R&D and Growth
at the Industry Level

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Abstract: Although research and development is widely considered to be an important source of growth, relatively little is known about how its effects differ across industries. This is mainly because much research on the effect of R&D has used either cross-section or time-series data and the remainder has mostly looked at the effect of R&D on panels of firms. This paper constructs a heterogeneous dynamic panel data model of total factor productivity in the nineteen sectors of UK manufacturing between 1972 and 1992. The effect of R&D is found to vary significantly across industries in line with various industry characteristics. In particular, industries with high R&D elasticities tend to be those with higher capital to labour ratios, higher propensities to use intermediate goods from high R&D industries, higher openness to imports and lower levels of unionisation and lower ratios of R&D capital to physical capital.

Keywords: Economic Growth, R&D, Total Factor Productivity, UK Manufacturing, Heterogeneous Dynamic Panels.

JEL Classifications: C23, O3, O47

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1. Introduction

Much of the recent work in growth theory has looked at the rôle played by research and development, often from a Schumpeterian perspective (see Aghion and Howitt, 1998, for example). In this view, the profit-seeking innovative activities of firms are the main source of economic growth in the long run. A great deal of attention has been paid to how the effect of R&D may differ across countries either because of the international transmission of ideas (see Quah, 1999, and Cameron, Proudman and Redding, 1999, for discussion) or because of scale effects (See Jones, 1999, and Dinopolous and Thompson, 1999, for reviews). Indeed, an almost incredible amount of intellectual effort has been devoted to the presence or absence of scale effects (or more correctly, whether they occur in the growth rate or in the level of income).

To some extent, this effort has concealed developments which suggest that the externalities inherent in the research process (even in a closed economy) may have important implications for the effectiveness of R&D. Consider the models of Jones and Williams (1998) and Barro (1999) that suggest that the familiar TFP regressions from the 1970s and 1980s (see Griliches, 1992, for a survey) can be reconciled with more rigorous endogenous growth foundations. Jones and Williams develop a model in the spirit of Romer (1990) that allows for four externalities to R&D. First, standing on shoulders reduces the costs of rival firms because of knowledge leaks and the movement of skilled labour. Second, even if there are no technological spillovers, surplus appropriability means that the innovator does not appropriate all the social gains unless she can price discriminate perfectly to rival firms and downstream users. Third, creative destruction means that new ideas make old production processes and products obsolete. Fourth, stepping on toes occurs because congestion or network externalities arise when the payoffs to the adoption of innovations are substitutes or complements. In the model of Jones and Williams, TFP regressions produce an under-estimate of the true social return to R&D with a maximum downward bias equal to the rate of growth of output.

Given that much of the theoretical and empirical attention in the 1990s has been on the performance of *countries*, with a respectable amount of work devoted to the performance of *firms*, it is not surprising that *industry* level studies have been slightly neglected (with notable exceptions such as Verspagen, 1995). This paper analyses the productivity performance of nineteen sectors of UK manufacturing between 1972 and 1992 and attempts to distinguish the effects of R&D in each of those sectors. In a panel framework, the simplest approach would be to restrict the coefficients on R&D to be the same across industries using either the Dynamic Fixed Effects (DFE) estimator or the Mean Group (MG) estimator, while Pesaran, Shin and Smith (1999) have recently proposed a Pooled Mean Group (PMG) estimator which allows short run coefficients and error variances to differ across groups in a panel, but constrains the long run coefficients to be identical. Instead, this paper argues that the long-run performance of the industries is heterogeneous and linked to industry characteristics that are assumed to be at least weakly exogenous. For example, it might be that a sector that has a high capital to labour ratio or faces a good deal of foreign competition will have a higher R&D elasticity than a typical sector. The rôle played by such industry characteristics could be thought of as causal - higher capital to labour ratios might lead to higher R&D elasticities; or merely due to a correlation with unobservable factors - a high capital to labour ratio might be a feature of industries with plenty of technological opportunities.

This paper has five sections. The second discusses the total factor productivity performance of UK manufacturing between 1972 and 1992. The third describes the data and econometric method used. The fourth presents econometric results and discusses related issues. The fifth draws conclusions. A data appendix discusses data sources.

2 Total Factor Productivity Performance in UK Manufacturing

From Solow (1957), suppose that value added in each sector *j*, where *j=1,... ,n*, is produced with the following neoclassical production function:

(1) $$Y_t(t) = A_j(t)F_j[K_j(t), L_j(t)]$$

where *Kj* denotes the stock of physical capital, *Lj* is hours worked and *Aj* is an index of technical efficiency (assuming that technical progress is Hicks-neutral and disembodied). Under the assumptions of perfect competition and constant returns to scale, the rate of growth of value added in each sector *j* may be decomposed into the contributions of increased hours worked, physical capital accumulation and changes in the efficiency with which existing factors of production are employed.

(2) $$\frac{\dot{Y}_j}{Y_j} = \frac{\dot{A}_j}{A_j} + (1-a_j(t))\frac{\dot{K}_j}{K_j} + a_j(t)\frac{\dot{L}_j}{L_j}$$

where $a_j(t) = ((A_j \partial F_j / \partial L_j L_j)/Y_j)$ denotes the share of payments to labour in value added in sector *j* at time *t*. Thus the rate of growth of TFP, $(\dot{A}/A)$, corresponds to that component of the rate of growth of output that cannot be attributed to either capital accumulation or increased labour input. In discrete time, growth of total factor productivity can be approximated by the following Thörnqvist-Theil Divisia index:

(3) $$\log\left(\frac{A_j(t+1)}{A_j(t)}\right) = \log\left(\frac{Y_j(t+1)}{Y_j(t)}\right) - (1-\bar{a}_j(t))\log\left(\frac{K_j(t+1)}{K_j(t)}\right) - \bar{a}_j(t)\log\left(\frac{L_j(t+1)}{L_j(t)}\right)$$

where $\bar{a}_j(t) = [a_j(t) + a_j(t+1)]/2$. This measure of TFP clearly imposes theoretical restrictions on the data, which can be relaxed in principle (see Hall, 1990, and Roeger, 1995, for discussion of imperfect competition, and Caballero and Lyons, 1989, for discussion of linear homogeneity of degree γ). Since TFP growth is determined as a residual, it encompasses all the influences on the efficiency with which factors of production are employed (for example, changes in trade union practices and regulation, capacity utilisation, and managerial efficiency).

The value-added concept of TFP used in this paper suffers from a number of measurement problems due to lack of appropriate deflators for the UK. The most important problem is that of the *Single Deflation Bias*, which arises because value-added is deflated by the gross output deflator, rather than gross output being deflated by the gross output deflator and inputs being deflated by an input deflator (see Stoneman and Francis, 1994).[1] A related problem arises because the official producer price series for output is calculated on a net sector basis (that is, refers to transactions only with other sectors), while measures of manufacturing output are on a gross sector basis (include transactions within manufacturing as well). Cameron (1999) concludes that for the UK, it is better to use single-deflated value-added corrected econometrically than to use double-deflated value-added since the input deflators available are not very reliable. Two bias terms are included in the dynamic panel regressions in this paper to correct for such problems: the ratio of input prices to home sales prices and the ratio of import prices to home sales prices. The input price ratio is expected to have a negative sign, while the sign of the import price ratio is ambiguous since the input price ratio contains some foreign import price data as well as reflecting part of the list price bias.[2] Mendis and Muellbauer (1984) find a negative effect of the input price ratio and a positive effect of the import price ratio in a similar production function based on the index of production.

Table 1 shows the resulting growth rates of TFP for nineteen sectors of UK manufacturing for the entire period 1970 to 1992, as well as the two 'peak to peak' business cycles of 1973 to 1979 and 1979 to 1989.[3] The nineteen sectors comprise over 95 per cent of manufacturing output.[4] Table 1 suggests both that rates of TFP growth differ substantially across industries, and also that they differed greatly across the two business cycles. Between 1973 and 1979, TFP in total manufacturing actually fell at the annual average rate of 1.01 per cent, with 13 of the 19 industries experiencing falls. Between 1979 and 1989, it rose at an annual average rate of 3.1 per cent, with none of the 19 industries experiencing falls. As Cameron (1999) notes, these differences overstate the extent of the 1970s slowdown and the 1980s speedup because of the measurement biases noted above. When input prices rise relative to output prices, single deflated value added understates the growth of TFP, and when input prices fall relatively, TFP growth is overstated. For aggregate UK manufacturing, around half the slowdown and around half the speedup are due to measurement bias, so that the corrected rate of growth in the 1970s is only around one percentage point lower than in the 1980s.

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[1] As discussed by Mendis and Muellbauer (1984), problems also arise because of the *domestic price bias* (the output price deflator is for home sales only) and the *list price bias* (the output price deflator captures list prices more accurately than the prices at which transactions actually take place).

[2] See Gollop (1987) for a discussion of how trade in foreign-produced intermediate inputs may lead to biases in the measurement of value-added.

[3] To the extent that business cycles are not synchronous across sectors, these growth rates are not directly comparable. The econometric results presented later include measures of capacity utilisation to attempt to correct for idiosyncratic cyclicality. Mendis and Muellbauer (1984) justify such a practice by arguing that measures of capacity utilisation convert stock variables (such as the capital and labour stock) into flow variables. Alternatively, it is necessary to condition upon the state of the business cycle to remove non-linearities and asymmetries in the business cycle, see Acemoglu and Scott, 1994.

[4] The only significant omission is part of other transport equipment (SIC 36). We include aerospace (SIC 364), but exclude the remainder of other transport equipment due to problems of data reliability (the excluded industries consist principally of shipbuilding and railway equipment).

It is interesting to ask whether the improvement in measured aggregate manufacturing TFP growth in the 1980s is due to switches of resources between sectors, rather than by faster growth within the sectors themselves. Formally, an aggregation bias will arise in the estimate of the change in TFP of total manufacturing if the deviations in sectoral rates of change are not distributed independently from sectoral shares of total inputs. Using the same dataset as this paper, Cameron, Proudman and Redding (1998) conclude that around 10 per cent of *measured* TFP growth in UK total manufacturing between 1970 and 1992 is due to switches in resources between sectors (with increases in the share in inputs of food, drink & tobacco and paper & printing being offset by declines in textiles & clothing and iron & steel), with the remaining 90 per cent due to TFP growth within the sectors themselves (with aerospace and pharmaceuticals making important contributions).[5]

There have been surprisingly few other attempts to produce estimates of sectoral TFP growth in UK manufacturing. Certainly the most comprehensive is that undertaken by Oulton and O Mahony (1994) using a substantially different method from that of this paper. They used a gross output production function with labour, capital, and intermediates as inputs and calculate levels of TFP for the years 1954, 1958, 1963, 1968, 1973, 1976, 1979, 1982, and 1986 only (all these are Census of Production years) for 124 three-digit industries. It is interesting to make such comparisons as are possible, bearing in mind the differences in approaches. Oulton and O Mahony found substantial negative TFP growth in the 1970s, although they do not report a figure for manufacturing as a whole over a comparable period. This is followed by a speedup in the 1980s. They also found a substantial fall in TFP in iron and steel between 1973 and 1979 (of around 40% over the whole period) followed by a substantial upturn between 1979 and 1982 (of around 50%), as well as substantial falls in TFP in the 1970s in aerospace, timber & furniture, non-ferrous metals, and motor vehicles.

[5] It has also been argued that the rise of foreign ownership in the UK has driven productivity growth. Comparable data for TFP in foreign-owned firms are difficult to obtain, but Cameron (1998) shows that the rise in foreign ownership made little difference to aggregate labour productivity growth between 1981 and 1991, the years for which the best data are available. See also Griffith (1999) and Oulton (1998) on foreign ownership and productivity.

Table 1
Total Factor Productivity Growth in UK Manufacturing
Annual percentage rates of growth

	1970-1992	1973-1979	1979-1989
Total Manufacturing	1.38	-1.01	3.10
Food, Drink, Tobacco	-0.26	-3.73	1.07
Textiles & Clothing	1.76	-0.10	3.21
Timber & Furniture	0.27	-2.73	1.21
Paper & Printing	1.32	-1.77	2.51
Minerals	-1.06	-3.66	1.39
Chemicals NES	1.10	-0.54	3.95
Pharmaceuticals	3.85	2.72	4.14
Rubber & Plastics	1.58	-1.50	3.57
Iron & Steel	2.22	-7.64	11.71
Non-Ferrous Metals	1.20	-0.15	4.32
Metal Goods NES	1.39	0.27	2.22
Machinery	0.72	1.27	1.46
Computing	5.67	6.11	8.06
Other Electricals	1.68	-0.52	2.12
Electronics	3.01	1.73	3.34
Motor Vehicles	0.93	-0.91	3.20
Aerospace	4.17	-1.34	7.53
Instruments	2.95	2.87	2.42
Other Manufacturing	1.27	-0.53	0.95

Note: *Data adjusted for double-counting of R&D inputs (see Schankerman, 1981).*

3. Econometric Method And Data

3.1 Methodology

The regressions that follow deal with a panel of nineteen industries observed over 21 years (1972 to 1992). The nature of this panel is rather unusual since it is almost square, while most panels encountered in econometrics consist of either many units and few observations, or many observations and few units. Pesaran, Shin and Smith (1999) have recently discussed estimation with panels where T and N are quite large and of the same order of magnitude. The usual approach is to either estimate N separate regressions and to calculate the coefficient means, which they call the Mean Group (MG) estimator, or to pool the data and restrict the slope coefficients and error variances to be the same, the Fixed Effects (FE) estimator. Instead, Pesaran et al. propose an intermediate method, called the Pooled Mean Group (PMG), which constrains the long run coefficients to be identical, but allows the short run coefficients and error variances to differ across groups. However, this paper is actually interested in the long run heterogeneity of R&D coefficients, so it adopts a dynamic panel framework that allows each industry to be treated as separately as possible while imposing restrictions across the panel.

In particular, a common-coefficient is imposed on the main variable of interest, R&D capital. This restriction is then relaxed by the interaction of the R&D variable with various industry characteristics. These characteristics can be seen as shifting the R&D coefficient up or down. The paper also imposes a common set of year dummies across the industries, while allowing each industry to have its own fixed effect, capacity utilisation term, and input price bias term. Later the year dummies are replaced with four variables that vary across time but not across industries, namely a time trend; a split trend from 1980 onwards; an import-price bias term; and a term which reflects the difference between real gross output and single deflated value added.

One benefit of pooling the data is that the R&D effects can be estimated separately from time effects. Studies that use time-series data often encounter multi-collinearity problems because R&D capital is difficult to distinguish from a time trend.[6] The interaction effects further allow the R&D elasticity to vary across industries according to industry characteristics that might reasonably be thought to have an impact upon the R&D elasticity. As is well known, the use of a lagged dependent variable in a panel data model can be a problem because of its correlation with the fixed effects. As Nickell (1981) shows, the fixed effects estimator is biased of order *O(1/T)* and its consistency relies upon T being large. A typical approach followed in the literature is that of Arellano and Bond (1991) or Anderson and Hsiao (1982) who recommend first differencing the data and then the use of GMM or IV. However, since the time period examined is much longer than usual in the GMM literature, the fixed effects estimator is likely to be consistent.

Panel data tends to suffer from both heteroscedasticity (a typical cross-section problem) and autocorrelation (a typical time-series problem). These problems are treated carefully. First, models are estimated using weighted least squares (using real output as weights) to help to control for heteroscedasticity. These results suggest that while it is relatively easy to control for the autocorrelation using a dynamic model with a single lagged dependent variable, some heteroscedasticity remains. This heteroscedasticity in the disturbances does not appear to be related to the size of the industry (since real output is used for weights) and the regressions also pass the Ramsey (1969) RESET test. However, a White (1980) type test which regresses the squared residuals on industry dummies rejects homoscedasticity. Since the unweighted OLS dynamic results are very similar to the weighted least squares results, however, we focus on the unweighted dynamic model, but use robust standard errors as suggested by White (1980). We also experimented with a more general error variance structure using the Seemingly Unrelated Regression (SUR) estimator of Zellner (1962) and found similar results to those reported here.

3.2 Data Description

Following the earlier discussion, the paper estimates dynamic equations of the following form (although with a richer lag structure):

$$\text{(4)} \qquad \log \mathrm{TFP}_j(t) = a_j + a_1 \log \mathrm{TFP}_j(t-1) + a_2 \log \mathrm{R\&D}_j(t-2) + y\,\mathrm{X}_j(t-1) \log \mathrm{R\&D}_j(t-2) + f\mathrm{Z}_j(t-1)$$

where the vector of variables, *Z*, includes capacity utilisation derived from the CBI capacity utilisation index, as described in Mendis and Muellbauer (1984) and bias terms to capture the single-deflation bias discussed in Cameron (1999).[7] Also included were a human capital variable (the log of the ratio of medium and high

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[6] See Srinivasan (1996) and Lee, Pesaran and Smith (1997) for discussion of the problems of non-stationary panel data.

[7] Unit root tests (not reported) using the panel data approach suggested by Levin and Lin (1992) and Bernard and Jones (1996) on the main variables of interest, as well as the utilisation and bias terms confirm that they test as I(1).

qualification workers to total workers) and a unionisation variable (the log of the percentage of manual males covered by collective agreements multiplied by the percentage of manual males in all total workers), as well as year dummies to capture time-series variation that is common to all industries (mainly unobserved cyclical, bias and trend effects) and industry fixed-effects. The measure of R&D capital, *R&D*, is the log ratio of industry-funded Business Enterprise R&D (BERD) to physical capital.

As discussed earlier, an important feature of this paper is that R&D effects are allowed to vary across industries according to industry characteristics, the vector X in equation (4). There are eight industry characteristics, all of which enter the regressions as log ratios, measured relative to the average of manufacturing as a whole. Therefore, a value of 0 for the K/L ratio means that the industry has the same capital to labour ratio as manufacturing as a whole. A greater (lesser) value indicates that it is more (less) capital intensive. The characteristics are described in table 2.

Table 2

Interaction Terms

1.	$\log(\frac{K_j}{L_j}) - \log(\frac{K}{L})$	Physical Capital/Labour
2.	$\log(\frac{H_j}{L_j}) - \log(\frac{H}{L})$	Human Capital/Labour
3.	$\log(C5_j) - \log(C5)$	Concentration
4.	$\log(\frac{R_j}{K_j}) - \log(\frac{R}{K})$	R&D Capital/Physical Capital
5.	$\log(\frac{U_j}{L_j}) - \log(\frac{U}{L})$	Unionisation
6.	$\log(BERDu_j) - \log(BERDu)$	R&D Capital Used
7.	$\log(\frac{X_j}{Q_j}) - \log(\frac{X}{Q})$	Exports/Output
8.	$\log(\frac{M_j}{Q_j + M_j - X_j}) - \log(\frac{M}{Q + M - X})$	Imports/Home Sales

Note: *For an industry with the same value of the characteristic as total manufacturing, the value of the interaction term will be zero.*

Table 3 shows the values of the various characteristics for the year 1985 of the nineteen industries in the data-set as well as the level of relative TFP. These data are not in logs, so a value of 1 is the same as manufacturing as a whole. The first data column of table 3 shows the relative levels of total factor productivity in the nineteen industries.[8] Twelve of the industries have levels of TFP within 20 per cent of that of total manufacturing, with five having levels more than twenty per cent higher, and two being more than twenty per cent lower. The leading industries on this basis are (highest productivity first) computing, aerospace, pharmaceuticals, electronics, and instruments. The lagging industries are iron & steel and textiles. Total factor productivity is

[8] Note that in order to construct an index relative to total manufacturing, it is necessary to constrain the share of labour to be the same across industries. In table 3, it is taken to be 0.608, which is the value of labour's share in total manufacturing value added in 1985.

highly pro-cyclical, and so these comparisons are distorted to the extent that the different industries have different business cycles. This is especially the case for iron & steel whose TFP level has the second highest standard deviation of all the industries - in 1979 it has a relative TFP level of 0.38 and in 1989 it has a relative TFP level of 0.83. The assumption that the iron & steel industry is in equilibrium at any one point in time is therefore rather questionable.

The next two columns of table 3 show the industries' labour productivity and capital to labour ratios. Just as computing has the highest level of relative TFP in 1985, it also has the highest level of labour productivity, closely followed by pharmaceuticals. Iron and steel performs much better in terms of relative labour productivity than in terms of relative TFP, due to its high capital intensity. In terms of capital to labour ratios, and iron & steel, chemicals nes, and non-ferrous metals are especially capital-intensive.[9] The next column of table 3 shows the industries' human capital to labour ratios. The measure of human capital used is the ratio of medium and high education workers to total workers. For total manufacturing, between 1970 and 1992 this rises from 44.4 per cent (6.8 per cent with high education) to 72.3 per cent (12.7 per cent with high education). Computing, instruments, electronics, and pharmaceuticals have the highest ratios, and textiles the lowest.

The next two columns of table 3 show the five-firm concentration ratio and the ratio of the R&D stock to the physical capital stock. Aerospace, motor vehicles, computing and iron & steel are the most concentrated industries, and other manufacturing, timber & furniture, and metal goods the least concentrated. Aerospace, electronics, computing, and pharmaceuticals have the highest R&D capital to physical capital ratios, with paper & printing, timber & furniture having the lowest.

The next two columns of table 3 show the unionisation ratios and stocks of R&D imported from other industries. The former is the proportion of workers covered by collective bargaining agreements, while the latter is measured according to the procedure outlined in the data appendix and measures the extent to which the industry uses intermediate goods from sectors with high ratios of R&D capital to physical capital. Iron & steel, motor vehicles, and minerals are the most highly unionised, while computing is the least unionised. Aerospace, rubber & plastics, and paper & printing are most reliant upon the R&D of other industries, while chemicals nes is least reliant. The final two columns of table 3 show the export and import ratios of the industries. These are highly correlated, so that instruments, aerospace, computing and electronics stand out as especially open, while metal goods, food, drink & tobacco, and paper & printing are least open.

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[9] As can be seen from table 3, there is quite a good correlation between levels of Total Factor Productivity and levels of labour productivity (the Pearson product moment correlation coefficient between the two measures of productivity across the industries in 1985 is 0.83). Note that if shares of labour and capital are constant over time (as they are for the case of the Cobb-Douglas production function), log TFP is a weighted average of log(Y/L) and log(K/L), $\log TFP = (1-a)\log(Y/L) + a\log(Y/K)$ where α is the capital share in value added.

Table 3 *Total Manufacturing=1.00*

Relative Industry Characteristics for UK Manufacturing in 1985

	TFP	Y/L	K/L	H/L	C5	R&D/K	U/L	BERDu	X/Q	M/HS
Total Manufacturing	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Food, Drink, Tobacco	1.00	1.05	1.11	0.87	1.14	0.24	1.13	0.83	0.35	0.54
Textiles & Clothing	0.70	0.57	0.59	0.78	0.82	0.24	1.22	1.24	0.89	1.25
Timber & Furniture	0.98	0.72	0.46	1.01	0.42	0.07	1.06	0.70	0.16	0.76
Paper & Printing	1.17	1.09	0.84	1.09	0.58	0.06	1.09	1.43	0.32	0.54
Minerals	1.00	1.11	1.27	0.81	1.35	0.24	1.24	0.86	0.42	0.33
Chemicals NES	1.19	1.88	3.24	1.02	1.11	0.72	0.84	0.40	1.52	1.18
Pharmaceuticals	1.81	2.51	2.30	1.26	1.02	2.44	0.68	1.22	1.43	0.85
Rubber & Plastics	0.95	0.92	0.92	0.90	0.57	0.19	0.89	1.56	0.75	0.78
Iron & Steel	0.66	1.15	4.04	0.87	1.57	0.17	1.38	1.29	0.79	0.61
Non-Ferrous Metals	0.84	1.06	1.78	0.88	0.96	0.44	1.09	0.88	1.41	1.49
Metal Goods NES	0.85	0.78	0.78	0.85	0.45	0.18	1.00	0.72	0.40	0.38
Machinery	1.08	0.93	0.69	1.10	0.59	0.77	0.90	0.56	1.14	0.88
Computing	3.36	2.80	0.63	1.45	1.70	6.66	0.30	1.13	2.21	2.04
Other Electricals	1.07	0.85	0.57	1.14	1.18	1.64	0.53	0.92	1.14	1.13
Electronics	1.63	1.27	0.52	1.25	1.10	6.94	0.88	0.92	2.08	1.91
Motor Vehicles	0.93	1.02	1.27	0.82	1.93	0.95	1.26	1.03	1.09	1.38
Aerospace	1.47	1.16	0.55	1.07	2.03	15.80	0.96	1.67	2.06	1.64
Instruments	1.29	0.93	0.44	1.30	0.67	2.73	0.57	1.16	2.31	2.10
Other Manufacturing	0.87	0.73	0.66	1.22	0.41	0.72	0.51	0.48	1.39	1.45

Notes:		*Actual Data for Total Manufacturing, 1985*
TFP	*Total Factor Productivity*	*n/a*
Y/L	*Gross Value Added per Labour Hour*	*£7.89*
K/L	*Physical Capital per Labour Hour*	*£25.50*
H/L	*Ratio of Medium and High Education Workers to Total Workers*	*0.59*
C5	*Proportion of Output Produced by Five Largest Firms*	*0.38*
R&D/K	*Ratio of BERD capital to Physical Capital*	*0.46*
U/L	*Proportion of Workers Covered by Collective Bargaining*	*0.44*
BERDu	*Stock of R&D Capital Imported From Other Industries*	*n/a*
X/Q	*Exports divided by Domestic Output*	*0.31*
M/HS	*Imports divided by Home Sales*	*0.35*

Table 4 shows a correlation matrix for the industry characteristics. Not surprisingly, import and export ratios are fairly highly correlated. Interestingly, unionization is negatively correlated with most of the variables except the capital to labour ratio and the BERD-use variable. Industries with high ratios of R&D capital to physical capital tend to have higher levels of human capital and concentration, high export and import ratios, and low unionization.

Table 4

Correlation Matrix for industry characteristics

	K/L	H/L	C5	R&D/K	U/L	BERDu	X/Q	M/Q
K/L	1.00							
H/L	-0.32	1.00						
C5	0.28	0.15	1.00					
R&D/K	-0.37	0.49	0.53	1.00				
U/L	0.29	-0.61	-0.09	-0.29	1.00			
BERDu	-0.15	0.02	0.31	0.36	0.06	1.00		
X/Q	-0.03	0.44	0.52	0.54	-0.50	0.06	1.00	
M/Q	-0.30	0.52	0.37	0.51	-0.48	0.03	0.72	1.00

4. Econometric Results & Discussion

4.1 Panel Data Results

Table 5 reports the results of a variety of regressions of log TFP against log R&D (the ratio of industry-funded R&D capital to physical capital) and the interaction terms using Weighted Least Squares (using output weights) to allow for heteroscedasticity.[10] Each regression also included industry fixed effects, industry-specific utilisation terms, industry bias terms and a full set of year dummies (not reported in table 5). As specified in equation (4), human capital and unionisation variables were initially included in the regressions as well as their interaction terms with R&D capital. In addition a unionization catch-up variable was also included to test whether heavily unionized industries caught up fastest between 1979 and 1984. However, the restriction that the effect of human capital and unionisation were jointly insignificant could not be rejected ($F(3,318)=1.33$ [$P=0.26$]), while their interaction terms were jointly significant. This suggests that at the industry level, human capital and unionisation have an impact on growth through their effect on the R&D elasticity rather than individually.

Regression 1 uses Weighted Least Squares (WLS), as does regression 2, with the addition of a lagged dependent variable. The lagged dependent variable reduces the coefficient on R&D somewhat but helps to correct for the autocorrelation suggested by the AR test. One feature of these weighted regressions is that they fail a White (1980) heteroscedasticity test while passing the Ramsey (1969) RESET test. Inspection of the residuals suggests that there are a couple of industries with significantly heteroscedastic residuals, and that this heteroscedasticity is not reduced by using output weights in the regressions.

Turning to the unweighted regressions, regression 3 reports the results of OLS regressions with heteroscedasticity-consistent standard errors (once again industry fixed effects, industry-specific utilisation terms, industry bias terms and year dummies are included but not reported). The OLS estimates are similar to the WLS estimates in regression 1, although the coefficient on the capital to labour ratio interaction is lower, and the coefficient on the R&D use interaction is higher. Regression 4 adds a lagged dependent variable, which is significant and the restriction of no serial correlation in the residuals cannot be rejected.

So far, all the regressions have included a complete set of year dummies. In order to derive a parsimonious specification these dummies were replaced with variables that vary in the time-dimension but not in the cross-section, and are likely to reflect the measurement biases, cyclical effects, and time trend effects that are captured by the year dummies. Recall that the discussion of the single-deflation bias earlier suggested that the bias was likely to be correlated with the ratio of input to output prices, the ratio of foreign to domestic prices, and the ratio of inputs to outputs. In order to capture these different effects, we experimented with five different variables in place of the year dummies. These variables were a simple time trend, a trend starting in 1980, the log competitiveness measure (*pw*), and two different bias trend term to capture the long-run effect of changes in the input to output ratio. The first bias trend term, *biasgo*, was equal to the log of aggregate single-

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[10] All regressions in this paper were carried out using TSP version 4.3a (Hall, 1995).

deflated value-added minus log real gross output, and the second bias trend term, *biasvadd*, was equal to the log of aggregate single-deflated value-added minus log double-deflated value-added. These bias trend terms attempt to correct for any systematic mismeasurement in single-deflated value-added, and assume that the mismeasurement is either correlated with the deviation of VASD away from real gross output, or with the deviation of VASD away from VADD. Note that since the regressions already contained industry-specific input to output price terms, the regressions already correct to some extent for single-deflation bias.

Table 6 reports the results of such regressions. The restriction that the coefficient on *biasvadd* was zero is easily accepted (F(1,317)=0.070 [P=0.79]), so it is not reported in table 6. Regression 5 includes the other four terms including *biasgo*, the deviation of VASD away from real gross output term. The coefficients on R&D, the interactions, and the lagged dependent variable are similar to those of regression 4. However, the two time trends are not significant while the two bias terms are significant and have the expected positive signs. The coefficient on competitiveness (*pw*) is 0.275, while in Cameron (1999) the long-run coefficient on *pw* for aggregate UK manufacturing was estimated to be 0.217. When the year dummies are included as well as the bias trend effects, a test cannot reject the restriction that the year dummies are not significant (F(21,300)=0.957 [P=0.52]). Regression 6 drops the insignificant time trends. Regressions 7 to 9 report the successive deletion of the insignificant interaction terms. Regression 9 suggests that R&D has a long-run coefficient of around 0.24, and that the capital to labour ratio, the BERD use ratio and the import to output ratio have positive effects on R&D effectiveness, while the BERD to capital ratio and the unionisation ratio have negative effects. Regression 9 is a simplified version of regression 5, with five restrictions which cannot be jointly rejected (F(5,318)=0.24 [P=0.99]).

A number of robustness tests were carried out. First, a version of regression 5 was estimated with a trend break in 1980 in the R&D coefficient was also estimated in order to test whether the R&D elasticity was different in the 1980s than in the 1970s. The coefficient on the trend break was very small (-0.0001) and not significant (F(1,321)=0.04 [P=0.84]), so the hypothesis of no trend break cannot be rejected. Second, the human capital and unionisation terms were allowed to reenter as levels effects, as well as interactions with R&D, but were jointly insignificant in levels. Third, the dynamic panel was estimated using the Seemingly Unrelated Regression (SUR) estimator of Zellner (1962) which allows the error variances to differ across industries but the results did not change significantly. Fourth, the results are robust to the piece-wise deletion of each industry. That is, any one industry can be omitted from regression 9 without changing any coefficient by more than one standard error.

Table 5

UK Sectoral TFP Regressions - using output weights

	Regression Number			
	1	2	3	4
Method	WLS	WLS	OLS	OLS
log(R&D $_{jt-2}$)	0.185	0.137	0.170	0.148
	(0.075)	*(0.071)*	*(0.091)*	*(0.090)*
log(TFP$_{jt-1}$)		0.290		0.207
		(0.060)		*(0.051)*
Interaction Terms:				
Physical Capital	0.028	0.025	0.016	0.014
	(0.012)	*(0.011)*	*(0.010)*	*(0.009)*
Human Capital	-0.001	-0.002	-0.001	-0.003
	(0.008)	*(0.008)*	*(0.007)*	*(0.008)*
Concentration	-0.003	-0.011	0.008	0.003
	(0.012)	*(0.011)*	*(0.011)*	*(0.010)*
R&D Capital	-0.021	-0.018	-0.024	-0.022
	(0.006)	*(0.005)*	*(0.009)*	*(0.008)*
Unionisation	-0.055	-0.038	-0.063	-0.050
	(0.008)	*(0.008)*	*(0.009)*	*(0.008)*
R&D Use	0.046	0.037	0.140	0.120
	(0.052)	*(0.050)*	*(0.070)*	*(0.063)*
Exports	0.015	0.008	0.010	0.005
	(0.008)	*(0.008)*	*(0.007)*	*(0.008)*
Imports	0.017	0.013	0.013	0.011
	(0.004)	*(0.005)*	*(0.006)*	*(0.006)*
Year Dummies	√	√	√	√
Fixed Effects	√	√	√	√
Robust SEs	√	√	√	√
R^2	0.9675	0.9695	0.9694	0.9714
s.e.	0.0561	0.0545	0.0545	0.0528
AR c^2(2)	17.4 [0.00]	3.53 [0.17]	8.00 [0.02]	2.53 [0.28]
HS F(19,379)	2.82 [0.00]	3.79 [0.00]	2.47 [0.00]	2.74 [0.00]
RESET F(2,396)	0.02 [0.98]	0.08 [0.92]	0.03 [0.97]	0.02 [0.98]

Key to Interaction Terms (all interacted with industry-funded BERD capital):
Physical Capital: Physical Capital to Labour Ratio
Human Capital: Ratio of medium and high education workers to total workers
Concentration: Proportion of output produced by five largest firms
R&D Capital: Ratio of BERD capital to physical capital
Unionisation: Proportion of workers covered by collective bargaining
R&D Use: Stock of BERD capital imported from other industries
Exports: Exports divided by domestic output
Imports: Imports divided by home sales

Notes: Sample Period 1972 to 1992. Heteroscedasticity-Consistent standard-errors in parentheses. Dependent Variable is log Total Factor Productivity (corrected for double counting and expensing bias). R&D is the ratio of the stock of BERD capital to the physical capital stock. All equations include industry fixed effects, industry utilisation terms, industry bias terms and year dummies and use real output weights.

OLS: Estimation is by Ordinary Least Squares. C-O: Estimation is by Cochrane-Orcutt (1949) two-stage method. HILU: Estimation is by Hildreth-Lu (1960) iterative method with step-size for rho of 0.01.

AR c^2(2) Breusch-Pagan (1980) LM test for 1st and 2nd order serial correlation.
HS F-test for heteroscedasticity, White (1980).
RESET F(j,T-j-K) F-version of the RESET test for j powers, Ramsey (1969).

Table 6

UK Sectoral TFP Regressions - robust & unweighted

	Regression Number				
	5	6	7	8	9
Method	OLS	OLS	OLS	OLS	OLS
log(R&D $_{jt-2}$)	0.180	0.209	0.206	0.203	0.193
	(0.091)	*(0.071)*	*(0.071)*	*(0.069)*	*(0.064)*
log(TFP$_{jt-1}$)	0.185	0.180	0.180	0.182	0.187
	(0.045)	*(0.043)*	*(0.043)*	*(0.044)*	*(0.043)*
trend	0.003				
	(0.005)				
trend80	-0.003				
	(0.004)				
biasgo	0.721	0.648	0.646	0.647	0.645
	(0.146)	*(0.121)*	*(0.122)*	*(0.122)*	*(0.121)*
pw	0.275	0.262	0.267	0.267	0.265
	(0.058)	*(0.051)*	*(0.051)*	*(0.051)*	*(0.050)*
Interaction Terms:					
Physical Capital	0.017	0.017	0.017	0.017	0.018
	(0.009)	*(0.009)*	*(0.009)*	*(0.008)*	*(0.009)*
Human Capital	-0.003	-0.003			
	(0.007)	*(0.008)*			
Concentration	0.003	0.003	0.013		
	(0.010)	*(0.010)*	*(0.010)*		
R&D Capital	-0.023	-0.024	-0.024	-0.024	-0.023
	(0.008)	*(0.008)*	*(0.007)*	*(0.007)*	*(0.007)*
Unionisation	-0.052	-0.052	-0.052	-0.051	-0.051
	(0.008)	*(0.007)*	*(0.007)*	*(0.007)*	*(0.006)*
R&D Use	0.133	0.144	0.143	0.147	0.150
	(0.064)	*(0.060)*	*(0.060)*	*(0.059)*	*(0.059)*
Exports	0.004	0.004	0.004	0.004	
	(0.007)	*(0.007)*	*(0.007)*	*(0.007)*	
Imports	0.014	0.015	0.015	0.015	0.016
	(0.006)	*(0.006)*	*(0.005)*	*(0.006)*	*(0.005)*
Year Dummies	*X*	*X*	*X*	*X*	*X*
Fixed Effects	√	√	√	√	√
Robust SEs	√	√	√	√	√
R^2	0.9695	0.9694	0.9694	0.9694	0.9694
s.e.	0.0531	0.0530	0.0529	0.0528	0.0528
AR χ^2(2)	2.69 [0.26]	3.95 [0.14]	4.20 [0.12]	4.42 [0.11]	3.84 [0.15]
HS F(19,379)	2.60 [0.00]	2.71 [0.00]	2.72 [0.00]	2.72 [0.00]	2.76 [0.00]
RESET F(2,396)	0.27 [0.76]	0.27 [0.76]	0.24 [0.79]	0.24 [0.79]	0.31 [0.73]

Notes: see Table 5.

Sample Period 1972 to 1992. Heteroscedasticity-consistent standard-errors in parentheses. Dependent Variable is log Total Factor Productivity (corrected for double counting and expensing bias). R&D is the ratio of the stock of BERD capital to the physical capital stock; biasgo is equal to log aggregate single-deflated value-added minus real gross output; pw is the log ratio of foreign to domestic output prices; trend is a simple time trend; trend80 is a time trend beginning in 1980. All equations include industry fixed effects, industry utilisation terms, industry bias terms and year dummies. Estimation is by OLS (Ordinary Least Squares).

4.2 Estimated R&D Effects

Regression 9 is the preferred specification of this paper. It suggests a significant effect for R&D on TFP in UK manufacturing, and that this effect varies across industries according to industry characteristics. Specifically, industries with higher capital to labour ratios and higher propensities to use intermediate goods from technologically-intensive industries have higher R&D responses. These characteristics may be capturing the higher technology nature of these industries or reflect greater technological opportunities. Furthermore, industries with high ratios of imports to home sales also have higher R&D responses, which may reflect the effect of competition. R&D has a lower elasticity in industries with high ratios of R&D to physical capital, which may reflect diminishing returns. R&D also has a lower elasticity in highly unionized industries. Note, however, that the negative effect in this paper is an indirect one, operating through the returns to R&D, and that once this interaction is allowed for, unionization does not appear to have a directly negative effect on TFP.

Table 7

Point Estimates of Long-Run R&D Elasticities in UK Manufacturing

	Coefficient	**Standard Error**
Total Manufacturing	0.237	*(0.087)*
Food,drink,tobacco	0.226	*(0.088)*
Textiles & clothing	0.297	*(0.091)*
Timber & furniture	0.220	*(0.084)*
Paper & printing	0.361	*(0.094)*
Minerals	0.220	*(0.088)*
Chemicals nes	0.117	*(0.099)*
Pharmaceuticals	0.288	*(0.091)*
Rubber & Plastics	0.367	*(0.097)*
Iron & Steel	0.335	*(0.097)*
Non-ferrous metals	0.252	*(0.089)*
Metal Goods nes	0.200	*(0.086)*
Machinery	0.133	*(0.088)*
Computing	0.285	*(0.085)*
Other Electricals	0.237	*(0.084)*
Electronics	0.173	*(0.084)*
Motor Vehicles	0.241	*(0.089)*
Aerospace	0.252	*(0.096)*
Instruments	0.268	*(0.086)*
Other Manufacturing	0.151	*(0.089)*

Notes:
Point elasticities calculated using results of regression 9. Heteroscedasticity-consistent standard errors (in parentheses) are calculated from estimated covariance matrix of parameter estimates of regression 9.

To put the differences in R&D elasticity into a more concrete form it is possible to calculate the R&D elasticity for each industry by multiplying the coefficient estimate for each interaction by the industry characteristic relative to total manufacturing. For example, if an industry otherwise had characteristics identical to aggregate manufacturing, but a capital to labour ratio 100 per cent higher, the R&D elasticity in that industry would be estimated as 0.260 (0.193+1*0.018)*1/(1-0.187). Table 7 reports the R&D elasticities for each industry, along with the standard errors of the estimates (calculated from the covariance matrix of the parameter estimates).[11] The estimates show that R&D elasticities vary significantly across industries. The highest elasticities are found in paper & printing (0.361) and rubber & plastics (0.367), while the elasticities are rather low in chemicals nes (0.117), machinery (0.133) and other manufacturing (0.151).

5. Conclusion

Much of the recent work on both theoretical and empirical growth has examined either the international transmission of ideas or the possibility of scale effects on growth. Although the work of Aghion and Howitt (1998), among others, has focussed attention on the importance of profit-seeking R&D, relatively little attention has been payed to how the returns to R&D might differ across industries. Following the work of Jones and Williams (1998) and Barro (1999), it seems reasonable that the familiar TFP regressions of the 1970s and 1980s (see Griliches, 1992, for a survey) can be seen as variants of simple R&D based growth models.

Using these insights, this paper has constructed a heterogeneous dynamic panel data model of TFP performance in nineteen sectors of UK manufacturing between 1972 and 1992. The effects of capacity utilisation and input price biases were allowed to differ across industries, while a common coefficient was imposed on the effect of the R&D capital stock. This restriction was then relaxed by allowing the R&D capital stock to interact with a variety of weakly exogenous industry characteristics. The rôle played by the interaction terms can be thought of as causal, so that a higher level of unionisation leads directly to a lower R&D elasticity, or as reflecting unobserved industry characteristics, so that a low R&D elasticity may just be a technological feature of highly unionised industries.

There are three main conclusions. First, the slowdown in TFP growth in the 1970s and the speedup in the 1980s was widespread and not concentrated in any particular subset of industries. The data show that TFP growth at the aggregate level reflects TFP growth in the individual sectors rather than sectoral shifts towards fast growing sectors. This is also the case for labour productivity growth. Sectoral shifts towards the high TFP growth sectors of pharmaceuticals, computing, and aerospace account make almost no contribution to overall TFP growth. Declining shares of textiles & clothing and iron & steel are counterbalanced by expansions in the food, drink & tobacco and paper & printing industries.

Second, the elasticity of output with respect to R&D is positive and significant (at around 0.24). This is somewhat lower than the 0.29 per cent estimated at the aggregate level in Cameron (1999), but previous studies (as reported by Griliches, 1992) have generally found lower returns at greater levels of disaggregation because spillovers are less well captured. A number of other papers has estimated the effect of R&D on TFP in individual industries. The closest approach to that taken in this paper is that of Englander et al. (1988), who estimate R&D elasticities for a variety of industries using a panel of data on TFP in six countries (Canada, France, Germany, Italy, Japan, the USA, and the UK) between 1970 and 1983. They find significant elasticities

[11] I am grateful to Michael Pitt for this suggestion.

in textiles, chemicals & rubber, and machinery and electricals, and negligible returns in food, paper, metals, and minerals. Verspagen (1995) also estimates R&D elasticities at the industry level. He divides manufacturing into panels of high, medium, and low technology sectors and estimates the elasticities in a variety of countries. For the UK he finds an elasticity in high-technology sectors of 0.109 (machinery and electricals, transport, instruments and chemicals) and insignificant returns elsewhere.

Hall (1993) estimates industry-specific R&D elasticities based on a panel of US firms and generally finds positive but relatively low coefficients (0.102 in pharmaceuticals for example). However, these results were obtained by deflating sales by a single manufacturing sector deflator. In Mairesse and Hall (1996), regressions on a smaller sample of manufacturing firms yield a coefficient on R&D of around 0.04 for a within-firm estimator. In contrast, when a sector specific (at the 2 digit level) deflator is used, the R&D coefficient for the same sample of firms is estimated as 0.17. This emphasises the importance of using the correct deflators. Unfortunately, Mairesse and Hall do not report their results for individual sectors.

Third, the R&D elasticity varies significantly across industries in line with various industry characteristics. In particular, industries with higher capital to labour ratios, higher propensities to use the R&D of other industries, and higher import openness, have higher R&D elasticities. The former two effects are compatible with there being increased technological opportunities in those industries, while the latter effect may be because of competition or knowledge spillovers (see Cameron, Proudman and Redding, 1999, for discussion). Industries with high unionisation and higher R&D to capital ratios, have lower R&D elasticities. Higher levels of human capital, higher rates of concentration, and higher export openness, have no significant effect on the R&D elasticity. Once the interaction effects are included, neither levels of human capital, nor unionization, appear to have a direct effect on TFP levels.

Data Appendix

***Real Output*:** Value added is gross value added at factor cost from the Census of Production. This is equal to gross output minus purchases, minus increases in stocks of materials, stores and fuel, minus the cost of industrial and non-industrial services. Gross value added was deflated by the producer prices (output) index, to give a Single Deflated Value-Added index. To allow for the expensing bias described by Schankerman (1981), an allowance for R&D intermediate spending was added to gross value added.

Producer Prices (output): Producer Prices (output) index supplied by the ONS and is on a net sector basis. The index was used to construct data on constant prices single deflated value added (VASD) for each of the nineteen industries. We then divided total manufacturing current prices value-added by the total of the industry VASD to obtain an implicit real output index for total manufacturing.

Producer Prices (input): Producer Prices (input) index supplied by the ONS and is on a net sector basis.

Labour Input: Total employment is from the Census of Production. From this, the number of R&D workers was subtracted. Normal and overtime hours worked per week (full-time males) are taken from the New Earnings Survey and from information supplied by the Employment Department. Weeks worked are taken from Employment Gazette (data for total manufacturing are assumed to apply to all industries). Hours worker per year in manufacturing is the result of multiplying employees by hours by weeks worked.

Capital Input: Data for 2 digit industries were supplied directly by the ONS. An estimate of capital equipment used for R&D purposes was subtracted. It was necessary to construct data for pharmaceuticals, electronics, and aerospace. We estimated a base stock for each sub-industry as equal to the base stock in the main industry multiplied by the average between 1970 and 1974 of the ratio of gross investment in the sub-industry to gross investment in the main industry. We took the depreciation rate in the sub-industry as being equal to the depreciation rate in the main industry. Current price data on investment in the sub-industries were available in OECD Industrial Structure Statistics and the Census of Production. We converted these to constant prices using the gross fixed capital deflator for the main industry. The method used to construct capital stocks can be summarised as follows. Say we have main industries 1..I, called i, each with 1...J sub-industries, called j. The stock of gross fixed capital in sub-industry i at time t is therefore

(A1) $$K_t^j = ((K_{t-1}^j) * (1 - d_t^j)) + I_t^j$$

where

(A2) $$K_{1970}^j = K_{1970}^i * \left(\frac{1}{5}\sum_{1970}^{1974} \frac{I_t^j}{I_t^i}\right)$$

Capacity Utilisation: The CBI Industrial Trends Survey asks the following question: ‘Is your present level of output below capacity (i.e. are you working below a satisfactory full rate of operation)?’ These data were used to compile a capacity utilisation index, following Mendis and Muellbauer (1984).

Constant prices Business Enterprise Research and Development (BERD): Data on Business Enterprise R&D at current prices were supplied by the ONS. Current price data were converted into constant prices using the Divisia price indices for UK BERD calculated in Cameron (1996). The flows of constant price BERD were converted into capital stocks using a 10 per cent depreciation rate assumption and the base stock assumption used by Cameron (1999).

BERD imported from other industries: Following Scherer (1982) we use a technology flows matrix based upon the 1984 UK input-output table of intermediate goods (the ‘Leontief inverse’) to weight the real BERD expenditures of the other industries. Say that we have a (19*19) matrix T of the proportion of intermediate goods produced by 19 industries (J=1..19) and sold to the same 19 industries (I=1..19). Then a typical element of the matrix is Tji , which is 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 we capture the effect of R&D within each industry separately). We then multiply the (19*19) matrix T by the (19*1) vector B, which contains the real BERD spending of each of the 19 industries. This gives us a (19*1) vector TB of where each element is the amount of BERD imported from other industries by industry i. However, any differences between industries at this stage are accounted for by the composition of inputs, and not by their level, whereas it seems likely that industries that use relatively more intermediate goods from other industries will benefit more than industries that use relatively less. We therefore multiply vector TB by the (1*19) transpose vector M', whose typical element Mi consists of the proportion of industry i's gross output that is accounted for by intermediate inputs from other industries[12]. The resulting (19*1) vector, called MTB, is the amount of R&D imported by industry i from the other 18 industries in each year. 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.

Ratio of medium and highly educated workers to total workers: This is the ratio of workers with high and medium qualifications to total workers. In the Labour Force Survey, workers with high qualifications are those with degrees and diplomas; medium qualifications are A- and O-levels, GCSEs and all trade certificates. Low qualifications are those with no formal qualifications. These data are available on a 1980 SIC basis from 1977 to 1992. They were extrapolated backwards to 1973 using the 1 digit data in the General Household Survey. I am grateful to Brian Bell for these data.

Collective Agreement Coverage: Proportion of manual employees covered by collective bargaining agreements. Data for 1973, 1978 and 1985 are available in the New Earnings Survey. Changes in union density were used to make interpolations between those years. These data were supplied by Brian Bell.

[12] Data on the ratio of intermediate inputs to gross output were obtained from the Census of Production. Because of problems in the compilation of these data, it was only possible to calculate the ratio from 1975 onwards. The ratio showed some procyclical properties (i.e gross output falls by proportionately more than intermediate purchases during recessions), so it was decided to use the average of the ratios in 1979 and 1989, the two peak business cycle years. In only two industries were these ratios different by more than four percentage points, and so the bias is likely to be small.

UK Industry Concordance

INDUSTRY	**SIC 1980**	**SIC 1968**	**Error %**
Manufacturing	2 to 4	III to XIX + 102/3/9 -261/2/3	-0.5
Food, Drink, Tobacco	41/42	III	0.9
Textiles & Clothing	43/4/5	XIII to XV - 411	2.8
Timber & Furniture	46	XVII	0.0
Paper & Printing	47	XVIII	0.1
Minerals	23/4	XVI + 102/3/9	-2.9
Chemicals	25/6+48	V+411+491+496	0.9
Chemicals nes	25+26-257	V+411-272-2796-(0.5*276)	1.2
Pharmaceuticals	257	272+2796	2.0
Rubber & Plastics	48	491+496+(0.5*276)	1.1
Basic Metal Industries	22	VI	4.7
Iron & Steel	221/2/3	311+312+394	7.2
Non-Ferrous Metals	224	323+0.8*(321+322)	0.5
Fabricated Metal Products	3		-2.4
Metal Goods nes	31	XII-394+313	7.2
Machinery	32	VII-338+0.2*(321+322)	-8.3
Computing	33	338+366	-4.7
Electrical Machinery	34	IX-366+0.5*(354)	0.3
Other Electricals	34-344-345	IX-363/4/6/7	3.6
Electronics	344/5	363/4/7+0.5*(354)	-2.9
Motor Vehicles	35	381	2.0
Aerospace	364	383	1.2
Instruments	37	VIII-0.5*(354)	-4.6
Other Manufacturing	49	XIX-491-496	-2.3

Notes: The concordance is based on Kong (1988), Oulton and O'Mahony (1994), and the author's calculations. The manufacturing dataset is composed of the nineteen industries not in bold. The industries marked in bold are various levels of aggregation. It was not possible to obtain a perfect concordance between SIC 1968 and SIC 1980. Column four shows the percentage error in the value-added data between the two classifications. The only significant omission is part of other transport equipment (SIC 36). We include aerospace (SIC 364), but exclude the remainder of other transport equipment due to problems of data reliability (the excluded industries consist principally of shipbuilding and railway equipment).

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