than the negligence of R&D.

The third question cannot be answered in a positive or negative sense. The reason for this seemingly unsatisfying conclusion is that models investigated cannot be rejected against each other. A simple comparison of the biases of models C and D that both correct for the double-counting is not conclusive. Model C is more traditional and corrects the standard production factors for R&D, model D only incorporates additional R&D as a separate production factor. A direct '*nested*' test of models C and D are not possible, for which reason a non-nested GMM test is applied. Results from this test show however that neither model C is rejected against D, nor model D against C. The model with only additional R&D as a separate production factor (D) has in practice the advantage (over model C) that it is more easy to carry out simply because no corrections in regular production factors have to be made.

The ranking of model A, B and D with respect to the meaningful incorporation of the information of R&D has been the subject of Likelihood Ratio tests, from which it can be concluded that model A is rejected by model B and by model D. This confirms once more our answer to question one that R&D is important indeed. The fact that for model D the parameter is significantly different from zero for three of the five sectors, instead of one of the five sectors as in model B, leads us to the conclusion that model D uses the information contained in the production factor R&D the best. This is the answer to the final question.

To summarize, R&D is highly relevant in explaining labour and physical capital demand. If detailed R&D information does not exist, and a choice between not including and including R&D double is to be made, a preference of the latter holds. The higher the R&D shares in "*regular*" production factors are, the less wrong the former option of course will be.

• References

CUNEO Ph., MAIRESSE J. (1984). – « Productivity and R&D at Firm Level in French Manufacturing », in Z. Griliches, ed., *R&D, Patents, and Productivity*, University of Chicago, Ill., pp. 375-92.

DAVIDSON R., MCKINNON J.G. (1981). – « Several Tests for Model Specification in the Presence of Alternative Hypotheses », *Econometrica*, 49, pp. 781-93.

DIEWERT W.E., WALES T.J. (1987). – « Flexible Functional Forms and Global Curvature Conditions », *Econometrica*, 55, pp. 43-68.

GHIJSEN P.W.Th. (1994). – « Technological Change in Static and Dynamic Factor Demand Models: Comparative Sectoral Analyses Using Japanese Data », *Master thesis with appendices*, University of Limburg, Maastricht, The Netherlands.

GRILICHES Z. (1994). – « Productivity, R&D, and the Data Constraint », *American Economic Review*, 84, pp. 1-23.

HALL B., MAIRESSE J. (1995). – « Exploring the Productivity of Research and Development in French Manufacturing Firms », *Journal of Econometrics*, 65, 263-93.

HANSEN L.P. (1982). – « Large Sample Properties of Generalized Method of Moments Estimators », *Econometrica*, 50, pp. 1029-54.

KURODA M. (1992). – *Economic Growth and Structural change in Japan, Unpublished Manuscript*, Tokyo.

JORGENSON D. (1995). – *Productivity-volume 2: International Comparisons of Economic Growth*, MIT Press, Stanford.

MOHNEN P.A., NADIRI M.I. (1985). – « Demande de facteurs et recherche-développement, Estimations pour les États-Unis, le Japon, l'Allemagne et la France », *Revue économique*, 5, pp. 943-74.

MOHNEN P.A., NADIRI M.I., PRUCHA I.R. (1986). – « R&D, Production Structure and Rates of Return in the US, Japanese and German Manufacturing Sectors: A Non-Separable Dynamic Factor Demand Model », *European Economic Review*, 30, pp. 749-71.

NAKAMURA S. (1993). – « An Adjustment Cost Model of Long Term Employment in Japan », *Journal of Applied Econometrics*, volume 8, pp. 175-194.

NEWEY W.K., WEST K.D. (1987). – « Hypothesis Testing with Efficient Method of Moments Estimation », *International Economic Review*, 28, pp. 777-87.

PINDYCK, R.S., ROTEMBERG J.J. (1983). – « Dynamic Factor Demand under Rational Expectations », *Scandinavian Journal of Economics*, 85, pp. 223-38.

PRUCHA I.R., NADIRI M.I. (1986). – « A Comparison of Alternative Methods for the Estimation of Dynamic Factor Demand Models under Non-Static Expectations », *Journal of Econometrics*, 33, pp. 187-211.

SCHANKERMAN M. (1981). – « The Effects of Double-counting and Expensing on the Measured Returns to R&D », *Review of Economics and Statistics*, 63, 3, pp. 454-58.

SINGLETON K.J. (1985). – « Testing Specifications of Economic Agents' Intertemporal Optimum Problems in the Presence of Alternative Models », *Journal of Econometrics*, 30, pp. 391-413.

SOETE, L., PATEL P. (1985). – « Recherche-développement, importations de technologie et croissance économique, une tentative de comparaison internationale », *Revue Économique*, 5, pp. 975-1000.

APPENDIX

Data of Japanese Industrial Sectors 1960-1985

Eight Japanese industry groups are distinguished:

I1. Agriculture, forestry and fishery;
I2. Light manufacturing: Materials;
I3. Light manufacturing: Fabricated products;
I4. Heavy manufacturing: Chemical materials;
I5. Heavy manufacturing: Metal materials;
I6. Heavy manufacturing: Fabricated products;
I7. Construction;
I8. Public utilities.

These eight industry groups comprise 31 two-digit industry groups, described by GHIJSEN [1994, appendix C, page C10]. In the econometric analyses all variables are indexed at 1970.

Production, energy and materials

These variables are measured in volumes. Data sources are the New system on National Accounts (1970 onwards) and the census of manufacturers report by commodity (before 1970), published by the Economic Planning Agency and the Current production statistics survey, reported by the Ministry of International Trade and Industry (MITI).

Labour

Labour is measured in hours, obtained by multiplying the average number of employees by the average number of hours worked. A correction is made for the quality of labour; the level of education is taken into account *via* the following method. The higher the education, the higher the labour input (according to KURODA [1992], page 47). Data sources are the System of National Account Statistics (the labour force survey, employment status survey and the population survey (five-annually)), and the Report on the basic wage structure survey and the Monthly labour survey, both published by the Ministry of Labour. See also KURODA [1992 chapter 2] and JORGENSON [1995] on the construction of the production factor labour and labour productivity.

Gross physical capital stock investment

Data are in volumes, obtained by deflating the values of gross investment with the price of capital stock. Data sources are the Gross capital stock of private firms, the Census of manufacturing, reported by industry, the capital formation matrix of input-output Table (edition 1975), the National Wealth Survey (edition 1955, 1960, 1965, 1970) and the general Annual report national accounts. They are all reported by the Economic Planning Agency for the period 1960-1985 unless otherwise stated. See also KURODA [1992, chapter 3].

Physical capital stock

Data were collected and calculated using gross investment series by the KEIO-Observatory group, Tokyo, under supervision of Professor KURODA. Capital stock series per sub-sector (31 in total) were constructed using the so-called double benchmark Perpetual Inventory Method. Capital stocks by industry, reported in 1955 and 1970, were used as benchmarks. Data sources are the National Wealth Survey. See also, KURODA [1992, chapter 3]. The depreciation rate was set at .1.

Gross R&D investment

Data are in volumes, obtained by deflating the investment values by R&D prices. Data sources are the Report on the survey of Research and Development, Statistics Bureau, Management and Coordination Agency, Japan, editions 1961-1991. The R&D investment comprise the components R&D capital, R&D labour, R&D materials and a R&D additional expenditures (including R&D energy). For each R&D component the according price is used as a deflator.

The construction of R&D stock

By means of the Perpetual Inventory Method, using R&D investment and a (constant) depreciation rate of 0.15, the R&D stock is calculated for each R&D component. On the basis of data on R&D expenditures from 1950 onwards, a starting value was calculated, using a weighting factor equal to the survival factor of a expenditure. In short, the starting value of the R&D capital stock (in 1960) was calculated by the enumeration of the surviving fraction of the R&D investment per vintage starting in 1950 until 1960. The survival fraction of expenditures of 1959 (1958, and more general 1960-i, for i=1957 to 1950) in the 1960 R&D capital stock is 0.85 (0.72, and more general 0.851960-i).

Factor prices

Data sources are the same as the data sources of the production factors. The R&D component prices are assumed to be the same as the non-R&D component prices. The price of R&D is the sum of each R&D component's price multiplied by the R&D share of the component. As a price of the additional R&D component does not exist, the product price is taken here.