ETLA

ELINKEINOELÄMÄN TUTKIMUSLAITOS
THE RESEARCH INSTITUTE OF THE FINNISH ECONOMY
Lönnrotinkatu 4 B 00120 Helsinki Finland Tel. 358-9-609 900
Telefax 358-9-601 753 World Wide Web: http://www.etla.fi/

Keskusteluaiheita - Discussion papers

No. 694

Petri Rouvinen*

ISSUES IN

R&D-PRODUCTIVITY DYNAMICS:

CAUSALITY, LAGS, AND 'DRY HOLES'**

* The author is a researcher at ETLA and a Ph.D. Candidate at Vanderbilt University.

** A revised version of a paper prepared for Dr. Stephen Bond's (Oxford and IFS) course *Econometrics of Panel Data: Estimation, Specification Tests and Applications* held in 3-7 May 1999 at NTNU Trondheim, Norway.

ISSN 0781-6847 09.11.1999

Rouvinen, Petri – **Issues in R&D–Productivity Dynamics: Causality, Lags, and 'Dry Holes'**, Helsinki: ETLA, Elinkeinoelämän Tutkimuslaitos, The Research Institute of the Finnish Economy, 1999, 29 p. (Keskusteluaiheita – Discussion Papers, ISSN 0781-6847, No. 694).

Abstract: This paper focuses on four key issues in the dynamic relationship between R&D and productivity, namely, (1.) does R&D cause productivity and/or *vice versa*, (2.) is there a lag between R&D and its productivity effects, (3.) does the potency of R&D vary in timing and magnitude, and (4.) what is the role of R&D spillovers and aggregate shocks? An unbalanced panel of 2.5-digit manufacturing industries in twelve OECD countries from 1973 to 1997 is being used.

The results suggest that (1.) R&D Granger causes total factor productivity (TFP) but not *vice versa*, (2.) productivity seems to respond to changes in R&D expenditure with a considerable lag, (3.) the potency of R&D indeed varies in timing and magnitude but at least during the sample period in a somewhat unpredictable manner, and that (4.) the elasticity of TFP with respect to aggregate shocks is high but negligible with respect to R&D spillovers.

Keywords: Panel data, total factor productivity, R&D, dynamics, causality, lag structure, spillovers.

JEL codes: C23, D24, O30, O40.

Rouvinen, Petri – **Näkökohtia tuotekehityksen ja tuottavuuden dynamiikkaan: kausaalisuus, aikaviiveet ja 'kuivat jaksot'**, Helsinki: ETLA, Elinkeinoelämän Tutkimuslaitos, The Research Institute of the Finnish Economy, 1999, 29 s. (Keskusteluaiheita – Discussion Papers, ISSN 0781-6847, No. 694).

Tiivistelmä: Tässä tutkimuksessa käsitellään neljää keskeistä seikkaa tuotekehityksen (T&K) ja tuottavuuden välisessä dynamiikassa: (1.) aiheuttaako tuotekehitys tuottavuuskasvua ja/tai päinvastoin, (2.) ilmenevätkö tuotekehityksen tuottavuusvaikutukset viiveellä, (3.) vaihteleeko tuotekehityksen vaikutusvoima yli ajan ja (4.) millainen on aggregaattishokkien ja tuotekehityksen ulkoisvaikutusten rooli. Havaintoaineistona on kahdentoista OECD-maan 2.5-numerotason teollisuustoimialoista muodostettu epätasapainoinen paneeli.

Tulosten mukaan (1.) T&K 'Granger' aiheuttaa kokonaistuottavuuden kasvua mutta ei päinvastoin, (2.) tuotekehityksen vaikutukset ilmenevät merkittävällä viiveellä, (3.) T&K:n vaikutusvoima vaihtelee määrän ja ajoituksen suhteen joskin vaikeasti ennustettavalla tavalla, ja (4.) aggregaattishokkien vaikutus kokonaistuottavuuteen on huomattava mutta tuotekehityksen ulkoisvaikutusten vähäinen.

Avainsanat: Paneeliaineisto, kokonaistuottavuus, tuotekehitys, dynamiikka, kausaalisuus, viiverakenne, ulkoisvaikutukset.

ACKNOWLEDGEMENTS

I would like to thank *The Academy of Finland*, *ASLA-Fulbright Foundation*, and *Yrjö Jahnsson Foundation* (in alphabetical order) for supporting my educational efforts at *Vanderbilt University*. The *Fulbright Center* in Finland and the *Institute of International Education* (Houston, Texas) have ably taken care of all practical arrangements regarding my stay in the United States.

The *Technology Development Centre* (TEKES) has in part financed this project. My employer, *The Research Institute of the Finnish Economy* (ETLA), has been supportive. In particular, I would like to point out the backing and encouragement of Kari Alho, Rita Asplund, Aija Leiponen, Pentti Vartia, Synnöve Vuori, and Pekka Ylä-Anttila.

I would also like to thank my advisor Professor Robert A. Driskill, my committee members – Professors J. S. Butler, A. Maneschi, R. A. Margo and D. C. Parsley (OGSM), faculty, staff, and fellow students at the Department of Economics (Vanderbilt University), as well as Professors Pekka Ilmakunnas and Mihkel Tombak at the *Helsinki School of Economics and Business Administration*.

This is a revised version of a paper prepared for Dr. Stephen Bond's course *Econometrics of Panel Data: Estimation, Specification Tests and Applications*, held in 3–7 May 1999 at *NTNU Trondheim*, Norway. Comments and suggestions Dr. Bond and course participants are gratefully acknowledged. This paper reports preliminary results of work in progress; additional comments are appreciated.

Petri Rouvinen
November 9, 1999

TABLE OF CONTENTS

DYNAMIC EFFECTS OF R&D ON PRODUCTIVITY
IN OECD MANUFACTURING INDUSTRIES

INTRODUCTION

The relationship between R&D and productivity[1] is one of the great folk theorems of the economic profession. On this issue Griliches (1995, p. 52) notes:

> "Most of us also share the conviction that both the public investment in science and the private investments in industrial R&D have been crucial contributors to world economic growth in the past and will also remain crucial as far as the future is concerned. Nevertheless, the quantitative, scientific base for these convictions is rather thin."

Griliches recognizes three main alternatives to analyzing the contribution of R&D to growth: historical case studies, invention count or patent statistics analyses, and econometric studies relating productivity to R&D and possibly other variables. In what follows, we will concentrate on the last alternative. We will study four important issues in the R&D–productivity relationship:

1. Does R&D cause, in the Granger sense, productivity growth and/or *vice versa*?
2. Is there a lag between R&D expenditure and the productivity growth it may cause?
3. Does the potency of R&D vary in timing and magnitude?
4. What is the role of R&D spillovers and aggregate shocks in the R&D–productivity dynamics?

Many econometric studies take for granted a causal relationship between R&D and productivity and/or assume that R&D is exogenous rather than endogenous (or predetermined) in productivity equations. Granger causality tests will be the starting point of our empirical analysis.

Given that R&D indeed contributes to productivity growth, the next obvious question is, how soon can we expect the positive effects of an R&D investment. Sterlacchini (1989) rightfully criticizes the literature for ignoring the lag structure in the relationship in the effects of R&D on TFP; most studies either construct R&D stocks using the perpetual inventory method[2] or ignore the issue altogether.[3] Park (1995) and Englander et al. (1988) use three-year lags of R&D stock measures. Strauss and Ferris (1996) implement a dynamic error correction model as suggested by Phillips and Loretan (1991). Ravenscraft and Scherer (1982) paper is one of the few studies explicitly discussing the timing of R&D effects. Deflated gross profits[4] are regressed on a distributed lag of deflated R&D outlays and other variables. After experimenting with several distributed lag specifications it is concluded that "There is strong evidence that the lag structure is roughly bell-shaped, with a mean lag of from four to six years." (p. 619).

Scientific breakthroughs seem to come about in a somewhat erratic manner. A range of related innovations follows a major invention or discovery (e.g., semiconductors). It is even argued that technological breakthroughs are the force behind 'long wages' or 'Kontratieff cycles' (Freeman & Perez, 1988). Similarly, there is no apparent reason why R&D should contribute to productivity in a predictable manner. It is quite possible, for instance, that the productivity improvement potential of current knowledge is exhausted to the extent that even considerable investments in R&D do not bear fruit until efforts are redirected after some promising discovery. Englander, Evenson, and Hanazaki (1988, p. 8) state that[5]

> "Given this long-run role of technological change, it is important to consider the possibility that a slowing of the generation or diffusion of new technology may have contributed to the slowdown in the growth of total factor productivity (TFP) … [many] [s]tudies… implicitly assume that the efficacy or potency of R&D is essentially constant [over time]… This a restrictive assumption, as there is no reason *ex ante* that R&D cannot be in a period of "dry holes", in which potency is temporarily reduced."

A peculiar feature of R&D is that a firm investing in it is often unable to exclude others from freely obtaining some of the benefits (for review see, e.g., Griliches, 1992; Mohnen, 1990; Mohnen, 1996; Nadiri, 1993). Given that these R&D spillovers exist, accounting for them should contribute to the explanatory power of a R&D–productivity model. There is also some discussion on 'productive spillovers' (Caballero & Lyons, 1989; Caballero & Lyons, 1990; Caballero & Lyons, 1992), which should be equally important in the R&D–productivity model. It has been suggested, however, that these spillovers are merely a specification error (Basu & Fernald, 1995), so we will rather call these 'spillovers' from productivity developments in other industries 'aggregate shocks'.

MODEL

We complement a standard Cobb-Douglas production function with an industry i's knowledge (R&D) stock, a disembodied technological shock at time t, a measure of **any** time invariant variables possibly affecting industry i's performance, and with a vector of other possible explanatory factors $\boldsymbol{X}_{it}$, i.e.,

$$Y_{it} = e^{\eta_i} e^{\gamma_t} K_{it}^{\beta_K} L_{it}^{\beta_L} R_{it}^{\beta_R} \boldsymbol{X}_{it}^{\boldsymbol{\beta}_X}, \tag{1}$$

where subscript $i = 1, 2, \cdots, N$ refers to a cross-sectional unit (*individual*), subscript $t = 1, 2, \cdots, T_i$ refers to a point in time, Y_{it} is the real value added of industry i at time t, K_{it} is the corresponding physical capital stock, L_{it} is the labor input, R_{it} is the knowledge stock, η_i is a measure of time-invariant variables affecting industry i's performance, γ_t is a time-varying technology shock, and $\boldsymbol{X}_{it}$ is a set of other possible explanatory factors. The measure of the time-invariant variables may include any country or industry specific variables, e.g., geographical location or a country's overall innovativeness in industry i, provided that they do **not** vary across time.

By dividing both sides with $K_{it}^{\beta_K} L_{it}^{\beta_L}$, the left-hand side of the equation coincides, after appropriate scaling, with the total factor productivity (TFP) measure used by OECD (see below).[6] After taking natural logarithms, we get

$$\ln(TFP_{it}) = \beta_R \ln(R_{it}) + \boldsymbol{\beta}_X \ln(\boldsymbol{X}_{it}) + \gamma_t + \eta_i + \upsilon_{it}, \tag{2}$$

where υ_{it} is an error term. There are, however, two problems with the specification in Equation (2). First, we do not observe R_{it}. Second, productivity may adjust to shock with a lag. Let us specify an autoregressive version of Equation (2):

$$\ln(TFP_{it}) = \beta_{TFP(t-1)} \ln(TFP_{i(t-1)}) + \sum_{k=0}^{n} \beta_{R(t-k)} \ln(IR_{i(t-k)}) + \boldsymbol{\beta}_X \ln(\boldsymbol{X}_{it}) + \gamma_t + \eta_i + \upsilon_{it} \tag{3}$$

where IR_{it} is industry i's R&D expenditure at time t. Thus, we are explicitly assuming that knowledge stock is accumulated through current and past R&D investments in some manner. We include the lagged dependent variable as a regressor in order to account for the dynamic adjustment of productivity.

DATA[7]

Two commercially available databases by the *Organisation for Economic Co-operation and Development* (OECD), namely, Analytical Business Enterprise R&D Database (known as ANBERD, OECD, 1998) and International Sectoral Database (known as ISDB, OECD, 1999), are our primary data sources. Both databases use International Standard Industrial Classification (ISIC revision 2, UN, 1968) currently used in the OECD National Accounts publication. We are forced to adapt the more aggregate ISDB industry definitions; we consider the fourteen manufacturing industries available (see Table 1).[8]

While both ANBERD and ISDB cover 15 countries, they overlap only on 13.[9] Furthermore, we also exclude Australia due to prohibitively many missing observations.[10] ANBERD and ISDB have data on both the Federal Republic of Germany (West Germany) and the United Germany (Germany), but we only included West Germany since at this point data on the United Germany consisted of only a few annual observations.[11] Thus, 12 OECD countries are included in the analysis.[12]

We construct a panel of fourteen industries in twelve OECD countries from 1973 to 1997.[13] Thus, in principle, we have a panel of 168 cross-sectional units observed in a period of 25 years – actual data patterns in the sample are illustrated in Table 2.

All-in-all 47 industries are lost due to missing or insufficient data. Nearly 80% of these are three-digit industries. A balanced 1973–91 sub-sample would include 103 cross-sectional units; years 1985–90 are observed for all 121 cross-sectional units.

Table 1. Manufacturing industries included in the study.

ISDB code	ANBERD code	ISIC major division	Corresponding NACE code	Title of category
FOD	31	31.	36	Food, beverages and tobacco
TEX	32	32.	42	Textiles, wearing apparel and leather industries
WOD	33	33.	–	Wood, and wood products, including furniture
PAP	34	34.	47	Paper, and paper products, printing and publishing
CHE	35	35.	17 + 49	Chemicals and chemical petroleum, coal, rubber and plastic products
MNM	36	36.	15	Non-metallic mineral products except products of petroleum and coal
BMI	37	37.	13	Basic metal industries
MEQ	38	38.	19 + 21 + 23 + 25 + 28	Fabricated metal products, machinery and equipment
BMA	381	381	19	Fabricated metal products, except machinery and equipment
MAI	(382-3825) + 3825	382	21	Machinery except electrical
MIO	385	385	23	Professional, scientific, measuring and controlling equipment n.e.c.
MEL	(3830-3832) + 3832	383	25	Electrical machinery apparatus, appliances and supplies
MTR	3841 + 3843 + 3845 + (3842+3844+3849)	384	28	Transport equipment
MOT	39	39.	48	Other manufacturing industries

Note: ISIC: International Standard Industrial Classification (*Classification Internationale Type par Industrie, CITI*). NACE: General Industrial Classification of All Economic Activities in the European Communities (*Nomenclature des Activités dans les Communautés Européennes, NACE*).

Table 2. Data patterns across twelve countries and fourteen industries by their sample frequency.

Freq. (no. of ind. across countries with the pattern)	No. of obs. (years)	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
27	21	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1				
26	22	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1			
25	23	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		
9	25	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
9	20	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1					
7	19	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1						
7	11													1	1	1	1	1	1	1	1	1	1	1		
7	18	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1							
3	16								1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		
1	16						1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1				
121	11–25													1	1	1	1	1	1							

Note: Bottom row refers to the whole sample.

There is a voluminous literature on the definition and measurement of productivity. Essentially, a typical measure of total factor productivity (TFP) is calculated as the difference between output growth and the weighted average of input growths. Commonly weights are factor cost shares, following a CD (Cobb & Douglas, 1928) production function framework.[14] There are known shortcomings of the standard measures of productivity, including inadequate control for returns to scale, level of capacity utilization, quality of inputs, and externalities. We nevertheless use the official OECD TFP indices from ISDB (1990=1.00, see OECD, 1999, pp. 50-52, Equation 13 in particular). Our estimation method and the choice of explanatory variables cure some of the shortcomings the productivity measure may have (see below). As mentioned in Endnote 6, we will 'reverse the scaling' of the official TFP measures (exchange rates as below) so that our specification will correspond exactly to Equation (2), without some arbitrary scaling of TFP figures.

ANBERD includes R&D figures in national currencies and current prices. These figures are transferred to 1990 prices by using industry-level implicit gross fixed capital formation price indices derived from ISDB (if not available, we used implicit manufacturing GDP deflators instead). We use gross fixed capital formation (gfcf) purchasing power parity (ppp) exchange rates from ISDB (OECD, 1999) to transfer the series to millions of 1990 U.S. dollars. Thus, we have series that are roughly comparable across countries *in 1990*, but the percentage changes correspond to those in national currency 1990 price series.[15] We take natural logs of both productivity and R&D series.

We will consider including the overall TFP in manufacturing industries (other than the representative one) as a measure of countrywide 'aggregate shocks'.[16] Furthermore, we experiment with a measure of domestic R&D spillover flow, defined as the sum of R&D efforts in other than the representative industry.[17]

See Table 10 in Appendix A for descriptive statistics.

METHODOLOGY

AUTOREGRESSIVE DISTRIBUTED LAG MODEL[18]

Let us consider the following autoregressive distributed lag model (ADL) in a time-series cross-section (TSCS) context (t refers to a point in time and i refers to a cross-sectional unit, individual):

$$y_{i,t} = m + \sum_{k=1}^{p} \alpha_k y_{i,t-k} + \sum_{l=0}^{q} \boldsymbol{\beta}_l \boldsymbol{x}_{i,t-l} + \lambda_t + \eta_i + \upsilon_{i,t}, \quad t = 1, \cdots, T_i; \; i = 1, \cdots, N \, , \tag{4}$$

where $\upsilon_{i,t}$ a time-varying stochastic error term with some properties, η_i and λ_t are, respectively, individual and time specific effects, $\boldsymbol{x}_{i,t}$ is a vector or explanatory variables, and m is a combination of a constant term and its coefficient. Let us define $\varepsilon_{i,t} = \eta_i + \upsilon_{i,t}$ and omit the time specific effect for the time being. For the present purposes there is no loss in generality in assuming that $p = q = 1$ and that there is only one explanatory variable. Now Equation (4) can be rewritten as ADL(1,1) model:

$$y_{i,t} = m + \alpha_1 y_{i,t-1} + \beta_0 x_{i,t} + \beta_1 x_{i,t-1} + \varepsilon_{i,t} \, . \tag{5}$$

Inverting the polynomial gives

$$y_{i,t} = (1 + \alpha_1 + \alpha_1^2 + \cdots)m + (1 + \alpha_1 L + \alpha_1^2 L + \cdots)(\beta_0 x_{i,t} + \beta_1 x_{i,t-1} + \varepsilon_{i,t}) \, , \tag{6}$$

where L is the lag operator. Thus, the current value of $x_{i,t}$ has an effect on the current and future values of $y_{i,t}$. This can be demonstrated by taking partial derivatives:

$$\begin{gathered} \frac{\partial y_{i,t}}{\partial x_{i,t}} = \beta_0 \\ \frac{\partial y_{i,t+1}}{\partial x_{i,t}} = \beta_1 + \alpha_1 \beta_0 \\ \frac{\partial y_{i,t+2}}{\partial x_{i,t}} = \alpha_1 \beta_1 + \alpha_1^2 \beta_0 \\ \vdots \end{gathered} \quad . \tag{7}$$

Immediate response of $y_{i,t}$ to a change in $x_{i,t}$ is followed by short-, medium-, and long-run responses. Assuming stability ($|\alpha_1| < 1$), the total effect is given by $(\beta_0 + \beta_1)/(1 - \alpha_1)$.[19] After specifying the initial equation (such as Equation (5)), at least four practical problems arise:

1. how to account for the presence and features of the unobserved component $\varepsilon_{i,t}$,
2. how to control for the time-series cross-section nature of the data,
3. how to determined the appropriate lag lengths of the ADL process, and
4. how to account for the nature of the data generation process of $x_{i,t}$.

Let us first focus on the last (4.) of the aforementioned issues. A typical assumption is that $x_{i,t}$ is stochastically independent of $\varepsilon_{i,t}$, i.e., $E(x_{i,t}, \varepsilon_{i,t+s}) = 0 \; \forall \; s$. This implies that past, current, and future shocks have no effect on $x_{i,t}$, in which case $x_{i,t}$ is said to be **strictly exogenous**. If $x_{i,t}$ is independent of current and future but not past disturbances, i.e., $E(x_{i,t}, \varepsilon_{i,t+s}) = 0 \; \forall \; s \geq 0$, $x_{i,t}$ is said to be **predetermined**. Otherwise $x_{i,t}$ is **endogenous**. The remaining three issues will be discussed below.

DYNAMIC PANEL DATA ESTIMATORS

Let us rewrite Equation (5)

$$y_{i,t} = m + \alpha_1 y_{i,t-1} + \beta_0 x_{i,t} + \beta_1 x_{i,t-1} + \eta_i + \upsilon_{i,t} \tag{8}$$

and assume that

1. the expected values of both unobserved components are zero, i.e., $E(\eta_i) = E(\upsilon_{i,t}) = 0$,[20]
2. the individual effect and the time-varying error term are uncorrelated, i.e., $E(\eta_i, \upsilon_{i,t}) = 0$,
3. there is no autocorrelation in the time-varying error term, i.e., $E(\upsilon_{i,t}, \upsilon_{i,t+s}) = 0 \; \forall \; s \neq 0$, and
4. the initial value of the dependent variable is not correlated with the future error terms, i.e., $E(y_{i,1}, \upsilon_{i,t}) = 0 \; \forall \; t \geq 2$ (the initial condition).[21]

Panel data estimators are obsolete unless the individual effect is indeed present, i.e., $\delta_\eta^2 > 0$. Explosive roots are ruled out, i.e., $|\alpha_1| < 1$.[22] The fact that the lagged dependent variable is included as one of the regressors, makes pooled ordinary least squares (OLS) as well as classic error component estimators[23] obsolete.[24] We could specify a maximum likelihood (ML) estimator for Equation (8),[25] but in order to do that we ought to have rather detailed knowledge of the properties of the error term, which we obviously do not. Therefore, we resort to instrumental variable (IV) or generalized method of moments (GMM) estimators (Hansen, 1982; White, 1982).

Anderson and Hsiao (1981) suggest first differencing the model in Equation (8) in order to eliminate η_i.[26] The transformed error term becomes $\upsilon_{i,t} - \upsilon_{i,t-1}$,[27] which is negatively correlated with the transformed lagged dependent variable $y_{i,t-1} - y_{i,t-2}$. However, assuming no autocorrelation and the 'initial condition' (see above), $y_{i,t-2}$ and $\Delta y_{i,t-2}$ are not correlated with $\upsilon_{i,t} - \upsilon_{i,t-1}$ and are presumably correlated with $\Delta y_{i,t-1}$, which makes them suitable instruments.[28] Anderson and Hsiao propose estimating the first-differenced equation, with either lagged levels or differences as instruments, by two stage least squares (2SLS). While this Anderson & Hsiao estimator (AH) is consistent as $N \longrightarrow \infty$, its efficiency can be improved since $y_{i,t-l}$ and $\Delta y_{i,t-l}$ for $l \geq 3$ also qualify as instruments. Furthermore, 2SLS does not account for the MA(1) process with an unit root we introduced to the transformed error term ($\upsilon_{i,t} - \upsilon_{i,t-1}$).[29]

Arellano and Bond (1991)[30] propose an 'optimal' GMM estimator for a dynamic first-differenced panel data equation,[31] where all possible lags (and possibly current and future values in case of strictly exogenous variables) of regressors are used as instruments. Let us define Z_i as a matrix of these orthogonality conditions for individual i (Z as a stacked version of these matrices across individuals).[32] We still have to account for the effects of the first-differenced transformation on the error term. Assuming that $\upsilon_{i,t}$ is $IID(0, \delta_\upsilon^2)$, the variance-covariance matrix takes the form $E(\Delta\upsilon_i \Delta\upsilon_i^{'}) = \delta_\upsilon^2 H_i$, where $\Delta\upsilon_i^{'} = (\upsilon_{i,3} - \upsilon_{i,2}, \cdots, \upsilon_{i,T_i} - \upsilon_{i,T_i-1})$ and

$$H_i = \frac{1}{2}\begin{bmatrix} 2 & -1 & \cdots & 0 & 0 \\ -1 & 2 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 2 & -1 \\ 0 & 0 & \cdots & -1 & 2 \end{bmatrix}. \tag{9}$$

Let us define $\Delta\upsilon$ as a stacked version of $\Delta\upsilon_i$ matrices. From orthogonality conditions we know that $E(Z'\Delta\upsilon) = 0$, and we can use the sample analogs of these conditions to specify a GMM estimator. Let us define $\Delta y_i^{'} = (y_{i,3} - y_{i,2}, \cdots, y_{i,T} - y_{i,T\text{-}1})$, and Y as a stacked version of these. Furthermore, if W is a matrix of stacked regressors and γ a vector of coefficients, a GMM estimator can be written as follows:

$$\hat{\gamma}_{GMM} = (W'Z\ A_N\ Z'W)^{-1} W'Z\ A_N\ Z'Y\,, \tag{10}$$

where A_N is an appropriately chosen weight matrix. An optimal GMM estimator will set

$$A_N = \left[\tfrac{1}{N} \sum_{i=1}^{N} (Z_i^{'} \Delta\hat{\upsilon}_i \Delta\hat{\upsilon}_i^{'} Z_i) \right]^{-1}, \tag{11}$$

which is efficient based on the finite sample moment conditions $E(Z'\Delta\upsilon) = 0$. However, a preliminary A_N has to be chosen in order to obtain consistent estimates of $\Delta\upsilon_i$ used for the construction of the optimal A_N. Arellano & Bond propose using H_i (see above) as the bases of the first-step weighting matrix, i.e., setting

$$A_N = \left[\tfrac{1}{N} \sum_{i=1}^{N} (Z_i^{'} H_i Z_i) \right]^{-1}, \tag{12}$$

which is asymptotically equivalent to $\hat{\gamma}^{*}_{GMM}$. Simulation studies suggest that the efficiency loss from using weighting matrix in Equation (12) is rather small, whereas results and tests based on the optimal weighting matrix in Equation (11) may be misleading in finite samples (Arellano & Bond, 1991; Blundell & Bond, 1998). Thus, we will base our results in the weighting matrix in Equation (11); on occasion we report both ‘one step’ and ‘two step’ results. Standard deviations and test statistics are nevertheless based on White (1980) heteroskedasticity consistent covariance matrices. In what follows the first-differenced Arellano & Bond (1991) dynamic panel data estimator will be referred to as DPD-DIF.

DPD-DIF exploits all available **linear** moment conditions in the absence of outside instruments. Ahn and Schmidt (1995) propose using additional nonlinear moment conditions, which offer potentially big improvements in efficiency when, e.g. in Equation (8), $\alpha_1 \longrightarrow 1$ (the dependent variable follows a random walk) and/or $\delta_\eta^2 \big/ \delta_\upsilon^2 \longrightarrow \infty$ (the individual effect dominates the time-varying error term). The downside is that a homoskedasticity through time restriction is imposed and that these additional conditions are implemented with a nonlinear estimator.

Arellano and Bover (1995) first proposed using lagged differences as instruments for equations in **levels**. The validity of these extra moment conditions depends on the initial conditions on the process generating $y_{i,1}$. As long as the entry period 'disequilibrium' of $\varepsilon_{i,t}$ from $\eta_i/(1-\alpha)$ is randomly distributed across individuals, the 'level' moment conditions remain valid. Blundell and Bond (1998) propose a linear GMM estimator (DPD-SYS) exploiting this idea. DPD-SYS can be defined as DPD-DIF above, but now we stack individual i's differenced equations **and** level equations. The instrument matrix is extended accordingly. One- and two-step GMM estimators can be defined as above, but now the one-step estimator is not asymptotically equivalent to the two-step estimator (not even in the IID case).

EMPIRICAL RESULTS

In what follows we study the properties of the model in Equation (3) with methods discussed in the above section. Recall that our objective is to study four related issues, namely:

1. Does R&D Granger cause productivity and/or *vice versa*?
2. Is there a lag between R&D expenditure and its productivity effects?
3. Does the potency of R&D vary in timing and magnitude?
4. What is the role of R&D spillovers and aggregate shocks?

BIVARIATE GRANGER CAUSALITY TESTING

Granger's (1969, p. 428) notion of causality states that "… Y_t is causing X_t if we are better able to predict X_t using all available information than if the information apart from Y_t had been used." Since the notion of 'all available information' is not particularly operational, Granger's suggestion to regress X_t on its own lags and a set of lagged Y_t s has become the norm. If the set of lagged Y_t s contributes statistically significantly to the explanation of X_t, Y_t *Granger causes* X_t.

Holtz-Eakin, Newey, and Rosen (1988)[33] propose using their panel VAR methodology to test Granger causality in a panel data context: we will implement a similar test by using the aforementioned DPD-DIF. Granger causality test assumes that the series are stationary, which should be the case after the first-difference transformation. Since we want the parameters to be identified under both the null and the alternative hypotheses, we model both variables as being endogenous, i.e., we will use lagged levels from the second lag onwards as instruments. To reduce the risk of overfitting and finite sample bias when the full set of orthogonality conditions are used, we use instruments up to the maximum lag length in the model.

Hall, Mairesse, Branstetter, and Crépon (1998) use cross-country firm-level data to study whether cash flow causes investment and R&D in a similar econometric framework. They experiment with lag lengths from 2 to 5, and generally settle for 4 or 5 lags. Since Granger causality tests are somewhat sensitive to the chosen lag length, we report results for lag lengths from 3 to 6.

Table 3. Granger causality tests.

Estimation information:				
Dep. variable Δy_t	ln(TFP)	ln(TFP)	ln(TFP)	ln(TFP)
Lags of Δy_t up to	6	5	4	3
Indep. variable Δx_t	ln(R&D)	ln(R&D)	ln(R&D)	ln(R&D)
Lags of Δx_t up to	6	5	4	3
Sample information:				
No. of observations	1,672	1,793	1,914	2,035
No. of parameters	30	29	28	27
No. of individuals	121	121	121	121
Longest time series	18	19	20	21
Shortest time series	4	5	6	7
Does x_t cause y_t?	15.49 (6) **	13.11 (5) **	7.612 (4)	5.406 (3)
Estimation information:				
Dep. variable Δy_t	ln(R&D)	ln(R&D)	ln(R&D)	ln(R&D)
Lags of Δy_t up to	6	5	4	3
Indep. variable Δx_t	ln(TFP)	ln(TFP)	ln(TFP)	ln(TFP)
Lags of Δx_t up to	6	5	4	3
Sample information:				
No. of observations	1,672	1,793	1,914	2,035
No. of parameters	30	29	28	27
No. of individuals	121	121	121	121
Longest time series	18	19	20	21
Shortest time series	4	5	6	7
Does x_t cause y_t?	7.356 (6)	2.120 (5)	2.135 (4)	1.568 (3)

Note: Computations with Ox 2.10 (see Doornik, 1999) and DPD 1.00a (Doornik, Arellano, & Bond, 1999). Implemented with Arellano and Bond (1991) dynamic panel data estimator (DPD-DIF). All estimations include a constant term and time dummies (instrumented by themselves). Question 'Does x_t cause y_t?' refers to the joint significance test of x s (χ^2-distributed Wald tests; degrees of freedom in the parenthesis). Notions ***, **, and * refer to the joint significance at 1, 5, and 10% levels. One-step results with robust standard errors.

Results in Table 3 would seem to suggest that R&D Granger causes TFP but not *vice versa*. With 5 and 6 lags, the tests for R&D causing TFP are nearly statistically significant at 1% level and therefore are clearly significant at 5% level. With four lags the test just misses the mark at 10% level, i.e., would be significant at 11% level. With three lags the test would be significant at 15% level. Even in the most favorable case of 6 lags, the reverse causality test would not be significant even at 25% level.

Besides Granger causality, the tests in Table 3 also suggest that lagged values of R&D may help to explain TFP in an economic model. Since causality is unidirectional, there does not appear to be feedback from TFP to R&D. This also leaves open whether R&D is exogenous or endogenous.[34]

TRADITIONAL PANEL DATA ESTIMATORS

Above we discussed problems and asymptotic biases associated with some traditional panel data estimators. It is nevertheless worthwhile to consider these, as they provide useful checks on the performance of the model when modern dynamic panel data estimators are being used.

Table 4 presents estimation results and an ADL(1,6) model with a few traditional panel data estimators. We use the largest available sample in all estimations. Note that the 2SLS results are not directly comparable to the OLS and WG results, since in the 2SLS case the first observation of each individual is lost as a consequence of the first-difference transformation. Even if R&D were strictly exogenous, OLS and WG results would be biased (see Endnote 24 for a brief discussion). The Anderson and Hsiao (1982) two-stage least squares instrumental variable estimator would be perhaps the simplest acceptable instrumental variables estimator in this context – again assuming the strictly exogeneity of R&D.

The results in Table 4 do not provide a very fruitful starting point for further analysis. The data generation process of TFP seems to be close to having an unit root, i.e., is close to a random walk, in which case first differences may not be very informative (see above). Current and past values of R&D seem to contribute relatively little to TFP. The fourth lag of R&D becomes consistently significant in these estimations. In what follows we will further examine ADL(1,4) specification.[35]

Table 4. Results with a few traditional panel data estimators.

Indep. variables below.[1] Method:[2]	OLS			WG			2SLS (AH) [9]		
Dependent variable: $\ln(TFP)_t$	Est.	St. dev.		Est.	St. dev.		Est.	St. dev.	
$\ln(TFP)_{t-1}$	.9609	.0072	***	.8356	.0221	***	.8165	.0478	***
$\ln(R\&D)_t$	.0020	.0078		-.0129	.0088		-.0220	.0124	*
$\ln(R\&D)_{t-1}$	.0060	.0096		.0051	.0092		.0087	.0093	
$\ln(R\&D)_{t-2}$	-.0062	.0132		-.0054	.0132		-.0098	.0136	
$\ln(R\&D)_{t-3}$	-.0102	.0125		-.0106	.0119		-.0104	.0115	
$\ln(R\&D)_{t-4}$	.0271	.0132	**	.0242	.0122	**	.0224	.0125	*
$\ln(R\&D)_{t-5}$	-.0118	.0128		-.0093	.0115		-.0133	.0112	
$\ln(R\&D)_{t-6}$	-.0044	.0071		-.0035	.0072		-.0019	.0076	
Transformation:	None			Within groups			First differences		
R-squared:	.9725			.8053			–		
No. of observations:	1,793			1,793			1,672		
No. of parameters:	27			147 [8]			26		
No. of individuals:	121			121			121		
Longest time series:	19			19			18		
Shortest time series:	5			5			4		
Joint significance of regressors:[3]	44,990.0	(8)	***	1,906.0	(8)	***	363.9	(8)	***
Joint significance of dummies:[4]	300.0	(19)	***	277.8	(18)	***	275.3	(18)	***
Joint signif. of time dummies:[5]	271.4	(18)	***	277.8	(18)	***	275.3	(18)	***
First-order autocorrelation:[6]	1.5	N(0,1)		1.3	N(0,1)		-5.2	N(0,1)	***
Second-order autocorrelation:[7]	-1.2	N(0,1)		-1.8	N(0,1)		-1.0	N(0,1)	

Note: Computations with Ox 2.10 (see Doornik, 1999) and DPD 1.00a (Doornik et al., 1999).

[1] A constant term and time dummies included in every estimation.

[2] Standard errors and test statistics are based on White heteroskedasticity consistent covariance matrices. Notions ***, **, and * refer to significance at 1, 5, and 10% levels.

[3] Joint significance of regressors excluding the constant term and time dummies (a χ^2-distributed Wald test; degrees of freedom in the parenthesis). A low p-value suggests that the null hypothesis of regressors being zero should be rejected.

[4] Joint significance of the constant term and dummies (a χ^2-distributed Wald test; degrees of freedom in the parenthesis). A low p-value suggests that the null hypothesis of the constant term and dummies being zero should be rejected.

[5] Joint significance of dummies excluding the constant term (a χ^2-distributed Wald test; degrees of freedom in the parenthesis). A low p-value suggests that the null hypothesis of dummies being zero should be rejected.

[6] Arellano and Bond (1991) test for first-order serial correlation. Based on standardized average residual autocovariances. As indicated, asymptotically distributed N(0,1) under the null of no serial correlation. A low p-value suggests that first-order serial correlation exists.

[7] Arellano and Bond (1991) test for second-order serial correlation. See above note.

[8] Includes the dummies implied by the within group transformation.

[9] Anderson and Hsiao (1982) instrumental variables estimator. Lagged dependent variable is being instrument by its second and third lagged levels; other variables instrumented by themselves, which suggests that R&D is assumed to be strictly exogenous. Note that due to the transformation we expect to find first-order serial correlation in the transformed error term.

As the title of this section suggests, DPD-DIF and DPD-SYS discussed above are efficient in the sense that they, in principle, exploit the maximum number of moment conditions under certain conditions. In practice, the number of orthogonality conditions may have to be limited not only for computational but also for theoretical reasons (see above).

In a sense the simplest overidentifying instrument set for a DPD-type estimation would be the same as the one used in implementing the Anderson and Hsiao (1982) estimator in Table 4:[36] this is equivalent to assuming that the original error term follows MA(0) process, and that R&D is strictly exogenous. Unfortunately, Sargan test for overidentifying restrictions in Table 5 (left) rejects the null hypothesis of instruments being valid.

Table 5. DPD-DIF estimates of an ADL(1,4) R&D–productivity model.

Indep. variables below. Method:	DPD-DIF (1-step)			DPD-DIF (1-step)			DPD-DIF (1-step)		
Dependent variable: $\Delta\ln(TFP)_t$	Est.	St. dev.		Est.	St. dev.		Est.	St. dev.	
$\Delta\ln(TFP)_{t-1}$	.7975	.0376	***	.7843	.0368	***	.7657	.0413	***
$\Delta\ln(R\&D)_t$	-.0170	.0105		-.0993	.0463	**	-.0703	.0378	*
$\Delta\ln(R\&D)_{t-1}$	.0105	.0081		.0260	.0124	**	-.0281	.0412	
$\Delta\ln(R\&D)_{t-2}$	-.0081	.0127		-.0184	.0139		-.0022	.0135	
$\Delta\ln(R\&D)_{t-3}$	-.0086	.0096		-.0196	.0119	*	-.0247	.0126	*
$\Delta\ln(R\&D)_{t-4}$	.0122	.0077		.0140	.0083	*	.0078	.0106	
No. of observations:	1,793			1,793			1,793		
No. of parameters:	25			25			25		
No. of individuals:	121			121			121		
Longest time series:	19			19			19		
Shortest time series:	5			5			5		
Joint significance of regressors:	500.6	(6)	***	483.1	(6)	***	401.6	(6)	***
Joint significance of dummies:	281.1	(19)	***	262.7	(19)	***	305.1	(19)	***
Joint signif. of time dummies:	281.1	(19)	***	262.7	(19)	***	305.1	(19)	***
First-order autocorrelation:	-4.9	N(0,1)	***	-4.9	N(0,1)	***	-4.8	N(0,1)	***
Second-order autocorrelation:	-1.3	N(0,1)		-1.2	N(0,1)		-1.2	N(0,1)	
Sargan test of overid. Restr.[1]	57.1	(38)	**	83.7	(75)		81.2	(74)	
Differenced Sargan test.[2]	–			2.5	(1)		–		

Note: Computations with Ox 2.10 (see Doornik, 1999) and DPD 1.00a (Doornik et al., 1999).
[1] Sargan test (also known as Hansen or J test) tests the validity of overidentifying restrictions, i.e., whether the instruments used in a GMM estimation are jointly valid (H0) or not (H1). Based on the idea that if the orthogonality conditions were true, their sample analogs should be reasonably close to zero. The test is χ^2-distributed with the degrees of freedom equal to the number of columns in the instrument matrix minus the number of parameters. Robust to heteroskedasticity only in 2-step estimations (reported).
[2] Differenced Sargan test can be used to test a nested hypothesis concerning the validity of some instrument(s). The full set of instruments under H0 is tested against a strict subset under H1. The χ^2-distributed test statistic and its degrees of freedom are equal to the differences between the usual Sargan tests under H0 and H1. In this particular case, we test the validity of the H0 of R&D being predetermined against H1 of R&D being endogenous.

The middle section of Table 5 uses the assumptions of MA(0) and R&D being predetermined instead; TFP is instrumented with its second through fifth lagged levels, and R&D is instrumented with first through fifth lagged differences. Sargan test suggests that the instrument set is fine.

The rightmost estimation in Table 5 in done under the assumption of MA(0) and R&D being endogenous. Comparing this to the middle column and performing a differenced Sargan test leads to the acceptance of the null hypothesis of R&D being predetermined. Since in none of the estimations the test statistics of serial correlation suggest anything but MA(0) in the untransformed error term, we accept this hypothesis.

The problem with the estimations in Table 5 is that they impose somewhat implausible long-run properties. In fact, they would seem to suggest that the elasticity of productivity with respect to R&D is negative! As discussed above, in our case the DPD-SYS estimator could offer significant improvements in efficiency since the coefficient of the lagged dependent variable is fairly close to one.

In Table 6 we use the DPD-SYS estimator to obtain results for the model discussed above. For the first-difference equations, we use the same instrument set as in the 2SLS estimation in Table 4 and in the first DPD-DIF estimation of Table 5. Note that as far as R&D is concerned, we can maintain the same instrument set also for the level equations; the lagged dependent variable in the level equations is instrumented by its lagged first difference.

The use of the level (Table 6) information seem to be somewhat problematic, although the test statistics do not suggest particular problems with the DPD-SYS specification at 5% level. To some extent this is expected, as levels are not strictly comparable across cross-sectional units. Only the level equations seem to have reasonable long-run properties: DIF-SYS estimates suggest that the long-run elasticity of TFP with respect to R&D is roughly .07. Only the data generation process of TFP is close to random walk.[37] Thus, we would expect that the introduction of the level equations would mainly improve the coefficient estimates of the lagged dependent variable.

Table 6. DPD-SYS estimates of an ADL(1,4) R&D–productivity model.

Indep. variables below. Method:	DPD-SYS (1-step)		DPD-SYS (2-step)	
Dependent variable: ln(*TFP*)$_t$	Est.	St. dev.	Est.	St. dev.
ln(*TFP*)$_{t-1}$	.8762	.0382 ***	.8719	.0095 ***
ln(*R&D*)$_t$	-.1307	.0681 *	-.1295	.0192 ***
ln(*R&D*)$_{t-1}$	.1224	.0564 **	.1166	.0176 ***
ln(*R&D*)$_{t-2}$	-.0139	.0123	-.0082	.0061
ln(*R&D*)$_{t-3}$	-.0053	.0133	-.0057	.0054
ln(*R&D*)$_{t-4}$	.0360	.0189 *	.0352	.0055 ***
No. of observations:	1,914		1,914	
No. of parameters:	26		26	
No. of individuals:	121		121	
Longest time series:	19		19	
Shortest time series:	5		5	
Joint significance of regressors:	3,832.0	(6) ***	2,770.0	(6) ***
Joint significance of dummies:	266.2	(20) ***	1,183.0	(20) ***
Joint signif. of time dummies:	264.6	(19) ***	1,169.0	(19) ***
First-order autocorrelation:	-5.5	N(0,1) ***	-5.2	N(0,1) ***
Second-order autocorrelation:	-1.4	N(0,1)	-1.4	N(0,1)
Sargan test of overid. Restr.	–		75.6	(60) *
Differenced Sargan test:	–		17.1	(23)

Note: Computations with Ox 2.10 (see Doornik, 1999) and DPD 1.00a (Doornik et al., 1999). In this case the differenced Sargan test refers to the test of level instruments, i.e., DPD-SYS results are tested against the results obtained with otherwise similar DPD-DIF specification (H0: additional assumptions of the DPD-SYS estimator are satisfied).

Stability of Parameters across Time

Several authors (for discussion see, e.g., Englander et al., 1988) have suggested that the lag structure and the effects of R&D on productivity may be "… highly variable, both in timing and magnitude…" (Griliches & Mairesse, 1984, p. 369). Below we will shed some light to the 'timing & magnitude' issue in our context.

Since the asymptotic properties of DPD-style estimators depend on $N \longrightarrow \infty$, results can be derived for arbitrarily short time periods, provided that the appropriate transformations can be made and the dependent variables can be instrumented. This idea is clearly demonstrated in the Panel VAR approach of Holtz-Eakin *et al.* (1988), who even suggest for allowing nonstationary individual effects. With the first-difference transformation and a DPD-style estimator, a minimum of three observations across time is needed.[38] Due to the measurement problems associated with the dependent variable and expected lengthy lags in responses, however, one should be cautious in using short periods while estimating R&D–productivity models.

In Table 7 we re-estimate the model across a few subsamples and perform F-tests to see whether any of the subsample coefficients appear to be different from those estimated for the full sample (Table 6). The results suggest that the coefficients for the third and fourth lags of R&D in the 1985–97 sample may be different from those obtained with the full sample. Also the long-run dynamics of the model are quite different in this subsample; the long-run elasticity of productivity with respect to R&D is near zero.

Table 7. DPD-SYS subsample estimates of an ADL(1,4) R&D–productivity model.

Indep. variables below. Method:	DPD-SYS (1-step)			DPD-SYS (1-step)			DPD-SYS (1-step)		
Dependent variable: $\ln(TFP)_t$	Est.	St. dev.	F [1]	Est.	St. dev.	F [1]	Est.	St. dev.	F [1]
$\ln(TFP)_{t-1}$	.8154	.0651 ***	.9	.8810	.0589 ***	.0	.9574	.0630 ***	1.7
$\ln(R\&D)_t$	-.0392	.1041	.8	-.1906	.0733 ***	.7	-.2817	.1211 **	1.6
$\ln(R\&D)_{t-1}$	.0703	.0946	.3	.1595	.0621 ***	.4	.1948	.0972 **	.6
$\ln(R\&D)_{t-2}$	-.0210	.0160	.2	-.0204	.0201	.1	.0251	.0385	1.0
$\ln(R\&D)_{t-3}$	.0003	.0164	.1	.0280	.0256	1.7	-.0513	.0216 **	4.6
$\ln(R\&D)_{t-4}$	.0024	.0276	1.5	.0324	.0204	.0	.1133	.0361 ***	4.6
First year in the sample:	1973			1979			1985		
First usable observation:[2]	1979			1985			1991		
Last year in the sample:	1985			1991			1997		
No. of observations:	883			916			565		
No. of parameters:	14			14			14		
No. of individuals:	111			121			114		
Longest time series:	7			7			7		
Shortest time series:	2			1			1		
Joint significance of regressors:	2236.0	(6) ***		4422.0	(6) ***		2767.0	(6) ***	
Joint significance of dummies:	115.3	(8) ***		81.9	(8) ***		75.9	(8) ***	
Joint signif. of time dummies:	115.1	(7) ***		54.5	(7) ***		75.3	(7) ***	
First-order autocorrelation:	-3.5	N(0,1) ***		-5.0	N(0,1) ***		-5.1	N(0,1) ***	
Second-order autocorrelation:	-0.8	N(0,1)		-0.5	N(0,1)		-0.8	N(0,1)	
Sargan test of overid. Restr.	29.7	(24)		40.4	(24) **		56.9	(24) **	

Note: Computations with Ox 2.10 (see Doornik, 1999) and DPD 1.00a (Doornik et al., 1999).
[1] F-test as discussed in Greene (1993, p. 208) Critical values for $F(1,\infty)$: 3.84 (5%), 6.63 (1%).
[2] A few observations are being lost due to transformations, lags, and instrumentation.

It is rather alarming that we do not get significant results in the two first subsamples of Table 7. Obviously degrees of freedom are being lost by slicing the data, but due to the asymptotic properties of the estimator reduction in the degrees of freedom alone should not drive this finding.

Rather than slicing the data across time, let us consider estimating separate coefficient estimates for some years and testing whether these are statistically significantly different from those of the full sample. Two alternatives are considered in Table 8: first, estimating separate coefficients for R&D variables alone; second, estimating separate coefficients for TFP and R&D variables. A time window of five years as well as each year separately are being considered.[39]

Table 8. DPD-SYS estimates of an ADL(1,4) R&D–productivity model with separate coefficient estimates for selected time periods.

Separate coefficients estimated for the following year(s):	Wald tests with 5 degrees of freedom (H0: R&D coefficients for the specified period do not differ from those of the whole sample)	Wald tests with 6 degrees of freedom (H0: TFP and R&D coefficients for the specified period do not differ from those of the whole sample)
1980–4	11.93 **	14.78 **
1981–5	12.49 **	13.68 **
1982–6	7.35	17.46 ***
1983–7	15.21 ***	26.73 ***
1984–8	13.11 **	12.35 *
1985–9	9.53 *	18.23 ***
1986–90	10.58 *	15.14 **
1987–91	14.11 **	18.50 ***
1988–92	6.51	32.09 ***
1989–93	4.82	8.31
1990–4	11.41 **	12.93 **
1991–5	8.28	13.07 **
1992–6	9.07	16.66 **
1993–7	6.06	7.31
1980	4.16	5.64
1981	2.74	0.41
1982	16.21 ***	15.30 **
1983	4.30	3.86
1984	7.54	13.37 **
1985	11.41 **	12.65 **
1986	2.66	4.93
1987	5.47	0.28
1988	5.42	1.86
1989	5.33	0.77
1990	6.98	1.67
1991	3.35	3.12
1992	2.38	15.44 **
1993	8.25	5.72
1994	20.56 ***	23.80 ***
1995	2.42	4.96

Note: DPD98 (ver. 30/12/98 in Gauss-386i 3.2.13, Arellano & Bond, 1998) is used for computations.

Wald tests are being performed for the joint significance of the time dummy interacted explanatory variables. Thus, the null hypothesis is, that the coefficients estimated for the specified period are not different from those obtained for the full sample.

The results suggest considerable turbulence in coefficient estimates across time: years 1982, 1985, and 1994 seem to be among the most turbulent ones as far as R&D–productivity dynamics are concerned. The five-year window estimates are obviously influence by these 'outlier' years. As such, we can not confirm whether there was 'dry holes' or periods of reduced potency of R&D during the sample period. We can, however, say that there is some indication the relationship may be varying significantly in timing and magnitude and that our findings are not inconsistent with the existence of 'dry holes'. Unfortunately we can not quantify to what extend these results may be driven by the shortcomings of the productivity measure.

SPILLOVERS

In a companion essay (Rouvinen, 1999), we discuss R&D spillovers quite extensively. As discussed above, we do not interpret our aggregate shock measure as suggested in the Caballero & Lyons (1989; 1990; 1992) tradition.[40]

Below we re-estimate our basic model in Table 6 with additional explanatory variables, namely measures of aggregative shocks (or productive spillovers) and domestic inter-industry R&D spillovers. We assume that respective lag lengths of aggregate shocks and R&D spillovers correspond, respectively, to those of TFP and R&D in the basic model. Since both of these measures should be strictly exogenous from the point of view of the representative industry, we estimate both variables by themselves. Results appear in Table 9: we consider adding the aggregate shock measure alone (left), the R&D spillover measure alone (middle), and the two together (right).

In all of the three specifications the long-run elasticity of TFP with respect to R&D is roughly .06, and the coefficient estimates remain similar to those of the basic model. The coefficients of aggregate shocks are highly significant and suggest that TFP is quite elastic with respect to them: the leftmost (rightmost) estimates suggest an elasticity of .38 (.56). R&D spillover coefficients are typically not significant and the elasticities of TFP with respect to them remain low (negative in the rightmost specification).

Table 9. DPD-SYS estimates of an ADL(1,4) R&D–productivity model with additional measures for aggregate shocks and domestic inter-industry R&D spillovers.

Indep. variables below. Method:	DPD-SYS (1-step)			DPD-SYS (1-step)			DPD-SYS (1-step)		
Dependent variable: $\ln(TFP)_t$	Est.	St. dev.		Est.	St. dev.		Est.	St. dev.	
$\ln(TFP)_{t-1}$	.8764	.0427	***	.8845	.0382	***	.8722	.0422	***
$\ln(R\&D)_t$	-.1403	.0712	**	-.1405	.0691	**	-.1594	.0743	**
$\ln(R\&D)_{t-1}$	.1319	.0583	**	.1304	.0570	**	.1472	.0603	**
$\ln(R\&D)_{t-2}$	-.0141	.0111		-.0137	.0124		-.0143	.0117	
$\ln(R\&D)_{t-3}$	-.0073	.0134		-.0055	.0135		-.0073	.0141	
$\ln(R\&D)_{t-4}$	.0369	.0195	*	.0367	.0189	*	.0416	.0210	**
$\ln(Aggr.\ shock)_t$	.5500	.0742	***	–			.5530	.0765	***
$\ln(Aggr.\ shock)_{t-1}$	-.5032	.0711	***	–			-.4817	.0728	***
$\ln(Inter\text{-}ind.\ spillovers)_t$	–			.1138	.0538	**	.0861	.0558	
$\ln(Inter\text{-}ind.\ spillovers)_{t-1}$	–			-.1344	.0715	*	-.0824	.0699	
$\ln(Inter\text{-}ind.\ spillovers)_{t-2}$	–			-.0089	.0574		.0120	.0586	
$\ln(Inter\text{-}ind.\ spillovers)_{t-3}$	–			.0342	.0550		-.0185	.0554	
$\ln(Inter\text{-}ind.\ spillovers)_{t-4}$	–			-.0031	.0293		.0000	.0283	
No. of observations:	1,914			1,914			1,914		
No. of parameters:	28			31			33		
No. of individuals:	121			121			121		
Longest time series:	19			19			19		
Shortest time series:	5			5			5		
Joint significance of regressors:	6,815.0	(8)	***	7,095.0	(11)	***	7,541.0	(13)	***
Joint significance of dummies:	74.3	(20)	***	221.9	(20)	***	62.6	(20)	***
Joint signif. of time dummies:	69.4	(19)	***	214.1	(19)	***	60.3	(19)	***
First-order autocorrelation:	-5.8	N(0,1)	***	-5.6	N(0,1)	***	-5.8	N(0,1)	***
Second-order autocorrelation:	-1.1	N(0,1)		-1.4	N(0,1)		-1.1	N(0,1)	
Sargan test of overid. restr.	64.6	(60)		77.1	(60)	*	65.3	(60)	

Note: Computations with Ox 2.10 (see Doornik, 1999) and DPD 1.00a (Doornik et al., 1999).

Conclusion

In light of the results derived above, we can conclude that R&D indeed Granger causes TFP, but not *vice versa*. At shorter lag lengths there were some ambiguity on the causality tests, but overall evidence is quite solid. This is comforting, especially since this is frequently taken for granted.

Productivity seems to respond to changes in R&D expenditure at a considerable lag. We include annual lags of R&D up to four in our ADL(1,4) specification: in most cases the fourth lag is significant at conventional levels and frequently the coefficient estimate value of the fourth lag is the highest as far as R&D is concerned (see, e.g., the leftmost results in Table 9). Our findings suggest that perpetual inventory method R&D capital stock and R&D-intensity approaches to productivity analysis, frequently applied in the literature, may have to be reconsidered.

The answer to the question on whether the potency of R&D vary in timing and magnitude is a solid 'yes'. We can not, however, identify clear points of structural change in the R&D–productivity dynamics; nor can we single-handedly argue that there would have been 'dry holes' or periods of reduces potency of R&D during the sample period.[41]

Our analysis of aggregate shocks (or productive spillovers) and R&D spillovers is perhaps somewhat superficial, but we can nevertheless conclude that adding these variables either jointly or separately seem to have minor influence on the long-run properties of our R&D–productivity model. The elasticity of TFP with respect to aggregate shocks, as proxied by the TFP in other manufacturing industries besides the representative one, seem to high and statistically significant. R&D spillovers, as proxied by domestic R&D efforts in other manufacturing industries besides the representative one, seem be redundant in our specification. This finding may, however, be driven by the fact that all of our estimations include time dummies which may in part capture externalities related to scientific and R&D efforts outside the representative industry.[42]

Can our findings be 'a figment of specification error' (a quote from the title of Basu & Fernald, 1995)? Our evidence is not solid enough to single-handedly rule out this possibility. We argue that our inability to get solid evidence across the board is rather related the sample size and measurement problems. Further analysis is nevertheless needed. In our own further work we will firm data to study the issue. Methodologically error correction specifications and distributed lag models with explicit parameter restrictions may be alternative the approach chosen here.

ENDNOTES

[1] Conventionally measured, total factor productivity (TFP), also called technological progress or economic growth in some contexts., is essentially the residual of a Solow (1956; 1970; 1957) model.

[2] Either the current or the one-year lags of the constructed R&D stocks are used as regressors.

[3] The R&D-investment intensity rather than variables derived from R&D stock measures are considered.

[4] One should note that profits and productivity are related, but nevertheless different, concepts.

[5] Griliches & Mairesse (1984) have suggested that the potency of R&D may vary considerably across time.

[6] We will, however, reverse the scaling in order to keep left- and right-hand side variables comparable. The two parameters in the denominator of the left-hand side variable are defined as discussed in OECD (1999, pp. 50–2)

[7] The data set, and the Stata (StataCorp, 1999) procedure used to create it, is available upon request.

[8] Note that ISIC division 38 is a sum of 381, 382, 383, 384, and 385. With the exception of two countries, however, one or more of the subdivisions of 38 are not available. Thus, including division 38 is justified as it provides additional information.

[9] Thus Ireland and Spain are excluded from the analysis.

[10] TFP figures were unavailable.

[11] In what follows *West Germany* will be referred to as *Germany*.

[12] Canada, Denmark, Finland, France, Germany, Italy, Japan, The Netherlands, Norway, Sweden, The United Kingdom, and The United States.

[13] The period covered in the current version of ANBERD.

[14] This is the index number approach, the other main alternative being the factor demand approach (for extensive discussion see Good, Nadiri, & Sickles, 1996, see also Handbook of Applied Econometrics (Vol. II) by Pesaran & Schmidt (eds.)).

[15] We proceed this way in order to get a series that is comparable with our TFP measure. As far as the choice of deflators and exchange rates are concerned, we treat R&D investment as we would treat physical capital investment.

[16] This measure has also been debated in the now rather extensive discussion in the Caballero and Lyons (1989; 1990; 1992) tradition of *productive spillovers* (for critique see, e.g., Basu &

Fernald, 1995). Note that we do not suggest the same interpretation of aggregate productivity as studies in the Caballero and Lyons tradition.

[17] Units of measurement as above. Both variables in natural logs.

[18] Unless otherwise mentioned, we draw from the discussion in Chapter 8 of Johnston and DiNardo's (1997).

[19] Similarly for a general ADL(*p*,*q*).

[20] In the presence of a constant term this would hold by construction with most reasonable panel data estimators.

[21] Note that in the presence of the lagged dependent variable as one of the regressors the model is not defined at $t=1$. Also note that no assumptions on the form of heteroskedasticity are being made.

[22] Having $\alpha_1 = 1$ would indicate that the dependent variables follows random walk, i.e., had an unit root.

[23] We are referring to the within groups (WG, also known as least squares dummy variable, fixed effects, and covariance), between groups, and random effects estimators.

[24] See Baltagi (1995, pp. 125-6) for a brief discussion on the problems in OLS and classic panel data estimators. Note that if an OLS estimator is used, a large realization of the lagged dependent variable suggests that the individual effect may be large, i.e., $E(y_{i,t-1}, \eta_i) > 0$. Thus, $\hat{\alpha}_1^{OLS}$ is upwardly biased. The within groups estimator introduces a different bias. The estimator can be implemented via the 'within' transformation, which in turn means that $\tilde{y}_{i,t-1} = y_{i,t-1} - \frac{1}{T_i}(y_{i,1}, \cdots, y_{i,t}, \cdots, y_{i,T_i})$ and $\tilde{\upsilon}_{i,t} = \upsilon_{i,t} - \frac{1}{T_i}(\upsilon_{i,1}, \cdots, \upsilon_{i,t-1}, \cdots, \upsilon_{i,T_i})$. It is immediately obvious that $E(\tilde{y}_{i,t-1}, \tilde{\upsilon}_{i,t}) < 0$. Thus, $\hat{\alpha}_1^{WG}$ is downwardly biased. The asymptotic biases in $\hat{\alpha}_1^{OLS}$ and $\hat{\alpha}_1^{WG}$ provide a convenient way to check the estimates of asymptotically unbiased estimators.

[25] See Hsiao (1986, Chapter 4) for discussion on ML estimators in panel data contexts.

[26] There are obviously a number of transformations that would get rid of the η_i; first differences is, however, widely used and convenient. Furthermore, it turns out that the actual choice of transformation has minor or no effect on the results (Arellano & Bover, 1995).

[27] Note that $\upsilon_{i,t} - \upsilon_{i,t-1}$ follows MA(1) process with a unit root.

[28] While either levels or differences qualify as instruments here, using differences will cause us to loose an additional observation. Furthermore, Arellano (1989) convincingly shows that levels are more appropriate instruments in this context.

[29] For discussion see Baltagi (1995, p. 126).

[30] See Baltagi (1995, pp. 126-32) for a textbook presentation.

[31] Optimal in the sense that the estimator exploits all **linear** orthogonality conditions in the absence of outside instruments. In a balanced sample, there are $\frac{(T-1)(T-2)}{2}$ of these orthogonality conditions.

[32] In case of $\Delta y_{i,t-1}$ (for $t \geq 3$), $Z_i = \begin{bmatrix} y_{i,1} & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & y_{i,1} & y_{i,2} & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & y_{i,1} & y_{i,2} & \cdots & y_{i,T_i-2} \end{bmatrix}$. The available instruments for $\Delta x_{i,t}$ will depend on whether x is strictly exogenous (all past, current, and

future values qualify as instruments), predetermined (past values qualify as instruments), or endogenous (available instrument set is similar to Z_i defined in this footnote, i.e., lags from $t-2$ on qualify as instruments).

[33] The panel VAR estimator, a 3SLS estimator on a system of equations, can be regarded as a special case of the GMM estimator used here. As compared to panel VAR, the standard form of the estimator used here imposes a stationary restriction on coefficients across time, assumes that the individual effect is time stationary, and exploits a larger instrument set.

[34] Granger non-causality in necessary for strict exogeneity.

[35] Also our 'general-to-specific' tests with the DPD-DIF estimator, starting from ADL(1,9) and working our way down towards ADL(1,1), suggesting that ADL(1,4) specification may be the most appropriate one.

[36] In this case the only improvement over the AH estimator would be the fact that the DPD-type estimators account for the peculiar properties of the transformed error term.

[37] If R&D would be the dependent variable in a specification such as Equation (5), $\hat{\alpha}_1$ would typically be less than 0.3.

[38] Assuming that the regressors include the lagged dependent variable and overall there are no lags beyond the first in the model, and that the untransformed error follows ARMA(0,0) process. This does not mean that we could calculate all the desired test statistics, e.g., Wald tests for serial correlation, with so few time-series observations.

[39] We will not consider years 1996 and 1997 separately due to the low number of observations.

[40] Note that also our construction of the measure is different: we calculate productivity in the **other** manufacturing industries besides the representative one.

[41] We choose not to discuss problems of productivity measurement here.

[42] Time dummies may be regarded as a measure for overall technological development, at least as far as country and industries are symmetrically influenced by them.

APPENDIX A. DESCRIPTIVE STATISTICS, COUNTRY AND INDUSTRY CODES.

Table 10. Sample descriptive statistics.

Variable	Number of obs.	Mean	St. dev.	Minimum	Maximum
Cross-section identifier	2519	–	–	1	121
Country code	2519	–	–	1	12
Industry code	2519	–	–	1	14
Observation year	2519	–	–	1973	1997
ln(TFP), scaling reversed	2519	7.01	0.36	5.01	7.99
ln(R&D), 1990 p., gfcf ppp ex. rates	2519	18.59	2.46	11.92	25.04
Aggr. shock: ln(other manuf. TFP)	2519	7.02	0.23	6.38	7.48
Spillovers: ln(manuf. R&D)–ln(R&D)	2519	21.90	1.75	18.06	25.26

Note: Country and industry codes are documented in Table 11 below.

Table 11. Country and industry codes.

Country code	Explanation
1	Canada
2	Denmark
3	Finland
4	France
5	West Germany
6	Italy
7	Japan
8	The Netherlands
9	Norway
10	Sweden
11	The United Kingdom
12	The United States
Industry code	**Explanation**
1	Food, beverages and tobacco
2	Textiles, wearing apparel and leather industries
3	Wood, and wood products, including furniture
4	Paper, and paper products, printing and publishing
5	Chemicals and chemical petroleum, coal, rubber and plastic products
6	Non-metallic mineral products except products of petroleum and coal
7	Basic metal industries
8	Fabricated metal products, machinery and equipment
9	Fabricated metal products, except machinery and equipment
10	Machinery except electrical
11	Professional, scientific, measuring and controlling equipment n.e.c.
12	Electrical machinery apparatus, appliances and supplies
13	Transport equipment
14	Other manufacturing industries

Note: Table 1 above gives additional information on the industrial classification used.

REFERENCES

Ahn, S. C., & Schmidt, P. (1995). Efficient Estimation of Models for Dynamic Panel Data. *Journal of Econometrics, 68*(1), 5-27.

Anderson, T. W., & Hsiao, C. (1981). Estimation of Dynamic Models with Error Components. *Journal of the American Statistical Association: Theory and Methods Section, 78*(375), 598-606.

Anderson, T. W., & Hsiao, C. (1982). Formulation and Estimation of Dynamic Models Using Panel Data. *Journal of Econometrics, 18*, 47-82.

Arellano, M. (1989). A Note on the Anderson-Hsiao Estimator for Panel Data. *Economics Letters, 31*, 337-341.

Arellano, M., & Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies, 58*(2), 277-297.

Arellano, M., & Bond, S. R. (1998). Dynamic Panel Data Estimation Using DPD98 for Gauss: A Guide for Users, *mimeo* . London: Institute of Fiscal Studies.

Arellano, M., & Bover, O. (1995). Another Look at the Instrumental Variables Estimation of Error-Components Models. *Journal of Econometrics, 68*(1), 29-51.

Baltagi, B. H. (1995). *Econometric Analysis of Panel Data*. Chichester, England: John Wiley & Sons Ltd.

Basu, S., & Fernald, J. G. (1995). Are Apparent Productive Spillovers a Figment of Specification Error?, *NBER Working Paper* (No. 5073). National Bureau of Economic Research, Cambridge, Massachusetts.

Blundell, R., & Bond, S. R. (1998). Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of Econometrics, 87*(1), 115-143.

Caballero, R. J., & Lyons, R. K. (1989). The Role of External Economies in U.S. Manufacturing, *NBER Working Paper* (No. 3033). Cambridge, Massachusetts: National Bureau of Economic Research.

Caballero, R. J., & Lyons, R. K. (1990). Internal Versus External Economies in European Industry. *European Economic Review, 34*, 805-830.

Caballero, R. J., & Lyons, R. K. (1992). External Effects in U.S. Procyclical Productivity. *Journal of Monetary Economics, 29*, 209-225.

Cobb, C., & Douglas, P. H. (1928). A Theory of Production. *American Economic Review, Supplement to Vol. 18*, 139-165.

Doornik, J. A. (1999). *Object-Oriented Matrix Programming Using Ox*. (3 ed.). London: Timberlake Consultants Press and Oxford: www.nuff.ox.ac.uk/Users/Doornik.

Doornik, J. A., Arellano, M., & Bond, S. R. (1999). Panel Data Estimation Using DPD for Ox. Oxford: www.nuff.ox.ac.uk/Users/Doornik.

Englander, S. A., Evenson, R., & Hanazaki, M. (1988). R&D, Innovation and the Total Factor Productivity Slowdown. *OECD Economic Studies, 11*(Autumn), 7-42.

Freeman, C., & Perez, C. (1988). A Taxonomy of Innovations. In G. Dosi & e. al (Eds.), *Technical Change and Economic Theory* : Columbia University Press.

Good, D. H., Nadiri, I. M., & Sickles, R. C. (1996). Index Number and Factor Demand Approaches to the Estimation of Productivity, *NBER Working Paper* (No. 5790). Cambridge, Massachusetts: National Bureau of Economic Research.

Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica, 37*(3), 424-438.

Greene, W. H. (1993). *Econometric Analysis*. (2 ed.). New York, NY: Macmillan Publishing Company.

Griliches, Z. (1992). The Search for R&D Spillovers. *Scandinavian Journal of Economics, 94*(Supplement), 29-47.

Griliches, Z. (1995). R&D and Productivity: Econometric Results and Measurement Issues. In P. Stoneman (Ed.), *Handbook of the Economics of Innovation and Technological Change* (pp. 52-89). Cambridge, Massachusetts: Basil Blackwell Ltd.

Griliches, Z., & Mairesse, J. (1984). Productivity and R&D at the Firm Level. In Z. Griliches (Ed.), *R&D, Patents and Productivity* (pp. 339-374). Chicago: University of Chicago Press.

Hall, B. H., Mairesse, J., Branstetter, L., & Crépon, B. (1998). Does Cash Flow Cause Investment and R&D: An Exploration Using Panel Data for French, Japanese, and United States Scientific Firms, *IFS Working Paper Series* (No. W98/11). London: The Institute for Fiscal Studies.

Hansen, L. P. (1982). Large Sample Properties of Generalized Method of Moments Estimators. *Econometrica, 50*(4), 1029-1054.

Holtz-Eakin, D., Newey, W., & Rosen, H. S. (1988). Estimating Vector Autoregressions with Panel Data. *Econometrica, 56*(6), 1371-1395.

Hsiao, C. (1986). *Analysis of Panel Data*. New York, NY: Cambridge University Press.

Johnston, J., & DiNardo, J. (1997). *Econometric Methods*. (4 ed.). United States: McGraw-Hill, Inc.

Mohnen, P. A. (1990). New Technologies and Interindustry Spillovers. *STI review*(7), 131-147.

Mohnen, P. A. (1996). R&D Externalities and Productivity Growth. *STI review*(18), 39-66.

Nadiri, I. M. (1993). Innovation and Technological Spillovers, *NBER Working Paper* (No. 4423). Cambridge, Massachusetts: National Bureau of Economic Research.

OECD. (1998). *ANBERD/ANRSE Research and Development in Industry: Expenditure and Researchers, Scientists and Engineers* (on diskette database user guide). Paris: Organisation for Economic Co-operation and Development / Directorate for Science, Technology and Industry.

OECD. (1999). *ISDB 98: International Sectoral Database* (on diskette database user guide). Paris: Organisation for Economic Co-operation and Development / Statistics Directorate.

Park, W. G. (1995). International R&D Spillovers and OECD Economic Growth. *Economic Inquiry, 33*(4), 571-591.

Phillips, P. C. B., & Loretan, M. (1991). Estimating Long-Run Economic Equilibria. *Review of Economic Studies, 58*, 407-436.

Ravenscraft, D., & Scherer, F. M. (1982). The Lag Structure of Returns to R&D. *Applied Economics, 14*, 603-620.

Rouvinen, P. M. (1999). R&D Spillovers among Finnish Manufacturing Firms: A Cost Function Estimation with Random Coefficients, *ETLA Discussion Papers* (No. 686). Helsinki, Finland: ETLA, Elinkeinoelämän Tutkimuslaitos, The Research Institute of the Finnish Economy.

Solow, R. (1956). A Contribution to the Theory of Economic Growth. *Quarterly Journal of Economics*, *70*, 65-94.

Solow, R. (1970). *Growth Theory*. New York, NY: Oxford University Press.

Solow, R. M. (1957). Technical Change and the Aggregate Production Function. *Review of Economics and Statistics*, *39*, 312-320.

StataCorp. (1999). *Stata Statistical Software: Release 6.0* (software manual). College Station, TX: Stata Corporation.

Sterlacchini, A. (1989). R&D, innovations, and total factor productivity growth in British manufacturing. *Applied Economics, 21*.

Strauss, J., & Ferris, M. E. (1996). A Dynamic Estimation of World Productivity Growth. *Applied Economics*, *28*, 195-202.

UN. (1968). International Standard Industrial Classification for all Economic Activity (ISIC), *Statistical papers, series M, No. 4, revision 2* . New York, NY: Department of Economic and Social Affairs, Statistical Office of the United Nations.

White, H. (1980). A Heteroscedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroscedasticity. *Econometrica, 48*, 817-838.

White, H. (1982). Instrumental Variables Regression with Independent Observations. *Econometrica*, *50*(2), 483-500.

E L I N K E I N O E L Ä M Ä N   T U T K I M U S L A I T O S (ETLA)
THE RESEARCH INSTITUTE OF THE FINNISH ECONOMY
LÖNNROTINKATU 4 B, FIN-00120 HELSINKI

Puh./Tel. (09) 609 900
Int. 358-9-609 900
http://www.etla.fi

Telefax (09) 601753
Int. 358-9-601 753

KESKUSTELUAIHEITA - DISCUSSION PAPERS ISSN 0781-6847

No 666 MIKKO MÄKINEN - MIKA PAJARINEN - SIRKKU KIVISAARI - SAMI KORTELAINEN, Hyvinvointiklusterin vientimenestys ja teollinen toiminta 1990-luvulla. 08.02.1999. 67 s.

No 667 OLAVI RANTALA, Tuotannon ja työllisyyden alueellisen ennustamisen menetelmät. 19.02.1999. 43. s.

No 668 JARI HYVÄRINEN, Globalisaatio, taloudellinen kasvu ja syvenevä alueellistuminen. 02.03.1999. 68 s.

No 669 JUKKA LASSILA, An Overlapping-Generations Simulation Model for the Lithuanian Economy. 02.03.1999. 21 p.

No 670 JUKKA LASSILA, Pension Policies in Lithuania - A Dynamic General Equilibrium Analysis. 02.03.1999. 44 p.

No 671 HENRI PARKKINEN, Black-Scholes-malli ja regressiopohjainen lähestymistapa stokastisen volatiliteetin estimointiin - Katsaus suomalaisten FOX-indeksioptioiden hinnoitteluun. 15.03.1999. 88 s.

No 672 JUHA SORJONEN, An Econometric Investigation between Volatility and Trading Volume of the Helsinki and New York Exchanges: A Firm Level Approach. 26.03.1999. 99 p.

No 673 ANTTON LOUNASHEIMO, The Impact of Human Capital on Economic Growth. 30.03.1999. 35 p.

No 674 PASI SORJONEN, Ex-Dividend Day Behaviour of Stock Prices in Finland in 1989-90 and 1993-97. 30.03.1999. 29 p.

No 675 PASI SORJONEN, Ex-Dividend Day Stock Returns and Tick Rules. 30.03.1999. 21 p.

No 676 PASI SORJONEN, Ex-Dividend Day Stock Price Behaviour, Taxes and Discrere Prices; A Simulation Experiment. 30.03.1999. 28 p.

No 677 JUHA HONKATUKIA, Kioton mekanismien käytön rajoittamisen vaikutukset Suomeen. 08.04.1999. 41 s.

No 678 ANSSI PARTANEN - INKERI HIRVENSALO, North and Westbound Foreign Trade Potential of the Baltic Rim. 28.04.1999. 17 p.

No 679 GRIGORI DUDAREV, The Role of Technology in Shaping the Energy Future in Russia. 06.05.1999. 48 p.

No 680 REIJA LILJA - EIJA SAVAJA, En översikt av systemet för arbetslöshetsskydd i Finland. 06.05.1999. 21 s.

No 681 REIJA LILJA - EIJA SAVAJA, Olika sätt att söka arbete, attityder och motivation hos arbetssökande i Finland. 06.05.1999. 73 s.

No 682 JARMO ERONEN, Cluster Analysis and Russian Forest Industry Complex. 24.06.1999. 16 p.

No 683 SEPPO HONKAPOHJA - ERKKI KOSKELA, The Economic Crisis of the 1990s in Finland. 09.08.1999. 53 p.

No 684 STEPHEN KING - ROHAN PITCHFORD, Private or Public? A Taxonomy of Optimal Ownership and Management Regimes. 12.08.1999. 33 p.

No 685 HANNU HERNESNIEMI - MIKKO HONGISTO - LASSI LINNANEN - TORSTI LOIKKANEN - PÄIVI LUOMA, Kioto-sopimus ja yritykset. Esitutkimus strategioista. 07.09.1999. 68 s.

No 686 PETRI ROUVINEN, R&D Spillovers among Finnish Manufacturing Firms: A Cost Function Estimation with Random Coefficients. 08.09.1999. 51 p.

No 687 ANNE ERONEN, Classification of Intangibles - Some Comments. 04.10.1999. 13 p.

No 688 HANNU PIEKKOLA, Rent Sharing and Efficiency Wages. 06.10.1999. 25 p.

No 689 MIKA PAJARINEN, Foreign Firms and Their R&D in Finland. 11.10.1999. 33 p.

No 690 PETRI ROUVINEN, Characteristics of Product and Process Innovators among Finnish Manufacturing Firms. 11.10.1999. 29 p.

No 691 HANS GERHARD HEIDLE, Market Microstructure and Asset Pricing: A Survey. 25.10.1999. 57 pages.

No 692 JUHA HONKATUKIA - PEKKA SULAMAA, Tekninen tehokkuus ja kokonaistuottavuus Suomen sähköjakeluverkkotoiminnassa 1996-1998. 03.11.1999. 69 s.

No 693 The Effects of Energy Saving on the Costs of Abatement Policies in Finland. 09.11.1999. 44 p.

No 694 Issues in R&D-Productivity Dynamics: Causality, Lags, and 'Dry Holes'. 09.11.1999. 29 p.

Elinkeinoelämän Tutkimuslaitoksen julkaisemat "Keskusteluaiheet" ovat raportteja alustavista tutkimustuloksista ja väliraportteja tekeillä olevista tutkimuksista. Tässä sarjassa julkaistuja monisteita on mahdollista ostaa Taloustieto Oy:stä kopiointi- ja toimituskuluja vastaavaan hintaan.
Papers in this series are reports on preliminary research results and on studies in progress. They are sold by Taloustieto Oy for a nominal fee covering copying and postage costs.

d:\ratapalo\DP-julk.sam/09.11.1999