The impact of Research and Development Spillovers on UK Manufacturing TFP

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Abstract

The main purpose of this paper is to present new evidence on the long run relationship between R&D efforts and productivity performance of UK manufacturing industries in the presence of inter-industry and international spillovers of technology. The main dataset used to perform this analysis is a panel of eight UK manufacturing industries over the period 1970 to 1997. The empirical results indicate that there is a positive and significant link between industry's R&D activities and productivity in the long run. In addition, robust evidence was found of positive and significant domestic R&D externalities. Conversely, the finding that international spillovers do not contribute to TFP suggests that R&D spillovers are primarily an intra-national phenomenon, which may serve as a warning against under-estimating the importance of domestic technological efforts and over-estimating the potential contribution of international spillovers.

Keywords: R&D spillovers, total factor productivity, panel data.

JEL Classification: C23, D24, O30, O47.

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1. INTRODUCTION

Advances in the state of knowledge through technological change tend to be the primary determinant of productivity growth over long periods of time. Since research and development (R&D) investment directly contributes to knowledge accumulation, R&D activities are a potentially important source of productivity gains. R&D capital stock aims at improving the quality or at reducing the average production costs of existing goods and services or simply at extending the range of intermediate inputs or final goods available to other economic agents. Indeed, a large number of empirical studies, at different levels, come to the conclusion that R&D is a major source of economic growth[1]. Quoting Coe and Helpman (1995) there exists "*convincing empirical evidence that cumulative domestic R&D is an important determinant of productivity*."

A distinctive characteristic of R&D activities is that benefits are not completely captured by R&D investors. The unappropriated benefits, referred to as R&D spillovers, provide a source of new knowledge and thereby potential productivity gains to spillover receivers. These spillovers must be taken into account when assessing the impact of R&D on sectoral productivity. Griliches (1992) reviews the basic model of R&D spillovers and comments on the empirical evidence for their existence and magnitude[2]. Though the contribution of R&D spillovers to productivity growth has been acknowledged a long time ago, it is only recently that the empirical measure of the magnitude and the direction of such effects has become a major point in the research agenda on the economics of innovation.

The recent revival of the growth theory has emphasised the contribution of international transmission of new technologies across national borders to economic growth and productivity (Grossman and Helpman, 1991). With international trade, foreign direct investment, and international information diffusion, it can be expected that R&D spillovers extend beyond national boundaries, at least in open economies. The mechanics of this engine and the power of spillovers have been under empirical scrutiny by many important scholars[3]. International R&D spillovers imply that productivity growth depends, not only on domestic spillovers, but also additionally on the R&D activities undertaken in other economies.

A priori, the "convincing empirical evidence" pointed out by Coe and Helpman (1995) can be criticised on some grounds. This refers to the problem of measurement and definitions of factor

[1] Classic references in this literature include Griliches (1980, 1992) and Griliches and Lichtenberg (1984).
[2] Other more recent surveys may be found in Nadiri (1993), Mohnen (1996) and Cameron (1999).
[3] See for example Coe and Helpman (1995), Berstein (1998) and Berstein and Mohen (1998), among others.

productivity. In this regard, most of these studies are based on growth accounting measures of productivity obtained from production functions in which only labour and capital are included as inputs. This implies the use of value added instead of gross output as a measure of real output and a potential source of bias when certain restrictive conditions are not met[4]. An even more relevant criticism is based on the possible bias deriving from the use of the "growth accounting" framework commonly employed to obtain productivity measures. This approach is based upon strong assumptions, mainly competitive output markets and absence of short-run fixities, that very often tend not to be representative of the real world. In these cases the use of the growth accounting Solow residual produces biases that can alter the relationship between productivity and its main determinants, in particular R&D efforts (Atella and Quintieri, 2001).

The objective in this paper is twofold. On one hand, it is seek to study the long-term relationship between R&D efforts and productivity, taken into account the above criticisms. Additionally, it assesses empirically the importance of domestic and foreign R&D spillovers for productivity in UK manufacturing industries. It combines an analysis at a sectoral level with the original approach from Coe and Helpman (1995). More specifically, data for eight manufacturing industries are used to explain the long run impact on factor productivity of R&D activities by the sector itself, by other UK manufacturing sectors and by foreign sectors. This allows one to answer the question whether externalities are important in the process of economic growth and whether R&D spillovers are national or international in scope.

Additionally, while some attention has been paid to the impact of R&D activities upon productivity in the context of static econometric models[5], the dynamic evidence is more limited, the exceptions being Frantzen (1998), Los and Verspagen (2000), and Guellec and Pottelsberghe (2001). However, where dynamic models are required, which will be the rule with non-stationary series (and the series under study are no exception), standard pooled models are not simply inefficient but may also be highly inconsistent, (Pesaran and Smith, 1995). A contribution of the present study is to provide additional insights on the relationship between productive knowledge and productivity in UK manufacturing sectors employing a dynamic heterogeneous error correction (ECM) panel model. Specifically, the ECM statistical framework is attractive in that is compatible with long run equilibrium behaviour and the concept of cointegration. Moreover, the ECM in the panel data setting can be estimated by using

[4] There is a long literature that argues against the use of value added for productivity measurement on various grounds (see Baily 1986; and Basu and Fernald 1997)

[5] Quoting Harris (1995: p. 5), "*long-run models are often termed 'static models', but there is no necessity actually to achieve equilibrium at any point in time… All that is required is that economic forces move the system toward the equilibrium defined by the long-run relationship posited…Thus, what matters is the idea of a steady-state relationship between variables which are evolving over time.*"

the Pooled Mean Group (PMG) estimator (Pesaran, Shin and Smith, 1999), which allows short-term adjustments and convergence speeds to vary across industries, and imposes cross-industry homogeneity restrictions on the long run coefficients. There are indeed good reasons to believe in common long run coefficients across UK manufacturing sectors, given that they have access to common technologies and have intensive intra-trade. Conversely, there is no reason to assume that the speed of convergence to the steady state or the dynamics should be the same across industries.

The rest of this paper is organised as follows. The next section describes previous studies on the impact of productive knowledge upon productivity; particularly those focused on the UK economy. Section 3 describes the empirical model relating productivity to the innovation and spillovers variables. Section 4 gives an overview of the data and characteristics of the sectors under consideration. The main empirical findings are presented in section 5. More precisely, some econometric issues are put forward with respect to the stationarity of the series and the econometric estimation method. The econometric results are presented along with comparisons with those results reported in related empirical studies. Finally, section 6 offers some conclusive remarks.

2. PREVIOUS STUDIES ON PRODUCTIVE KNOWLEDGE IN RELATION TO FACTOR PRODUCTIVITY

The literature on the impact of productive knowledge on factor productivity and the presence of spillovers is large and diverse in terms of approaches followed and questions addressed. As Sakurai *et al*. (1996) point out, comparisons across different studies may be misleading or meaningless, given that studies not only differ in the data and methodologies used but also in terms of measurement. In spite of this cautious note, the majority of studies in this tradition found that R&D spending (measured in a variety of ways) contributed significantly to productivity growth. In this regard, Nadiri (1993) indicates that, for industry data, the estimated elasticity of output with respect to R&D is usually found to be between 0.10 and 0.30, while rates of return to R&D range between 20 and 40 per cent.

Although most empirical work on the relationship between knowledge and productivity has been for the United States, Table 1 summarises the results of a number of studies for the UK economy. Despite the shortcomings and differences in approach, the majority of the selected studies tend to find a strong and enduring link between own R&D activities and output, or productivity. Indeed, the average estimated elasticity of R&D stock on output (performed on the basis of the estimates in Table

1, fourth column) is about 0.17, with a lower bound of 0.02 and an upper bound of 0.37. Moreover, the estimated rate of return to R&D lies between 0.12 and 0.27.

Table 1:
Empirical studies on the impact of R&D on UK productivity

Study	*Database*	*Model*	*Direct Effect*	*Weights*	*Domestic Spillovers*	*Foreign Spillovers*
1. Primal Approach						
Cross-Sectional Studies						
Sterlacchini (1989)	15 ind. 1945-83	ΔTFP, IR	0.12-0.2 [2]	I/O flows Innovation flows	0.09-0.12 [2] 0.15-0.35 [2]	
Wakelin (2001)	170 firms 1988-92	LP, IR	0.27 [2]	Innovation flows	0.00	
Time Series Studies						
Cameron & Muellbauer (1996)	Manuf. 1962-92	ΔTFP, RD	0.15-0.37 [1]			
O'Mahony & Wagner (1996)	Manuf. 1973-89	ΔLP, IR	0.00 [2]			
Panel Data Studies						
Geroski (1991)	79 ind. 1976-79	ΔLP, I	0.015 [3]	Innovation flows	0.00	
Coe & Helpman (1995)	22 Ec. 1970-91	TFP, RD	0.234 [1]	Bilateral trade flows		0.06-0.08 [1]
Cameron (1999)	19 ind. 1972-92	TFP, RD	0.237 [1]			
McVicar (2002)	7 ind. 1973-92	TFP, RD	0.015 [1]	FDI Bilateral trade flows	 0.076 [1]	0.00 -0.015 [1]
2. Dual Approach						
Nadiri & Kim (1996)	G-7 Ec. 1964-91	C, RD	0.142 [2]	Bilateral trade flows		0.061 [2]
Hubert & Pain (2001)	15 ind. 1983-92	ΔL, RD	0.029 [1]	FDI Bilateral trade flows	 0.032 [1]	0.008 [1] 0.003 [1]

Notes: Estimates derived from data on ind.: industry level; Manuf.: total manufacturing; Ec.: country level; TFP: total factor productivity; LP: labour productivity; L: labour demand; C: total costs; IR: R&D intensity; RD: R&D capital stock; I: innovation variables other than R&D. 1: output elasticity; 2: rate of return; 3: coefficient estimate.
Source: Author.

Less extensive is the literature dealing with national and international spillovers in the UK context. Results are mixed depending on the weights considered to obtain the inter-industry and foreign knowledge capital stocks, with the balance in favour of the recognition of their existence. Nevertheless, when significant, the estimates presented in Table 1 suggest that international spillovers contribute to productivity growth significantly less than domestic inter-industry spillovers.

Consequently, these results imply that R&D spillovers for the UK economy are primarily intra-national in scope.

Since Griliches' (1979) article, there is a clear conceptual distinction between rent or "pecuniary" spillovers and knowledge spillovers. The formers arise because the prices of intermediate inputs are not fully adjusted for quality improvements resulting from R&D investments in other industries or countries. For example, quoting Los and Verspagen (2000, p. 130), "*a new personal computer that can perform certain calculations twice as fast as the existing ones, will often be sold at a price between once and twice the price of the existing machines. As an immediate consequence, the price per efficiency unit has fallen, and the productivity of the firms or industries using the new computer will rise.*" Part of the effect of rent spillovers is in fact due to mis-measurement: if prices could accurately reflect quality improvements, productivity growth could be attributed more precisely to its original source. Studies estimating the impact on productivity of the so-called indirect R&D embodied in traded inputs (e.g. Coe and Helpman, 1995) generally concentrate on this interpretation of spillovers.

The second type of R&D externality is knowledge spillover that can be defined as the potential benefits for a given industry due to the research efforts of other industries. This kind of spillovers is related to the diffusion and imperfect appropriability of the knowledge associated with an innovation, which partly posses the characteristics of a public good (non-rival and non-excludable[6]). Due to this property the benefits of R&D spread beyond the limits of the original performer, contributing to the innovation process of other industries or countries. Knowledge spillovers are generally characterised by the transfer of technology that may occur via different channels: foreign direct investment, foreign technology payments[7], and international R&D collaboration, among others. Since these knowledge spillover channels are often associated with an economic transaction, the extent to which they also reflect some rent spillover is not so obvious.

Certainly, if the distinction between the two spillover concepts is clear from the analytical point of view, it appears more ambiguous once an empirical analysis is to be implemented. The ambiguity is due to the fact that it is difficult to dissociate empirically rent spillovers from knowledge spillovers. Rent spillovers are approximated through economic transactions, which may also be associated –or imply- some knowledge transfers. Additionally, quoting Cincera and van Pottelsberghe (2001: p. 2) "*the two types of R&D spillovers might not be combined but their respective profiles across industries might be similar.*

[6] Non rivalry means that the costs required to reproduce an innovation once it is made is negligible with respect to the original investment involved to discover it so that the technology can be seen as a public good. Partial excludability means that the owner of an innovation cannot exclude others from obtaining a part of the benefits free of charge.

Therefore, since each type of R&D spillover is estimated under a common econometric procedure, serious collinearity bias might emerge." It is due to these arguments that in the present study we prefer to rely on a broader concept of R&D spillover, instead of attempting to distinguish rent- from knowledge spillovers.

Another important issue in this literature is the distinction between the private (or "own", "direct") and the social (or "indirect", "external") rate of return to R&D. The former relates to the benefits that can be appropriated by the original R&D performer. The latter refers to the total benefits from research activities, i.e. the returns that revert to the industry or sector in which the R&D performer is located in or to society at large. The basic methodology used to evaluate social returns to R&D consists in estimating a production function –i.e., the primal approach- or a cost function-, which incorporates one or more variables proxying an outside (or external) R&D capital stock. The key issue is then to determine how this outside R&D capital stock (the pool of external knowledge) has to be aggregated.

In the literature on R&D spillovers a variety of different weights have been used to obtain a measure of the aggregated external R&D stock (see Mohnen, 1996, for a review). A first group of studies analyses the influences of R&D spillovers by treating them as an unweighted sum of R&D of all other firms, industries or countries (Berstein, 1988; and Levin, 1988). A second group treats the R&D spillover variable as a weighted sum of all external R&D (Coe and Helpman, 1995; Sakurai, *et al*, 1997). This second approach can be additionally subdivided according to the proximity measure used to construct the weights. This proximity can be based on the inter-industry flows of goods and services, capital goods, R&D personnel, patents, innovations, citations or R&D co-operation agreements. Another set of measures of proximity is the distance between position vectors in different spaces (Bernstein, 1997), such as patent classes, qualifications of R&D personnel, lines of business or types of R&D. In the present study, inter-industry spillovers are estimated using R&D expenditures, input-output statistics and bilateral import transactions.

3. THE PRODUCTION FUNCTION FRAMEWORK AND THE MEASUREMENT OF R&D CAPITAL STOCK

This section aims at reviewing the production function framework as a model to study the relationship between productivity and knowledge capital. Changes in TFP can be explained by many factors: innovative activities or productive knowledge, scale economies, changes in the quality of labour and

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[7] Foreign technology payments include royalties, licensing fees and patent sales.

capital, organisational change, etc. Among these underlying factors, this study focuses on the role of productive knowledge, proxied by the R&D capital stock, and R&D embodied in products purchased as inputs into production in explaining industry's TFP. Particular attention is paid to the empirical measurement of knowledge capital and R&D spillovers.

3.1. The model

The model used for the analysis of the role of productive knowledge is built on the traditional production function approach[8] (Griliches, 1980), where a measure of innovative effort is included as one of the production factors[9]. Unlike most of the empirical evidence on the contribution of innovative activity to productivity, this study does not rely on non-parametric measures of TFP derived from the traditional approach suggested by Solow (1957). According to this methodology, measures of TFP are based on assumptions that are difficult to accept as maintained hypotheses, particularly perfect competition and long run equilibrium. However, evidence suggest the importance of the role of market power (Hall, 1988) and of accounting for deviations from long run equilibrium in measuring productivity (Berndt and Fuss, 1986; Bernstein and Nadiri, 1991). Certainly, if the hypotheses maintained by the growth accounting approach are not satisfied the use of the "Solow residual" as a proxy of technical change can lead to misleading interpretations of the role played by productivity and its ultimate determinants.

To formulate the relationship between TFP and cumulative productive knowledge, this study partly borrows from Berndt and Fuss (1989) and Harrigan (1999) and proceeds by assuming that the actual level of production (Y) is the product of potential or capacity output (Y^*), and an index of the level of capacity utilisation (U). In this way, capacity utilisation is defined by how far actual (observed) output is from their appropriately defined potential value. The specification has the feature that capacity utilisation is fully utilized (100%) when $U = 1$, value that is achieved in the steady state[10].

$$Y_{it} = Y^*_{it} U^{\delta}_{it} \tag{1}$$

[8] It should be noted that, besides the "primal" approach, another way to study the contribution of R&D has followed in the literature. This refers to the "dual" approach which usually rests on a representation of technology by a cost function and from which a system of factor demand equations is then estimated. Among others, Mohnen, *et al*. (1986), Bernstein and Nadiri (1991), and Nadiri and Kim (1996) have implemented the dual approach.
[9] See Cuneo and Mairesse (1984), Jaffe (1986), Griliches and Mairesse (1984), Griliches (1986, 1995), and Hall and Mairesse (1995), among others.

To model this, potential output can be written using a conventional Cobb Douglas production function, being the result of a combination of two separable functions, the technical progress function, A_{it}, and a traditional input function, $F_{it}(.)$, which depends on primary inputs (labour, L_i, and physical capital stock, K_{it}), as well as on intermediate inputs (M_{it}).

$$Y^*_{it} = A_{it} F(L_{it}, K_{it}, M_{it}) = A_{it} L_{it}^{\varepsilon_{QL}} K_{it}^{\varepsilon_{QK}} M_{it}^{\varepsilon_{QM}} \tag{2}$$

Following Basu and Fernald (1997), the level of capacity utilisation (U) can be considered a function of the non-observed intensity with which labour and capital are used, namely labour effort, E, and capital utilisation, Z. Due to short run fixities of capital and because of labour hoarding, producers do not vary inputs in the short run proportionately with outputs, leading to cyclical movements in capacity utilisation and measured TFP.

$$U_{it} = G(Z_{it}, E_{it}) = E_{it}^{\varepsilon_{QL}} Z_{it}^{\varepsilon_{QK}} \tag{3}$$

Substituting expression (2) and (3) into (1) and re-arranging gives:

$$Y_{it} = A_{it} F(L_{it}, K_{it}, M_{it}) G(Z_{it}, E_{it}) = A_{it} (L_{it} E_{it})^{\varepsilon_{QL}} (K_{it} Z_{it})^{\varepsilon_{QK}} M_{it}^{\varepsilon_{QM}} = A_{it} L_{it}^{\varepsilon_{QL}} K_{it}^{\varepsilon_{QK}} M_{it}^{\varepsilon_{QM}} U_{it}^{\zeta} \tag{4}$$

Regarding equation (4) one can establish three important differences with respect to the traditional approach to study the contribution of productive knowledge to productivity. Firstly, this research focuses on the use of gross output instead of the commonly used value added as a measure of real output[11]. Secondly, while most of the empirical evidence in this tradition has been conducted assuming that industries are at their potential production level at any moment in time ($Y_t = Y_t^*$), in this study we argue that producers adjust toward their potential level through successive short run or temporary disequilibria ($Y_t \neq Y_t^*$). Quoting Bernstein and Mohnen (1998, p. 317), "*mistakenly assuming that producers are at their long run desired* …[input demand levels] *can lead to significant biases in measured productivity growth rates and biases in accounting for the various determinants of productivity growth*." Finally, we proceed without assuming perfect competition in output markets, or in other words, without

[10] The parameter δ in equation (1) is the elasticity of capacity utilisation with respect to the business cycle (see Harrigan, 1999). In the steady state U=1, therefore Y=Y* independently of the value of δ.
[11] There is an extensive literature that shows the inadequacy and the resulting biases of using value added for productivity measurement (see Basu and Fernald, 1997).

imposing the relationship between production elasticities and income shares as in the growth accounting approach.

Taking logs in (4), and after assuming constant returns to scale in the traditional input function $F_i(.)$, one can rearrange to yield (where lower case letters denote the variables in terms of physical capital stock):

$$\ln y_{it} = \ln A_{it} + \varepsilon_i^{Q,L} \ln l_{it} + \varepsilon_i^{Q,M} \ln m_{it} + \zeta_i \ln U_{it} \tag{5}$$

Additionally, the TFP parameter, lnA_{it}, is modelled by a combination of a sector specific intercept, allowing disembodied productivity to vary across sectors, a time trend (being λ the rate of disembodied technical change), and cumulative productive knowledge (R_{it}):

$$\ln A_{it} = \eta_i + \lambda_i t + \xi_i \ln R_{it} + \nu_{it} \tag{6}$$

The subscripts i and t denote the industry and the period (year) respectively. Additionally, ν_{it} is a white noise residual and ξ represents the output elasticity with respect to productive knowledge.

Combining equation (5) and (6) one can obtain the long run (stationary) form of the model[12], which is represented as follows[13]:

$$\ln y_{it} = \eta_i + \lambda_i t + \varepsilon^{Q,L} \ln l_{it} + \varepsilon^{Q,M} \ln m_{it} + \delta_i \ln U_{it} + \xi_i \ln R_{it} + \nu_{it} \tag{7}$$

Although equation (7) is usually considered suitable for estimation, some problems arise from the application of standard regression techniques. These difficulties occur when unit roots are present in the data (and the series under exam are no exception). When dealing with non-stationary data, equilibrium is synonymous with the concept of cointegration (Engle and Granger, 1987). Failure to establish cointegration often leads to spurious regressions which do not reflect long run economic relationships but, rather, reflect the common trends contained in most non-stationary series. For this reason, there is a need to use the appropriate modelling procedure. Detrending is not appropriate and

[12] Note that by construction, the capacity utilisation measure, U, has a mean or steady state value of one (see Table A.3 in the appendix).

[13] The alternative approach followed by most of the empirical evidence would be to use TFP as the dependent variable, which involves the implicit assumption of perfect competition. This amounts to inferring the output elasticities (as the input revenue shares) from the data, which in this study we prefer to avoid.

simply differencing the variables is not a solution since this then removes any information about the long run.

An alternative procedure for obtaining meaningful estimates of the long run elasticities of TFP with respect to the innovative variables is to estimate the corresponding error correction formulation (ECM) to equation (7). The ECM statistical framework is attractive in that it is closely bound up with the concept of cointegration, thus providing a useful and meaningful link between the long run and short run approach to econometric modelling, with disequilibrium as a process of adjustment to the long run model.

Thus, the basic equation to be estimated, adapted from (7), is the following error correction model, that allows one to separate short-term from long-term effects:

$$\begin{aligned}\Delta \ln y_{it} &= \alpha_L \Delta \ln l_{it} + \alpha_M \Delta \ln m_{it} + \alpha_C \Delta \ln U_{it} + \alpha_R \Delta \ln R_{it} + \theta_i y_{i(t-1)} + \\ &+ \beta_{li} \ln l_{i(t-1)} + \beta_{mi} \ln m_{i(t-1)} + \beta_{ci} \ln U_{i(t-1)} + \beta_{ri} \ln R_{i(t-1)} + \eta_i + \lambda_i t + \nu_{it}\end{aligned} \tag{8}$$

In equation (8), the long run elasticity of output with respect to, say productive knowledge (*R*) in industry *i*, is ($-\beta_{ri}/\theta_i$).

There are two immediate practical challenges to implement an equation like (7) or (8): there are neither direct measures of the capacity utilisation term nor observable measures of the productive knowledge stock. In order to proxy capacity utilisation[14], data on deviations from the hours trend for each industry are used to construct the respective indices. On the other hand, following previous literature (see Keller, 1998), the present study models *R* as a function of the own industry R&D stock, based on the sum of past R&D spending, and the domestic and foreign embodied R&D stock.

3.2. Empirical measurement of productive knowledge, inter-industry and international R&D Spillovers.

a) Innovation variables

Comprehensive attempts to describe the technological performance of countries, industries or firms have usually relied on a variety of partial indicators of innovative effort (R&D expenditures, patents,

[14] A more refined treatment of capacity utilisation would define capacity as the minimum of the short run average cost curve, however the data required for such an adjustment is not available. See Morrison (1993).

royalties or innovation surveys, among others). While there is no single, perfect measure of innovative effort or productive knowledge, following previous studies we argue that an appropriate indicator of successful innovations, and of increase in the stock of knowledge, is an increase in knowledge capital through new investment in R&D[15, 16].

As any other capital stock variable the construction of the R&D stock is not devoid of problems such as the choice of an appropriate depreciation rate, lag structure, base value and deflators. Although, the approach followed in this research on the construction of the R&D stock is discussed at length in the appendix, some comments may be in place. In the present study, the R&D or knowledge capital stock is computed using the well-known perpetual inventory method. This method assumes that the current state of knowledge is a result of present and past R&D expenditures discounted by a certain rate of depreciation (see Appendix A).

Two other renowned issues encountered when estimating the contribution of R&D remained to be mentioned. The first problem is the "double counting" of R&D. This double counting arises since conventional inputs generally include the components of R&D expenditures. As shown by Scahnkerman (1981) and Mairesse and Hall (1996), this double counting reflects itself in downward estimates of R&D elasticities and rates of returns[17]. As a consequence, when the input factors are not cleaned from their R&D components, the rate of return to R&D has to be interpreted as an excess rate. The second issue is related to the way current and past values of R&D investments have to be deflated when measuring the R&D capital. Some authors have paid attention to this issue by

[15] Industries perform R&D to design new or better products which will provide more value per unit of resources used, or new process which will reduce the resource requirements of existing products (Griliches and Lichtemberg, 1984). To the extent that TFP measures are appropriate indicators of technological progress, R&D activities may contribute to expanding or shifting the production possibility frontier in R&D-conducting industries. At the same time, some industries that might be less R&D intensive can obtain large productivity benefits simply by acquiring quality improved inputs or capital goods into their production process (i.e. embodied R&D).

[16] Criticisms to the wide use of R&D spending are present in the literature. Pavitt and Patel (1988) argue that expenditures on R&D may be an inadequate measure of both the inputs into and the outputs into the innovative process. R&D expenditure is an input measure, much of which will not result in innovative output. Sterlacchinni (1989) points out that R&D expenditure do not represent satisfactory indicator of technological change as they account primarily for patterns of production (or performance) rather than patterns of use (or diffusion) of technological innovation among industries.

[17] Quoting Mairesse and Hall (1996: p. 5), *"Conceptually, the value added, labor, and capital measures used to estimate [the productivity equation] should be purged of the contribution of R&D materials, physical capital used in R&D laboratories, and R&D personnel, since these inputs do not produce current output, but are used to increase the stock of R&D capital. If this is not done, the cross section estimates [...] will not necessarily be incorrect, but the measured R&D coefficient will be some kind of 'excess' elasticity of output to R&D rather than a total elasticity, i.e. the incremental productivity of R&D rather than a total elasticity."*

constructing 'counpound' and 'two digit level' price indexes[18], but in general, there seems to be no substantial differences in the results according to whether these price indexes or the GDP deflator are used.

b) Inter-industry Spillovers

Modelling the economic effects of R&D spilling over from one industry to another raises two empirical issues. The first concerns the more general question of how to measure spillovers and to interpret their existing measures while the second is related to the specification of the transmission mechanism. The methodology on constructing domestic embodied R&D indicators followed in this study builds on the seminal work of Terleckyj (1974) which used input-output data to measure inter-sectoral flows of technologies. This type of technology flow indicator focuses on R&D embodied in products purchased by an industry. The concept of "R&D embodiment" relies on the fact that market commodity flows among industries can be regarded as the channel for the transfer of technology developed by supplying industries.

In contrast to other previous work which directly uses input-output tables to capture R&D in purchased products, the current R&D embodiment indicators have been formulated in the basis of a Leontief inverse, and more precisely, in the basis of the output multipliers[19], taking into account the cumulative nature of inter-industrial R&D flows. The merit of the Leontief inverse model is that enables the measurement of second-round R&D gains for a specific industry of R&D performed by industries elsewhere[20]. Such multiplier effects in R&D embodiment estimates can be important. Thus, the proxy for domestic (intranational) inter-industry spillovers, IRD_i, is computed as:

$$IRD_i = \sum_{j \neq i} \omega_{ji} RD_j \qquad , j \neq i \tag{9}$$

[18] Bernstein (1986) has constructed for Canada a Divisia price index that incorporates the prices of different components of R&D, while Cameron (1996) have considered divisia price indices for the UK business enterprise R&D.

[19] These output multipliers (Miller and Blair, 1985: p. 328) are less than or equal to traditional Leontief multipliers defined by final demand. While the use of the Leontief multipliers cannot avoid the double counting of the R&D embodiment of industry *i* by the extend of increase in industry *i*'s output during the propagation, the use of such adjusted multipliers enables to exactly define total R&D embodiments of industry *i* by the simple sum of direct R&D and indirect R&D embodied in the purchased products.

[20] The structure of the output-to-output Leontief inverse is shown in the appendix in Table A.2. The industry raw data matrix is aggregated up to the 8*8 industry classification used in this study.

Here RD_j is the R&D capital stock of industry j and ω_{ij} is the (j, i) element of the output-to-output Leontief inverse.

c). International R&D Spillovers

It has already been mentioned that within the literature on R&D spillovers, international R&D spillovers seem to be of increasing interest, with a number of recent studies exploring this dimension. Nevertheless, results are mixed depending on the country and/or the transfer channel considered, with the balance tending to tilt towards the recognition of their existence, if not agreement on their direction or actual magnitude. For example, Coe and Helpman (1995) and Bernstein and Mohnen (1998) find strong and significant evidence of inter-country spillovers, while Soete and Verspagen (1992) find no evidence for embodied R&D spillovers, but some evidence for the disembodied kind. Recently, however, Coe and Helpman's (1995) results have come to under some criticism. Keller (1998) provides evidence that foreign R&D stocks weighted by randomly generated trade matrices perform nearly as well as regressors as the true foreign RD stocks, which questions whether any of Coe and Helpman's results can be interpreted as indicating a link between knowledge flows and imports. On the other hand, Kao *et al* (1999) applying panel cointegration methods to Coe and Helpman's estimation conclude that the evidence of the relationship between imports and research spillovers is weak.

In the present research, the contribution of foreign R&D to the domestic knowledge stock in each sector is modelled by utilising bilateral import shares as weights as in many preceding empirical studies (Coe and Helpman, 1995)[21] alongside the import transaction matrix from the UK 1990 Input-Output Tables (Keller, 2001). The focus is on the indirect benefits emanating from the import of goods and services proceeding from the same and other industries that have been developed by trade partners. Let m_{ik} be the bilateral import share from country k for industry i and a_{ij} denote the import share of the j intermediate input that go to the i industry. The pool of foreign R&D, denoted by FRD_i, is defined as:

$$FRD_i = \sum_j \sum_k \alpha_{ij} m_{ik} RD_i^k \ , \ \forall\, i. \tag{10}$$

[21] Although informative, there exist clearly limitations to this approach. The assumption that the spillover of R&D stock is proportional to import flows is a strong one. Other channels of technology transmission as foreign direct investment, licenses, trade in high-tech products and co-operation in research and exchange of information might be important as well.

where RD^k_i is the stock of capital R&D in the *i* industry in country *k*.

Since the interest in the present research lies not only in the impact of performed R&D but also in that embodied R&D acquired from the purchased of domestic and imported intermediate inputs, an expression for TFP analogous to (6) can be written as:

$$\ln A_{it} = \eta_i + \lambda t + \xi_{RD} \ln RD_{it} + \xi_{IRD} \ln IRD_{it} + \xi_{FRD} \ln FRD_{it} + \nu_{it} \tag{11}$$

Equation (11) allows one to answer how and to what extent embodied R&D from other industries or from abroad can affect productivity in the user industries. In this expression productive knowledge (*R*) represented in equation (6) is function of cumulative R&D in the industry itself (denoted RD_i) as well as to R&D in other industries and trade partners (denoted *IRD, FRD,* respectively).

4. CHARACTERISATION OF SECTORS AND DATA

This section discusses briefly some features of the data and characteristics of the eight manufacturing sectors considered[22]. Summary statistics of the data are presented in Table A.3 in Appendix A.

4.1. Data

The present empirical analysis is conducted on a balanced panel of 8 two-digit UK manufacturing industries over the period 1970-1997. For these industries we construct direct R&D stocks, indirect domestic R&D stocks, and foreign R&D stocks combining data on R&D expenditures, input-output transactions and bilateral trade data. The trade partners considered are: Canada, France, Germany, Ireland, Italy, Japan, Netherlands, Spain, and United States; which represent to a great degree the most important source of imports for the UK. In addition, this data set encompasses most of the world's innovative activity, as measured by R&D, during this period: in 1995, the R&D conducted in the sample accounted to at least 91% of the OECD business R&D in the manufacturing sector.

[22] These industries are: (1) FBT Food, beverages, and tobacco; (2) TL Textiles and leather; (3) WWP Wood and wood products; (4) PPP Paper, paper products and printing; (5) CH Chemicals, man-made fibres, and rubber and plastic products; (6) NMM Non-metallic mineral products; (7) BMM Basic metal and fabricated metal products; and (8) MOT Machinery, optical and transport equipment.

Following Shankerman (1981)[23] data on labour, physical capital stock and intermediate inputs have been adjusted for R&D double counting. In Appendix A details about data sources and the construction of variables for estimation purposes are provided.

4.2. Industry Characterisation

In Table 2 some features of the data for the eight manufacturing industries are highlighted. The first column of the table shows the gross R&D intensity –i.e. the ratio of real R&D investment to real gross output- by industry averaged over the period 1970-1997. These industry-specific figures regarding gross R&D intensity reflect to a large extent the degree of technological opportunity associated with each sector. On average, the UK manufacturing sectors devoted 1.2% of gross output to research activities, with industries like Chemicals and Machinery devoting 3.27% and 4.37% respectively. However, relatively little R&D was conducted in the wood, paper and textile industries.

Table 2:
Sectoral statistics in 1997 (1970 = 1.0)

Industry	***Symbol***	***R&D Intensity***†	***Sectoral R&D Stock***	***Domestic Embodied R&D***	***Foreign R&D Stock***
		(%)	RD_{97}/RD_{70}	IRD_{97}/IRD_{70}	FRD_{97}/FRD_{70}
Food, Beverages & Tobacco	FBT	0.28	1.14	1.43	1.72
Textile & Leather	TL	0.26	0.17	1.52	1.71
Wood and Wood Products	WWP	0.10	0.61	1.27	1.68
Paper and Paper Products	PPP	0.14	0.88	1.42	1.73
Chemicals, man-made fibres, rubber & plastic products	CH	3.27	4.10	1.07	1.78
Other Non-Metallic Mineral Products	NMM	0.52	0.47	1.34	1.66
Manufacture of Basic Metals & Fabricated Metal Products	BFM	0.47	0.62	1.33	1.66
Machinery, Optical Equipment & Transport Equipment	MOT	4.37	1.22	1.66	1.65
Average		1.20	1.15	1.38	1.70

Sources: R&D Data are from ANBERD (OECD). Other data are from the Census of Production (ONS), UK 1990 input-output data (OECD) and bilateral trade (OECD).
†: Ratio of real R&D investment over gross output. Yearly average in percentage (%) terms

[23] Shankerman (1981) pointed out that the labour and capital component of R&D are double counted in TFP regressions, because they appear once in the traditional measures of labour and capital and once again in the R&D expenditure input. He also notes that another bias accounts because current R&D spending is usually committed as an expense by firms, and is therefore treated as an intermediate good in the national accounts.

Although on average the sectoral R&D stock experienced an increase of about 15% over the sample period, this performance was not uniform across the several industries. Between 1970 and 1997 the sectoral R&D stocks increased only for the food, the machinery industry and, above all, for the chemical industry while decreased for the rest of industries considered, especially for the textiles. On the other hand, the indirect domestic R&D stock increased substantially everywhere, with a relatively more homogeneous pattern. Additionally, changes over time in the foreign R&D stock were somewhat more pronounced although very similar across industries, with an average increased of 70 per cent.

5. EMPIRICAL FINDINGS

The major findings are presented in this section. However, before turning to the results some econometric issues must be discussed. Particularly, this section summarises the non-stationary panel data tests for unit roots and cointegration[24] together with the econometric estimation methods in the context of dynamic heterogeneous panel models that are used in this paper.

5.1. Econometric Issues

a) Panel Unit roots and Cointegration tests

The main purpose of the present study is to estimate the long run relationship between productivity and domestic plus foreign R&D capital stock in the UK manufacturing sectors. If all the variables in the model are stationary, then traditional estimation methods can be used to estimate the relationship between them. If, however, at least one of the series is determined to be non-stationary then the long run elasticities in equation (7) cannot be consistently estimated unless the series are cointegrated, otherwise there exists the risk of estimating a spurious regression[25]. Therefore, the first step in

[24] The analysis of unit roots and cointegration in panel data has been fruitful area of study in recent years, with Levin and Lin (1992; 1993) and Quah (1994) being the seminal contributions. See Banerjee (1999) and Maddala and Wu (1999) for a survey.

[25] If cointegration can not be accepted then one encounters the problem of estimating a spurious regression. As discussed in Granger and Newbold (1974) a spurious regression of two independent non-stationary series will tend to show a significant relationship when none exists. This problem generally increases with the sample size. In the absence of a cointegration relationship, the specification is spurious. A spurious regression has the following characteristics: (a) estimates are not consistent and converge to random variables, not constant; (b) *t*- and *F*- statistics do not have standard distribution, so the usual statistical

determining a potentially cointegrated relationship is to test whether the variables involved are stationary or non-stationary, i.e. whether individual series contain unit roots.

Among the various tests proposed in the literature, the Im, Pesaran and Shin (1997) (IPS) panel unit root test is suitable here. The power of the panel unit root tests is substantially greater than the test for a single time series in the sense that the failure to reject a unit root occurs much less frequently. The IPS *t*-bar test is based on an average of the individual industry augmented Dickey Fuller (ADF) tests while allowing for heterogeneous coefficients under the alternative hypothesis and different serial correlation patterns across groups. Under the null hypothesis all groups exhibit a unit root while under the alternative this is not the case for some *i*. A more detailed discussion of the test can be found in Baltagi and Kao (2000). Table B.1. in the Appendix presents the results of the unit-root tests. Following the procedure suggested by Im *et al* (1997) and applying the *t*-bar test to the variables in levels we obtain test statistics below the critical value to reject the hypothesis of a unit-root, based on an ADF regression with one and two lags. Therefore the null of non-stationarity cannot be rejected at the 1 per cent level, suggesting that all variables in levels are generated by a non-stationary stochastic process. Furthermore, Table B.2. reports that the *t*-bar test can reject the null of unit root for the first difference variables, except for the intra-industry R&D capital stock.

While a number of cointegration tests are documented in the time series literature, there are few cointegration tests developed in panel data. Here, the cointegration tests proposed by Kao (1999) Pedroni (1995) and Pedroni (1999) are used to test whether long run relationship exists in the estimated panel equations. The first two panel cointegration tests assume that the cointegrating vector (slope coefficients) is the same across industries, whereas Pedroni's (1999) test allows for heterogeneous slope coefficients. The null hypothesis for the panel cointegration tests of Kao (1999) and Pedroni (1995; 1999) is that the estimated equations are not cointegrated.

Table B.3 in the Appendix reports cointegration test results using the "homogeneous" panel cointegration tests of Kao (1999) and Pedroni (1995), assuming slope coefficients being the same across all units. Kao (1999) presents two types of cointegration tests in panel data, the Dickey-Fuller (DF) and augmented Dickey-Fuller (ADF) types. Building on the assumption that the regressors are strictly exogenous, Pedroni (1995), on the other hand, provides a pooled Phillips and Perron-type test. The residuals obtained from the static fixed effect or long run cointegrating equation presented in the next section (Table 3) are used to test whether the estimated equation is cointegrated or not. For the models without trend and common trend the null of cointegration is rejected at 10% level or higher,

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inference is invalid; c) R^2 may not tend to 0. Thus caution is suggested when interpreting results from with the exception of the DF_{tp} test statistic. On the other hand, for the model with industry specific time trends all test statistics are significant, so that the null of no cointegration is strongly rejected. Therefore, the cointegration relationship among variables for all equations is strongly supported.

On the other hand, the Pedroni (1999) tests allow for heterogeneity among individual members of the panel, including heterogeneity in both the long run cointegrating vectors and the dynamics. In these tests, the null hypothesis is that for each member of the panel the variables involved are not cointegrated and the alternative that for each member of the panel there exists a single cointegrating vector. Moreover, this vector need not be the same in all cases. Pedroni (1999) proposes seven tests. Of these tests, four are based on pooling along the within dimension (panel statistics), and three are based on pooling along the between-dimension (group mean statistics). Both cases present the panel version of the Phillips and Perron ρ and t-statistics, as well as an ADF-type test.

The results obtained with Pedroni's (1999) heterogeneous panel cointegration tests are reported in Table B.4 in the Appendix. For the model with industry specific time trends almost all test statistics reject the null of no cointegration, the exception being the panel-v, the panel-ρ and the group-ρ statistics. However, in small panels ($T = 20$), Pedroni (1997) shows, that in terms of power, the group-*ADF* statistic generally performs best, followed by the panel-ADF statistic, while the panel-v and the group-ρ statistics do poorly.

b). Econometric Estimation Method

The empirical analysis of the ECM in equation (8) above generally involves a system of NT equations (N industries and T time observations) that can be examined in different ways. The choice of the econometric approach partially depends upon the size of N and T and the quality of data across these two dimensions. In the type of data set we are considering T is sufficiently large to allow individual industry estimation. Nevertheless, we may still be able to exploit the cross-section dimension of the data to some extent. As static models are rarely adequate for typical time series, dynamic models are usually more appropriate. The small T problems with dynamic panels[26] are not relevant here as the fixed-effects problem from the initial conditions declines rapidly as T rises. But instead, there are profound problems that result from heterogeneity in the model parameters that emerge as soon as a lagged dependent variable is introduced (Pesaran and Smith 1995).

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spurious estimated regressions.

[26] Arellano and Bond (1991).

The primary difference between the various panel data models is the degree to which they impose homogeneity across the industries with respect to variances, short or long-run regression slope coefficients and intercepts. In this section we consider four specifications according to the dimensions of our panel: the Mean Group (MG), the PMG (Pesaran, Shin and Smith, 1997), the seemingly unrelated regression equation (SUR) and the Dynamic Fixed Effect model (DFE). The four models are nested within the specification (8) with the restriction either on the dynamic specification or the homogeneity of error variances and/ or the equality of short or long run slope coefficients across the industries.

The most restrictive procedure is the dynamic fixed-effect (DFE). Instrumental variables (e.g. Arellano and Bond, 1991; Arellano and Bover, 1995) are generally applied to overcome the usual small-sample downward lagged dependent variable bias (see Nickell, 1981). However, Pesaran and Smith (1995) show that, unlike in static models, pooled dynamic heterogeneous models generate estimates that are inconsistent even in large samples. The DFE specification generally imposes homogeneity of all slope coefficients, allowing only the intercepts to vary across industries. In other words, DFE imposes $(N-1)(2k + 2)$ restrictions on the unrestricted model in equation (8): i.e. k long-run coefficients, k short-run coefficients plus the convergence coefficient and the common variance. The validity of DFE, in particular, depends critically on the assumptions of common technology and common convergence parameter that in turn requires both common technological change and input factor growth across industries.[27] Pesaran and Smith (1995) suggest that, under slope heterogeneity, the convergence estimates are affected by a heterogeneity bias.

The least restrictive procedure is the MG. This imposes no homogeneity and is calculated as the mean (across the individual groups) estimates of the long run, the short run and adjustment coefficients (*e.g.* Evans, 1997; Lee *et al.*, 1997). In particular, there are $N(2k + 3)$ parameters to be estimated: each equation has $2k$ coefficients on the exogenous regressors, an intercept, a coefficient on the lagged dependent variable and a variance. The small-sample downward bias in the coefficient of the lagged dependent variable remains. Moreover, while consistent, this estimator is likely to be inefficient in small group samples, as is the case here, where any industry outlier could severely influence the averages of the industry coefficients.

[27] Instrumental variable estimators suggested by Arellano and Bond (1991) are particularly suited for dealing with dynamic panel data when N is large and T relatively small. As shown by Nickell (1981) the downward lagged dependent variable bias depends on $1/T$ and it is less of a concern when T is large and of the same order of magnitude of N. In this latter case, heterogeneity of individuals (industries) is a more serious problem and imposing homogeneity of all (short and long-run) parameters risk leading to inconsistent results (see Lee *et al.*, 1997).

The intermediate choices between imposing homogeneity on all slope coefficients (DFE) and imposing no restrictions (MG) are the Seemingly Unrelated Regression (SUR) approach and the pooled mean group (PMG). On one hand, the Zellner's SUR method, which is a form of feasible GLS, imposes homogeneity on the long-run coefficients and the speed of convergence while allows the short run coefficients to differ across industries. The SUR approach requires the estimation of Nk coefficients plus ½$N(N+1)$ elements of the covariance matrix. On the other hand, The PMG allows short-run coefficients, the speed of adjustment and error variances to differ across industries, but imposes homogeneity on long-run coefficients. In other words, the PMG imposes $(N\text{-}1)k$ restrictions on the unrestricted model shown in equation (8).

Given the access to common technologies, and the intense trade relations between manufacturing industries, the assumption of common long-run production function parameters is reasonable. By contrast, it might be more difficult to assume homogeneity of speed of convergence, as in the SUR approach[28] and, short-term dynamics as in the dynamic fixed effects specification. Under the long-run slope homogeneity the PMG estimator increases the efficiency of the estimates with respect to mean group estimators (Pesaran *et al.*, 1999). Formally, conditional on the existence of a convergence to a steady state path, the long-run homogeneity hypothesis permits the direct identification of the parameters of factors affecting steady state path of output per capital ($\beta_i / \phi_i = \theta_i$, see below). In other words, with the PMG procedure, the following restricted version of equation (8) is estimated on pooled cross-industry time-series data:

$$\begin{aligned}\Delta\ln y_{i,t} = &-\phi_i\Big(\ln y_{i,t-1} - \theta_l \ln l_{i,t-1} - \theta_m \ln m_{i,t-1} - \theta_c \ln U_{i,t-1} - \theta_{rd} \ln RD_{i,t-1} - \theta_{ird} \ln IRD_{i,t-1} - \theta_{frd} \ln FRD_{i,t-1} - \lambda_i t - \theta_{0,i}\Big) \\ &+ b_{l,i}\Delta\ln l_{i,t} + b_{m,i}\Delta\ln m_{i,t} + b_{m,i}\Delta\ln m_{i,t} + b_{c,i}\Delta\ln U_{i,t} + b_{rd,i}\Delta\ln RD_{i,t} + b_{ird,i}\Delta\ln IRD_{i,t} + b_{frd,i}\Delta\ln FRD_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{12}$$

The hypothesis of homogeneity of the long-run parameters cannot be assumed *a priori* and is tested empirically in all specifications. In particular, in the next section, the Hausman test (Hausman, 1978) is used for this purpose: under the null hypothesis, the difference in the estimated coefficients between the MG and the PMG are not significantly different and PMG is more efficient. Nevertheless, if the homogeneity assumption is not valid, then pooling the cross-section information might still have some merits since it yields to more efficient estimates than running independent regressions for each group and then computing an average of the estimated coefficients, the MG estimator. Moreover,

[28] SUR is generally concerned with linear cross-equation restrictions, whereas common long-run coefficients and idiosyncratic speed of adjustment in equation (12) above imply non-linear restrictions across different industry equations.

when N is small as is the case here, the PMG estimator is less sensitive to outliers since it weights the individual unrestricted country coefficients according to their precision (Pesaran, Shin & Smith (1999) for a more detailed discussion).

5.2. Econometric Results

The first results presented are based on the commonly used static equation (13), in which an identical form of the long run production function is assumed for all industries. As such model misses the dynamics of the linkages between the variables, the purpose is primary to look for simple, static relationships. The pooled OLS estimates with heteroskedastic consistent standard errors are reported in Table 3 (industry fixed effects are included but not reported, although these are highly significant in all regressions). These results are reported partly to illustrate how misleading they may be.

$$\ln y_{it} = \eta_i + \lambda t + \varepsilon^{Q,L} \ln l + \varepsilon^{M,L} \ln m + \delta \ln U_{it} + \xi_{rd} \ln RD_{it} + \xi_{ird} \ln IRD_{it} + \xi_{frd} \ln FRD_{it} + \nu_{it} \qquad (13)$$

The estimates of equation (13) are reported for three alternative cases: first (column 1) the time trend is excluded from the regression, which is the form most commonly used in these studies; second, a common trend across industries is assumed, and finally (column 3) it is allowed for specific industry time trends. In general, for the first two regressions the estimated coefficients are similar, with the expected sign and statistically significant, although the size of the coefficient on the labour elasticity is greater than expected, according to the average labour revenue share. In particular, the impact of domestic R&D upon productivity is positive and significant and, inter-industry and foreign R&D spillovers appear also positive and statistically significant.

In column 3, a specific time trend for each industry is allowed, which is the option used in the PMG estimator. Moreover, the null hypothesis of a common trend is rejected ($F(6,194) = 9.06$, [Prob. = 0.000]). In general, although the point estimates are rather different, the coefficient estimates keep the sign and significance, except for the impact of own domestic R&D efforts. Nevertheless, the distribution of the estimators of the cointegrating vector provided by such static regression is generally non-normal (Kao et al, 1998) and so inference cannot be drawn about the significance of the individual parameters by using standard "*t*" test.

Table 3:
UK sectoral TFP static regressions

Variable		Regression number 1 OLS	2 OLS	3 OLS
Labour per capital	$ln(l)_t$	0.427‡	0.415‡	0.397‡
		(0.064)	(0.067)	(0.047)
Intermediates per capital	$ln(m)_t$	0.663‡	0.673‡	0.519‡
		(0.059)	(0.061)	(0.038)
Capacity utilisation	$ln(CU)_t$	4.546†	4.230‡	8.618‡
		(1.934)	(2.013)	(1.169)
Own domestic R&D	$lnRD_t$	0.083‡	0.082‡	0.027
		(0.029)	(0.029)	(0.088)
Domestic intra-industry R&D	$lnIRD_t$	0.570‡	0.588‡	0.408‡
		(0.165)	(0.167)	(0.108)
Foreign R&D	$lnFRD_t$	0.185‡	0.224‡	0.209‡
		(0.045)	(0.067)	(0.034)
Time trend	t		-0.002	0.000
			(0.003)	(0.002)
Industry specific dummies		√	√	√
Robust Ses		√	√	√
R^2		0.978	0.978	0.994
s.e		0.061	0.061	0.031
LL		304.36	304.62	458.77
Nobs		216	216	216
Significance FE		$F(7,202)=60.22$	$F(7,201)=49.68$	$F(7,194)=145.3$
		[0.00]	[0.00]	[0.00]

Notes: Sample period is 1971-1997, 8 sectors. Industry-specific dummies are included. Dependent variable is log(Y/K). Heteroscedaticity-Consistent Standard errors are given in parentheses under the estimates. ‡ and † denotes statistical significance at the 1% and 5% level, respectively.

Estimation of the heterogeneous dynamic panel

The investigation of the data properties in the previous section imply that an estimation of equation (8) with variables expressed in log levels provides reliable inferences about the long and short-term influences of the R&D efforts upon productivity. Deviations from the long run relationship are possible in the short run. There are various reasons for such deviations, including adjustment costs. Table 4 reports the results from the dynamic heterogeneous panel estimation of the empirical specification provided by equation (12) for 8 UK manufacturing sectors. We estimate a common autoregressive distributed lag (ARDL) model for each industry where the lag length is selected to be 1 for all variables.

As discussed above, results are also likely to vary significantly with respect to the estimation method- *i.e.* from the least restrictive, but potentially not efficient MG, to the PMG[29], SUR and to the most restrictive DFE, which only allows intercepts to vary across countries. Table 4 reports results using these four approaches to specifications with and without a country-specific linear time trend. Although the reported "pooled" time trend appears non-significant, in the industry specific regressions this is significant for five of the eight industries considered. Additionally, the equation with the linear time trend appears to be more robust to the different specifications. Therefore, from now on, we only focus on the results from the second panel in which the industry specific time trend is included, which allows for different rates of disembodied technical change across industries in the long run.

The next step is to test for homogeneity in the speed of convergence and short-term dynamics, *i.e.* from PMG to the DFE model. The latter yield a much lower speed of convergence due to a downward bias in dynamic heterogeneous panel data. Moreover, restricting the short-term dynamics affects the sign and significance of the long-run coefficients. The DFE is also sensitive to panels with small groups and seems overly restrictive. In both cases, moving from MG to PMG (*i.e.* imposing long-run homogeneity to all but the time trend) reduces the standard errors and reduces significantly the measured speed of convergence, with impact on the size and the statistical significance (but not the sign) of the estimated long-run coefficients.

So we want to test for homogeneity of the parameters in the model. Pesaran, Shin and Smith argue that in panels, omitted group specific factors or measurement errors are likely to severely bias the individual industry estimates. This may explain why is a commonplace in empirical panel to report a failure of the poolability test. Nevertheless, the individual Hausman test does not reject poolability of the long run parameter. This means that the efficient estimates of the common long run parameters are given by the PMG method. The inefficient MG estimates differ from the PMG estimates but are also much worse determined, reflecting the inefficiency of the MG for this dataset.

Moreover, if the focus of the analysis is on the average (across industries) elasticities, then the PMG estimates are probably preferable to the MG estimates on the grounds of their better precision and the fact that they are less sensitive to outlier estimates, especially in small group samples. Under the assumption that the long-run elasticities are identical across industries but allowing the short run

[29] This is implemented in a GAUSS procedure, downloadable as JASA.EXE, made available at Hashem Pesaran's website. This software is used in estimation, being grateful to the authors for making it available.

elasticities to vary (PMG), there is significant support for the hypothesis that own R&D stock and intra-industry R&D capital stock are linked to productivity in the UK manufacturing industry.

Table 4:
Alternative Estimates of the ARDL model

Dependent variable : Δ log y	*Without time trend*					*With time trend*				
	Mean Group (MG)	**Pooled Mean Group (PMG)**	**h-test**	**SUR**	**Dynamic Fixed Effect**	**Mean Group (MG)**	**Pooled Mean Group (PMG)**	**h-test**	**SUR**	**Dynamic Fixed Effect**
Convergence Coefficient										
logY	-0.748 *** (0.14)	-0.286 ** (0.13))		-0.128 *** (0.03)	-0.094 *** (0.03)	-0.820 *** (0.14)	-0.464 *** (0.08)		-0.476 *** (0.05)	-0.093 *** (0.03)
Long-Run Coefficients										
log m	0.321* (0.17)	0.645 *** (0.05)	4.16	0.356 * (0.20)	0.296 (0.24)	0.443 ** (0.18)	0.642 *** (0.06)	1.34	0.530 *** (0.05)	0.322 (0.22)
log l	0.449 *** (0.15)	0.343 *** (0.05)	0.58	0.703 *** (0.16)	0.656 *** (0.19)	0.315 * (0.19)	0.231 *** (0.07)	0.23	0.379 *** (0.06)	0.621 *** (0.18)
log CU	13.161 *** (3.74)	3.687 ** (1.76)	8.27	-3.241 (8.02)	-5.044 (9.20)	13.447 *** (4.01)	8.918 *** (1.78)	1.59	5.605 *** (1.97)	-6.400 (10.24)
log RD	0.039 (0.27)	0.081 * (0.05)	0.02	0.303 *** (0.07)	0.282 *** (0.10)	0.310 (0.39)	0.331 *** (0.11)	0.00	0.315 ** (0.13)	0.281 *** (0.10)
log IRD	0.526 (0.39)	0.622 *** (0.16)	0.08	2.327 *** (0.36)	2.498 *** (0.60)	0.421 (0.41)	0.942 *** (0.14)	1.87	1.078 *** (0.16)	2.553 *** (0.62)
log FRD	-0.001 (0.07)	-0.123 ** (0.06)	32.3	-0.237 (0.17)	-0.266 (0.19)	-0.008 (0.06)	-0.048 (0.05)	2.40	0.009 (0.07)	-0.162 (0.24)
Time trend						-0.002 (0.01)	-0.003 (0.00)		-0.001 (0.00)	-0.001 (0.00)
Short Run coefficients										
Δ *log m*	0.508 *** (0.13)	0.571 *** (0.12)		0.539 *** (0.03)	0.625 *** (0.05)	0.553 *** (0.13)	0.602 *** (0.08)		0.563 *** (0.03)	0.626 *** (0.04)
Δ *log l*	0.259 ** (0.11)	0.224 *** (0.08)		0.212 *** (0.05)	0.259 *** (0.08)	0.205 ** (0.11)	0.236 *** (0.06)		0.268 *** (0.05)	0.260 *** (0.05)
Δ *log CU*	6.808 *** (1.98)	4.944 *** (1.44)		5.112 *** (1.28)	3.554 *** (1.85)	7.460 *** (1.98)	4.045 *** (0.81)		3.844 *** (1.11)	3.506 ** (1.32)
Δ *log RD*	-0.553 (0.37)	-0.422 *** (0.17)		-0.278 (0.14)	-0.356 *** (0.17)	-0.396 (0.37)	-0.305 (0.26)		-0.133 (0.13)	-0.342 ** (0.16)
Δ *log IRD*	-0.225 (0.64)	-0.687 (0.44)		-0.645 *** (0.26))	-0.290 (0.43)	-0.142 (0.64)	-0.963 *** (0.31)		-1.060 *** (0.26)	-0.283 (0.24)
Δ *log FRD*	-0.012 (0.05)	-0.017 (0.02)		-0.010 (0.04)	-0.048 (0.02)	-0.009 (0.05)	-0.009 (0.01)		0.016 (0.04)	-0.041 (0.04)
No. of industries	8	8		8	8	8	8		8	8
No. of obs.	216	216		216	216	216	216		216	216
Log Likelihood	659.9	576.4		596.9	510.8	667.5	597.8		630.8	510.9

All equations include a constant industry-specific term. Standard errors are in brackets. The standard errors of the SUR long run estimated coefficients are calculated from the estimated variance-covariance matrix of the respective parameter estimates (see Greene, 2000 p. 297-300). The rest of long run estimated standard errors are given by the JASA program.
*: significant at 10 % level; ** at 5% level; *** at 1 % level. The Joint Hausman test statistic is indeterminate if the difference between the variance-covariance matrices of the MG and PMG estimators is not positive definite (see Pesaran et al. (1999) for more details). The unrestricted short run coefficient estimates are the MG estimates under the restriction of long run homogeneity.

SUR estimates are reported alongside PMG estimates. The difference between both methods depends on different assumptions on the speed of adjustment and cross-section correlation of the errors terms. While SUR imposes homogeneity on the speed of adjustment, the PMG allows for idiosyncratic convergence coefficients, which imply imposing non-linear restrictions across the industry equations (not possible in SUR). The PMG estimates of the speed of convergence coefficient differ considerably across industries, with these varying from (-0.762) in the paper industry to (-0.078) in the basic metal industry. These differences give support to the PMG estimates.

Additionally, SUR estimation is appropriate on the assumption of contemporaneous correlation of disturbances. In fact, the Breusch-Pagan LM test based on equations with homogenous speed of convergence coefficients establishes the presence of non-diagonal error covariance matrices confirming the appropriate of SUR estimation under the homogeneity convergence restriction. PMG, on the other hand, assumes that the error term is independently distributed across t and i, although variances may be heterogeneous across. The cross-sectional independence assumption of the error term is rather strong and restrictive. For example, it is not hard to imagine shocks that affect all industries at the same time. However, this assumption is standard in the dynamic panel literature.

Despite these comments, the results under both approaches appear quite similar in terms of size, sign and significance of the point estimates, although the PMG seem economically more plausible. We rely on the appropriateness of the PMG to comment the results, on the assumption of the existence of different convergence coefficients across industries. The PMG estimates indicate that the long run elasticities of output with respect to inputs are close to the respective average revenue shares. Additionally, the long run impact of own R&D efforts on productivity is positive and significant.

The impact of intra-manufacturing R&D upon productivity is positive and significant. This effect is robust to specification changes. Our results suggest that, at least internally, there is evidence that the UK manufacturing social rate of return to R&D is higher than the private rate of return at industry level. Conversely, the estimated effect on TFP of the foreign R&D stock variable is negative, although not significant at standard levels. This insignificant effect is consistent across the majority of the alternative specifications estimated as a test of robustness. The only exception to this, is when a static model is estimated, what it is indicative that the dynamic clearly matters. Possible explanations to this finding are given in the next section.

It could be argued that, in small industry samples, one individual industry could significantly affect the estimated parameters, even when the Hausman tests do not reject the assumption of common long run coefficients. A sensitivity analysis was thus performed on the preferred specification (corresponding to PMG estimates with specific time trends reported in Table 4) in order to asses the robustness of the results to variations of industry coverage, by eliminating one industry at a time and re-running the PMG estimation procedure. Fig C.1 to C.4 in the Appendix reports results of sensitivity analysis on the long run coefficients of labour, intermediate inputs, own R&D and inter-industry R&D spillovers. Taking into account the width of the confidence intervals, these estimates seem sufficiently stable to exclusion of industries from the sample. Point estimates remain in the bound of the confidence intervals of the baseline estimate (Main).

Table 5 reports the estimated long run elasticities of output with respect to the input factors intermediate inputs and labour and to the own R&D capital stock. The estimated long-run elasticity of own R&D is 0.331. Such elasticity is in line with estimates reported in the literature (see Table 1), although it is in the high range.

Table 5:
PMG long run input elasticities

	Intermediate inputs	***Labour***	***Own domestic R&D***
Coefficient	0.642	0.231	0.331
Std. Err.	(0.06)	(0.07)	(0.11)

Source: Coefficient estimates and standard errors from Table 4

On the other hand, the PMG short-run coefficients are not restricted to be the same across industries, so there is no pooled estimate for each coefficient. Nevertheless, one can still analyse the average short run effect by considering the mean of the corresponding coefficients across industries, which is reported in Table 6.

It was found that the average short-run relationship between own sectoral R&D and productivity growth is negative, although non-significant. In particular, the industries for which the short run coefficient was found positive were the wood and machinery, optical and transport equipment industries, while was found negative for the others, particularly, for the chemical industry.

Due to the way in which R&D stocks are defined, the short run impact of R&D on productivity growth mainly reflects the effect of R&D investment costs at the beginning of the period upon changes in current output and productivity. In the short run, it seems plausible to assume that investments in R&D do not lead necessarily to successful innovations and that industries may finance large parts of their R&D expenditures by setting higher prices. This is particularly true for industries, like chemicals, where innovation processes tend to be product orientated instead of process orientated. In this case, additionally, downstream industries will be faced with higher prices from their inputs. Thus negative externalities are likely to occur, as it is found in our results. Only in markets with strong competition and relatively weak product differentiation, industries could arguably decide to let R&D costs erode their profit margins, expecting that their R&D projects yield them future innovation.

Table 6:
PMG short run growth effects

Industry	***RD***	***IRD***
FBT	-0.365	-0.732
TL	-0.621	-1.775
WPP	1.268	-1.051
PPP	-0.510	-1.821
CH	-1.179	-1.050
NMM	-0.659	-1.128
BMM	-0.435	0.852
MOT	0.062	-0.994
Average	-0.305	-0.963

Source: Results from Table 4.

A few further remarks on the econometric procedure are in order: The coefficients on the lagged dependent variables are subject to the familiar small sample (small *T*) downward bias (one would expect at least short run elasticities to differ from average revenue shares, indicating the presence of mark-ups). Since this downward bias is in the same direction for each group, averaging or pooling does not remove the bias. Kiviet and Phillips (1993) have proposed a procedure to remove this bias, which applies to the short run coefficients. Since the long run coefficients are non-linear transformations of the short run coefficients such bias corrections can leave the long run coefficients biased. We are not aware of any procedure in the literature that has resolved this problem.

Comments on results and comparisons with previous studies

Robust evidence was found of a positive and significant link between industry's R&D effort and productivity. Particularly, the long run output elasticity with respect to own sectoral R&D was estimates to be 0.331. Such elasticity is in line with previous studies. Nadiri (1993), for instance, reports elasticities at the industry level of 6 to 42%, while Cameron (1999), in a more comparable set up, finds an elasticity of 24% for the UK manufacturing sector.

One of the main questions in the introduction was the relative importance of domestic versus foreign spillovers (is domestic or international R&D the driving force behind UK manufacturing productivity growth?). The results reported above suggest that domestic spillovers seem to overwhelm foreign spillovers. The findings that domestic spillovers are important confirms results found elsewhere, see e.g. Sterlacchini (1989), Keller (1997), and McVicar (2002). Nadiri's (1993) overview reports findings for the domestic spillover elasticities ranging from 10% to 26%.

One of the striking features of the reported results, however, is the frequency with which foreign spillovers are estimated to have a negative impact on innovative output, though in many cases the coefficients are not significant at standard levels. This effect is consistent across the majority of alternative specifications as a test of robustness. However, this result of negative or no significant impact of foreign spillovers upon productivity is not at odds with findings from other related studies (e.g. Aitken and Harrison, 1999; Branstetter, 2001; and McVicar, 2002)

Branstetter (2001) encounters negative and non-significant foreign technology spillovers and provides three potential explanations for this finding. The first explanation points out at data inaccuracies, which shouldn't be discarded. An alternative argument, supported as well by Mohnen (1996), is that this finding is an artefact of the data, driven by multicollinearity problems between the various R&D measures combined with a low number of observations. In fact the domestic and foreign spillover terms are highly correlated with one another. Because there is little independence variation in the two series, regressions could in principle, produce coefficients with the "wrong sign", as often happens in the case of severe multicollinearituy.

Finally, the third argument, and most intuitively appealing, refers to the dominance of a negative competition effect over any positive technological spillovers. In this sense, Aitken and Harrison (1999) describe how a market stealing effect might drive domestic industries further up their average cost curves as they reduce output in response to competition from the technological superior foreign sector, which could threaten or even interrupt the growth of national economies.

Quoting Mohnen (1996: p.51), "*In a world of certainty and free disposal, R&D spillovers are expected to have beneficial effects, since it is reasonable to assume that firms do not adopt new ideas which reduce their profits. However, one can raise a number of arguments claiming that R&D can have detrimental effects on profit, productivity growth or* *welfare. For strategic reasons, firms may feel obliged to enter an R&D race without necessarily benefiting from it. R&D spillovers can increase or decrease the price that a producer can charge for his product, depending on whether the new product from outside R&D is substitutable or complementary to the firm's own product. New products can displace old ones. This process of creative destruction can be harmful if innovators do not have time to recover their R&D investments. Firms* [industries] *may have to incur heavy adjustment costs to learn the new technologies.*"

In Jaffe's opinion (1986: p. 984) too, "*from a purely technological point of view, R&D spillovers constitute an unambiguous positive externality. Unfortunately, we can only observe various economic manifestations of the firm's R&D success. For this reason, the positive technologically externality is potentially confounded with a negative effect of other's research due to competition*". The author continues by stating that it is not possible with available data, to distinguish between these two effects but in his study, he finds evidence that both are present.

6. CONCLUSIONS.

The purpose of this paper was to study the impact of productive knowledge upon industry's economic performance as measured by total factor productivity. More specifically, the stress was put on the long-run relationship between innovative efforts and productivity and the nature of the R&D spillovers accruing to a panel of eight UK manufacturing industries over the period 1970 to 1997.

The outlines of the production function framework necessary to perform this study were summarized in section 3. In contrast to other empirical studies in this tradition, this study focused on gross output as measure of real output and allowed for imperfect competition and temporary disequilibria. In particular, an ECM was adopted for estimating the long-run parameters in a pooled framework. As mentioned, the ECM statistical framework is attractive in that is closely bound up with the concept of cointegration, thus providing a useful a meaningful link between the long run and the short run approach to econometric modelling when series are non-stationary. In fact, individual and panel tests for order of integration reveal that the core variables are non-stationary. Thus for estimation to be valid, the data must also satisfy tests for the existence of long-run relationships. The test for cointegration using Kao's and Pedroni's residual based panel unit root tests shows evidence for the existence of cointegrating relationships in the panel members. Another advantage of the ECM framework in the panel data setting is that it can be estimated by using the PMG estimator, which allows short-term adjustments and convergence speeds to vary across industries, and imposes cross-industry homogeneity restrictions on the long run. This restricted poolability was tested for by individual Hausman tests, which couldn't reject pooling of the long run coefficients.

The results of the empirical analysis indicated that there is a positive and significant link between industry's R&D activities and productivity in the long run. Particularly, the estimated long run output elasticity with respect to own R&D is 0.331. In addition, robust evidence was found of positive and significant domestic R&D spillovers. These results certainly support the view that private R&D has public good aspects and that the private marginal product of investment in R&D may be considerably lower than the social marginal product at the industry level. The presence of spillover effects means that the market will tend to under-invest in innovation. This provides a rationale for Government intervention to sharpen incentives for firms to increase the level of privately funded R&D[30].

On the other hand, the results showed that international spillovers do not significantly contribute to TFP in UK manufacturing sectors. This finding suggests that R&D externalities are primarily an intranational phenomenon, which may serve as a warning against under-estimating the importance of domestic technological efforts and over estimating the potential contribution of international spillovers.

[30] *"The UK's strongest innovative industries are global leaders, but too many of our sectors are significantly lagging behind international investment levels in R&D. In 2000, the Government started to tackle this, through introducing tax incentives for R&D among smaller technology-based firms. This year, the Government has widened these fiscal reforms to encompass all UK-based business R&D." (*DTI and HMT, 2002).

Appendix A. Data definition and Sources

Gross Output: An annual series of nominal gross output is published in the Census from 1970. It is defined as sales and work done plus the increase during the year of stock of work in progress and goods on hand for sale. Up to and including 1979, the Census is classified in accordance with the 1968 SIC; in subsequent years, it is classified in accordance with the 1980 SIC until 1993, when it is published according to a 1992 SIC. We reclassified the data prior to 1979 and 1993 in terms of 1992 SIC. Additionally, following (Oulton and O'Mahony, 1994) methodology, gross output figures are adjusted for stock appreciation.

The producer price indices for home sales classified by 1992 SIC, published in various issues of The Annual Abstract of Statistics, were used to deflate nominal gross output. Their use as deflators is not devoid of problems due to the fact that producer price indices reflect only home sales. A "domestic price bias" may arise if domestic price indices diverge from unobserved export prices (Cameron, 1996), and its importance will vary according to the industry's share of exports in total sales. Although we did not adjust for this possible bias, Stoneman and Francis (1994) and Cameron (1996) noted the problem and attempted to correct for it using different approaches. Stoneman and Francis conclude that the producer price index and the export price series differ little from each other in manufacturing. On the other hand, Cameron finds that the domestic price bias is significant, although of reduced magnitude.

Intermediate Inputs: These are obtained as the difference between nominal gross output and nominal value added, after adjustment for stock appreciation and reclassification to SIC-1992. As manufacturing industries are their own largest consumers, the intermediate inputs price index deflator is obtained as a weighted combination of the producer price index deflator (home sales) for the whole manufacturing sector and the price index of materials and fuel purchased by the corresponding industry. The respective weights are: 0.80 and 0.20, which were assumed to be constant over the 1970-1997 period.

A point that deserves special mention when defining the variables for this kind of study is the convenience of adjusting the variables for double counting (Schankerman, 1981). An estimate of material and equipment expenditures on R&D has been subtracted form the nominal figures on intermediate inputs to avoid the expensing bias. Particularly, this estimate is constructed using the percentage of material and equipment expenditure on R&D over total expenditure on R&D (see

Table A.1), for 1985 data (ONS), under the assumption that this share behaves stable over the sample period.

Labour input: The labour input refers to the number of annual hours worked in manufacturing, which are computed as numbers employed times the annual average of hours worked. The number of persons engaged is from the Census of Production. The annual average of hours worked in manufacturing are from (O'Mahony, 1999) and several issues of the Employment Gazette.
Employees engaged on R&D (sourced by the OECD, ANRSE data set) have been subtracted for the total number of persons engaged in each industry.

Physical Capital Input: Data for manufacturing industries classified by 1992-SIC at 1995 prices were supplied directly by the Office of National Statistics.
An estimate of the capital R&D stock has been obtained from data on capital expenditure on R&D, and then subtracted from the physical capital stock. Particularly, this estimate is constructed using the percentage of capital expenditure on R&D over total expenditure on R&D (Table A.1), for 1985 data (ONS). We assume that this share behaves stable over the sample period.

Table A.1.
Percentage of capital and materials & equipment expenditure over total expenditures on R&D (Data for 1985).

	FBT	TL	WPP	PPP	CH	NMM	BM	MOT
% of capital expenditure on R&D over total expenditure on R&D	16,2	10,0	3,4	9,6	14,3	9,9	10,8	7,9
% of materials & equipment expenditure on R&D over total expenditure on R&D	13.4	14.3	9.1	14.8	12.2	15.6	17.2	26.5

Source: Data supplied by the ONS.

Stock of R&D: The measure of domestic productive knowledge is based on data of UK R&D expenditure from the OECD data set (ANBERD). These data have been transformed in real terms using the UK GDP deflator (1995=100). To construct the stock of R&D for the industry, a perpetual inventory method is followed like the commonly used for the physical capital (see Hall and Mairesse, 1995). This method specifies the capital for each period as the sum of the capital of the previous period minus the depreciated capital and plus the investment of the previous period. Thus, the equation defining R&D capital stock is the following:

$$RD_t = (1-\delta)RD_{t-1} + B_{t-1} \qquad (A.1)$$

Where RD_t is the period capital stock and B_t is real R&D expenditures during the period. Our base assumptions are those which have been most frequently used previously in this type of estimation. We assume a depreciation rate[31] (δ) of 10 percent (Cameron, 1996), a pre-sample growth rate (g) of the industry average growth rate in real R&D expenditures during the overall period[32], and we start the perpetual inventory method with the earliest year of R&D data available. The knowledge capital at the beginning of the first year is defined by the following equation:

$$RD_0 = B_0 / (g+\delta) \qquad \text{(A.2)}$$

Inter-industry R&D stock: Particularly, following Scherer (1982) and Cameron (1996) a technology flows matrix based upon the 1990 UK input-output table of intermediate goods (the 'Leontief inverse') is constructed to weight the real BERD expenditures of the other industries. Say that we have a (8*8) matrix Ω of the proportion of intermediate goods produced by 8 industries (j =1...8) and sold to the same 8 industries (i = 1,8). Then a typical element of the matrix w_{ji} represents the proportion of the intermediate goods purchased by industry i that are produced by industry j. We set the diagonal of the matrix to 0 (since the effect of R&D within each industry is captured separately).

Table A.2:
Input-Output relations (%)

	FBT	TL	WP	PPP	CH	NMM	BM	MOT
FBT		0.58	0.08	0.21	0.79	0.11	0.28	0.74
TL	0.21		1.13	0.50	0.92	0.25	0.22	1.99
WP	0.55	0.26		1.07	0.85	0.43	1.83	4.45
PPP	6.19	1.45	0.72		3.62	0.90	1.47	6.63
CH	4.96	1.97	1.19	1.94		0.76	2.41	9.81
NMM	3.46	0.29	0.63	0.28	1.83		2.86	7.81
BM	4.86	0.40	1.63	0.81	4.22	0.73		28.24
MOT	0.57	0.16	0.11	0.31	0.73	0.33	1.12	

Source: author's calculation form (1990) input-output table.

The resulting (8*8) matrix Ω (Table A.2) is then multiply by the (8*1) vector B, which contains the real BERD spending of each of the 8 industries. This gives us a (8*1) vector ΩB in which each

[31] Changes in the rate of depreciation do not generally alter the results substantially (see, for instance, Coe and Helpman, 1995).
[32] The pre-sample growth rate is approximately the mean growth rate for the industry, which we observe during the whole period considered. In any case, the precise choice of growth rates affects only the initial stock and declines its importance as time passes, unlike the choice of depreciation rate

element is the amount of BERD imported from other industries by industry *i*. This can be cumulated into a stock in the same way as for BERD in each industry to give a capital stock of used-BERD industries (i =1...8). This stock is represented by IRD_{it}.

Foreign R&D stock: The foreign research and development capital stock is a bilateral import-share weighted average of the domestic research and development capital stocks of each country's trading partners. The R&D expenditure data for the trading partners was collected from the ANBERD (OECD) database. To calculate the R&D stock, nominal expenditures were deflated by the respective country GDP deflator (1995=100) and converted to constant price sterlin flows using 1995 PPP exchange rates. R&D stocks for each industry and country were calculated from these expenditures following equations (A.1) and (A.2). The bilateral import shares were calculated for each year from 1970-1997 based on the data from the STAN bilateral Trade Database, provided by the OECD. This is available for Canada, Denmark, France, Germany, Ireland, Italy, Japan, The Netherlands, Spain and The United States. The available length of time series is 1970 to 1997.

Table A.3:
Data Summary Statistics

	Variable	Obs	Mean	Std. Dev.	Min	Max
Ratio output to capital	$ln(y/k)$	224	0.024	0.414	-0.710	1.149
Ratio labour to capital	$ln(l/k)$	224	-3.519	0.515	-4.469	-1.948
Ratio Intermediates to capital	$ln(m/k)$	224	-0.427	0.374	-1.127	0.343
Capacity Utilisation	$ln(cu)$	224	0.000	0.002	-0.006	0.006
Direct R&D	$ln(rd)$	224	7.425	1.800	4.100	10.712
Intra-industry R&D	$ln(ird)$	224	6.257	1.103	4.775	8.384
Foreign R&D	$ln(frd)$	224	9.993	0.960	8.528	11.963
Labour Share	S_l	224	0.224	0.056	0.104	0.324
Intermediates Share	S_m	224	0.635	0.071	0.492	0.786

Appendix B. Panel Unit Root and Cointegration tests

Table B.1:
Panel Unit Root test for variables in levels (timetrend and intercept included)†

Variables	**1 lag**	**2 lags**
	t-bar	*t-bar*
ln(y/k)	-2.045	-2.098
ln(l/k)	-1.075	-1.192
ln(m/k)	-2.328	-2.492
ln(u)	-2.719**	-2.450
ln(rd)	-2.021	-2.166
ln(ird)	-1.135	-1.502
ln(frd)	-2.646**	-2.102
Critical values t-bar (Im et al.)	1%	-2.79
	5%	-2.60
	10%	-2.51

† *, ** and *** denote statistical significance at the 10% level, the 5% level, and the 1% level, respectively.

Table B.2:
Panel Unit Root test for variables in first differences (intercept included)†

Variables	**No-lags**	**1 lag**
	t-bar	*t-bar*
Δ*ln(y/k)*	-4.770***	-4.330***
Δ*ln(l/k)*	-4.241***	-3.375***
Δ*ln(m/k)*	-4.921***	-4.480***
Δ*ln(u)*	-5.921***	-5.428***
Δ*ln(rd)*	-2.127**	-1.927*
Δ*ln(ird)*	-1.029	-1.320
Δ*ln(frd)*	-5.790***	-5.962***
Critical values t-bar (Im et al.)	1%	-2.18
	5%	-1.99
	10%	-1.88

† *, ** and *** denote statistical significance at the 10% level, the 5% level, and the 1% level, respectively.

Table B.3:
Cointegration tests based on results from Table 3.

	No trend		**Common trend**		**Different trends**	
	Test	***Prob***	***Test***	***Prob***	***Test***	***Prob***
Kao (1999)[1]						
$\mathbf{DF_{\varrho}*}$	-3.348	0.000	-3.711	0.000	-14.298	0.000
$\mathbf{DF_{t\varrho}*}$	-1.091	0.138	-1.205	0.114	-5.535	0.000
ADF	-1.356	0.088	-1.362	0.087	-6.032	0.000
Pedroni (1995)[2]						
PC1	-6.064	0.000	-6.293	0.000	-25.007	0.000
PC2	-5.951	0.000	-6.175	0.000	-24.540	0.000

Note: All tests are left-hand side, i.e. large negative values are used to reject the null of no cointegration.

1: The DF tests are analogous to the parametric Dickey-Fuller test for non-stationary time series. Particularly, DF_{ϱ}^* and $DF_{t\varrho}^*$ statistics are based upon endogenous regressors. The ADF test is analogous to the parametric Augmented Dickey Fuller test for nonstationary time series.

2: PC1 and PC2 are the non-parametric Phillips-Perron tests.

Table B.4:

Pedroni's (1999) Cointegration tests for heterogeneous panels

	No trend	Different trends
Panel v-stat.	0.225	-0.370
Panel ρ-stat.	1.185	1.421
Panel $\rho\rho$-stat.	-1.349	-2.000*
Panel ADF-stat.	-1.642*	-1.651*
Group ρ-stat.	1.899	2.026
Group $\rho\rho$-stat.	-1.600	-2.428*
Group ADF-stat.	-2.608*	-2.494*

Note: The cointegration tests reject the null hypothesis of no cointegration above the value –1.64 (10% probability threshold). One exception is the panel v-static which diverges to positive infinite under the alternative hypothesis, so rejection of the null requires values larger than 1.64. The calculations of the panel statistics were carried out in RATS 4.2 using an algorithm provided by Pedroni. The number of lag truncations used in the calculation of all Pedroni statistics is 2.

Appendix C. Sensitivity of long-run coefficients to reduction of industry coverage
(Pooled Mean Group estimates)

Figure C.1: Coefficient of log(M/K)

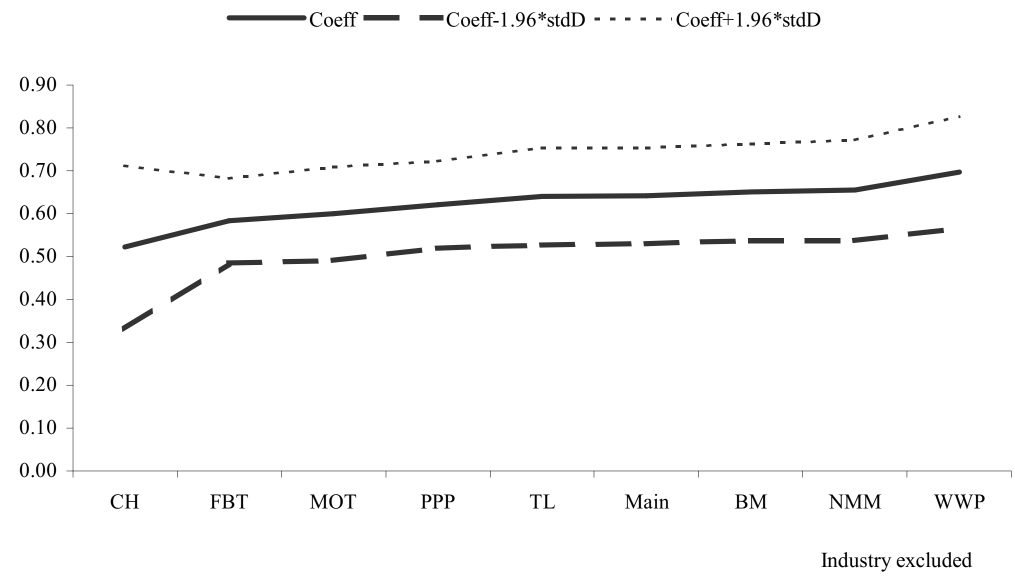


Figure C.2: Coefficient of log(L/K)

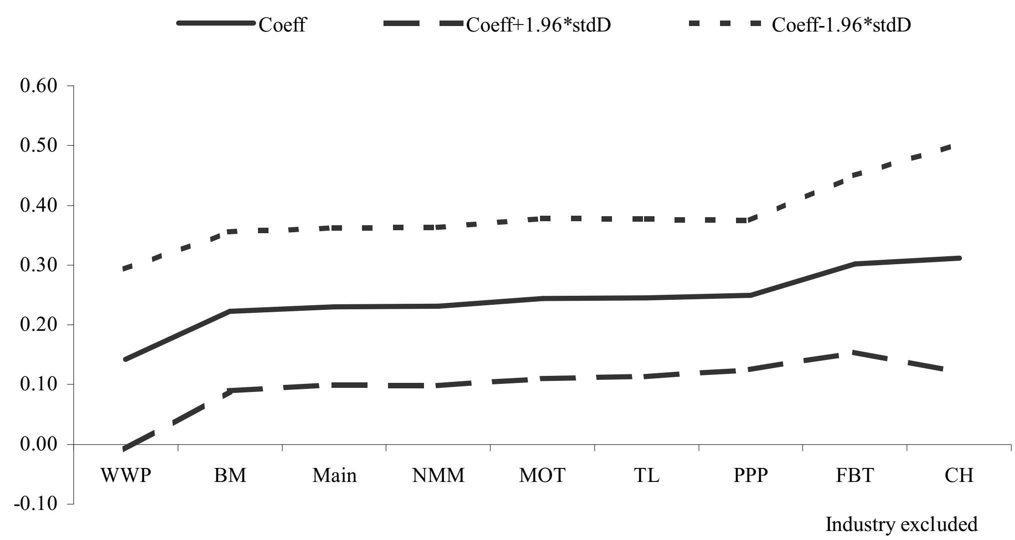


Figure C.3: Coefficient of log(RD)

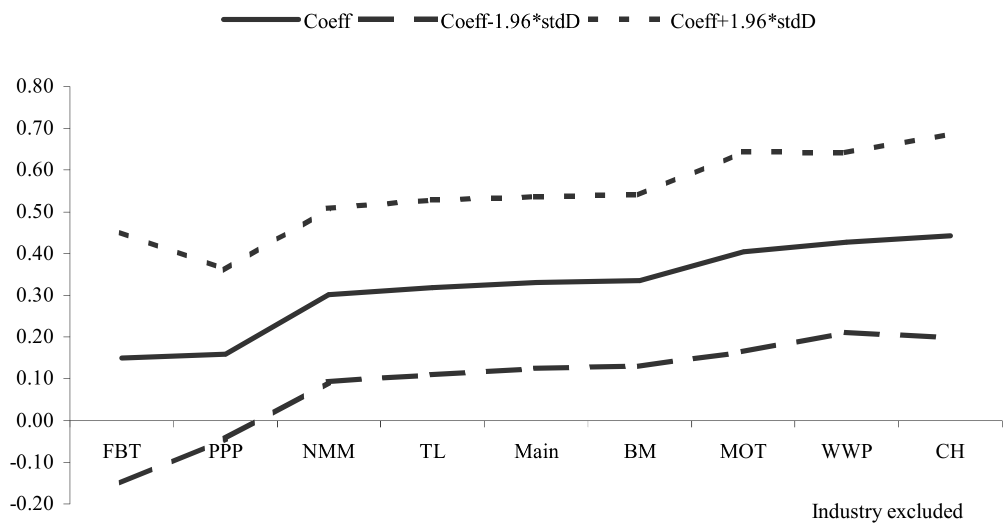
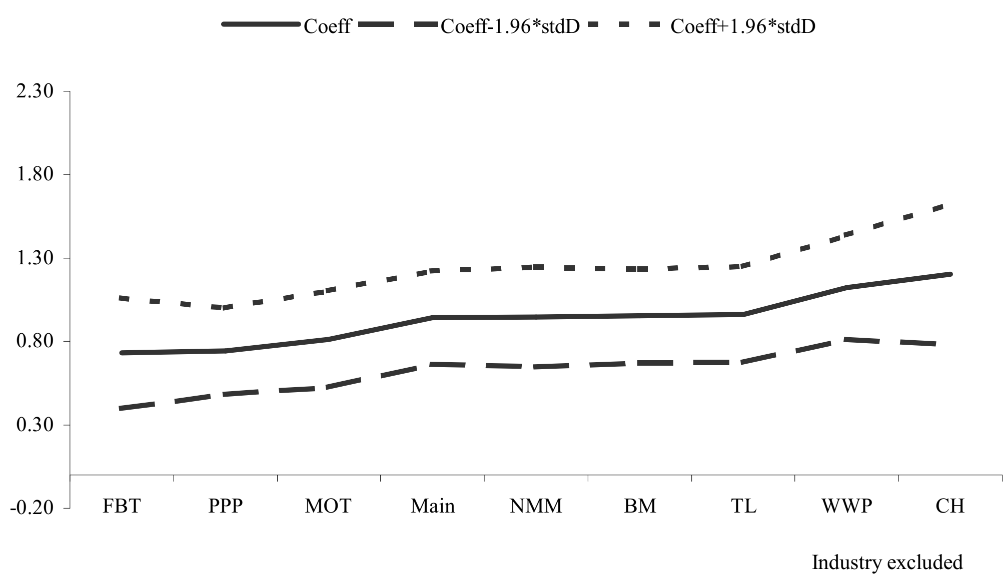


Figure C.4: Coefficient of log(IRD)



Note: Coefficient estimates and standard error bands according to PMG (95% confidence interval around coefficient estimates) when excluding one industry at a time from the sample. The coefficient estimates are arranged in increasing order. "Main" indicates the baseline estimation (cf. Table 4).

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