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R&D AND PRODUCTIVITY IN THE UK: EVIDENCE FROM FIRM-LEVEL DATA IN THE 1990s

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R&D and Productivity in the UK: evidence from firm-level data in the 1990s *

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Abstract

The UK's business R&D (BERD) to GDP ratio is low compared to other leading economies, and the ratio has slowly declined over the 1990s. This paper uses data on large UK firms to analyse the link between R&D and productivity over the 1989-2000 period. Using a production function approach, and a sample of up to 719 firms, various different samples and estimators are used to assess the elasticity of, and rate of return to, R&D. The results indicate that UK returns to R&D are similar to returns in other leading economies. Furthermore, the returns to R&D have been relatively stable over the 1990s. There is no evidence to suggest that stock market listed firms, or firms with higher past profitability, have significantly different returns. Overall, the results suggest that the low BERD to GDP ratio in the UK is unlikely to be due to direct financial or human capital constraints (as these imply finding relatively high rates of return). Instead, the low BERD to GDP ratio appears to reflect low (perceived) opportunities by firms and the inability of firms to manage R&D to generate value. The paper provides some, tentative evidence, that high rates of competition in the science-based sector are associated with low returns to R&D.

Keywords: R&D, productivity.

J.E.L. classification: L10, O31, O34

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1 Introduction

There is a widely held belief that UK firms invest too little in R&D. In comparison with other leading economies, the UK's business R&D as a percentage of GDP (the BERD ratio) is low. Furthermore, the aggregate statistics show a small decline in the UK's BERD ratio in the 1990s, whereas other leading economies have experienced rises. In 2000 the UK government reacted to this with the introduction of a R&D tax credit, initially for SMEs, but extended to all companies in 2002.[1] The issue of under investment in R&D becomes even more critical when the UK's productivity growth record is considered. Although there have been periods of relatively good growth performance, overall the UK's level of labour productivity has been consistently lower than its major competitors over recent decades. This appears to be true both for the manufacturing sector and the service sector (DTI, 2003, Griffith and Harrison, 2003, Griffith et al, 2003).

These two issues – low BERD ratio and relative poor productivity performance – are, in the views of many economists, directly linked. Low investment in business R&D is thought to reduce innovation and knowledge creation, which in turn reduces total factor productivity, as well as investment in both physical and human capital. Despite a general acceptance of this by economists and, given the introduction of R&D tax credits, by policy makers in the UK, there is relatively little empirical analysis that investigates these issues at the firm-level. This paper uses firm-level data on UK firms to investigate the link between R&D and productivity. The basic idea at the centre of this paper is as follows. Low investment in R&D by UK firms suggests *either* relatively few investment opportunities for UK-based R&D projects *or* some form of external constraint on firms that prevents them from investing more. The former case could arise from low levels of appropriability, which in turn could be caused by poor management, high spillovers or intense competition, or simply a failure to identify projects. In terms of possible external constraints, two important ones are lack of finance and lack of specialised human capital.

[1] The effectiveness of the tax credit has not yet been evaluated. Inland Revenue (2003) report that in 2001-2 there were 3,200 claims under the scheme covering a R&D spend of only £200 million (around 1.5% of total BERD).

This paper attempts to unravel some of these issues by analysing the returns to R&D in a sample of large UK firms for the period 1989-2000. An initial task is to compare the estimated returns to R&D in the UK with studies from other countries. If there are various constraints, or other conditions specific to the UK, the implication is that the rate of return may be different from other countries. A second issue is whether the returns to R&D have been constant through time. It might be that the aggregate fall in BERD in the UK is driven by falling returns to R&D. Alternatively, it is possible that improvements in R&D effectiveness over time have *raised* rates of return. If this were true then the focus on R&D intensity by policymakers is, to some extent, misguided and the falling R&D intensity is less likely to be a cause of the UK's poor productivity performance.[2]

The structure of the paper is as follows. Section 2 outlines the basic, economy-wide features of business R&D in the UK in comparison to other countries and through time. Section 3 sets out the various theoretical and empirical difficulties in assessing the productive impact of R&D. Section 4 discusses the data available. Section 5 provides various baseline regression results for the elasticity and rate of return to R&D. Regressions are run separately for manufacturing and non-manufacturing samples, and a variety of estimators are used to allow comparisons and check for robustness.

Section 6 analyses three additional aspects of R&D performance. First, this section looks at whether the impact of R&D has varied during the 1990s, finding that returns have been broadly constant. Second, it analyses whether the past profitability of the firm is informative in determining the returns to R&D. If external financing constraints are important, then firms with lower past profitability may have lower R&D levels and correspondingly higher rates of return to R&D (assuming a common shared production function). Lastly, section 6 takes a first look at the role of competitive conditions. Analysing the returns to R&D at the sector level, the results suggest only the science-based sector has significantly higher levels of competition in the 1990s. This sector also has the lowest estimated return to R&D.

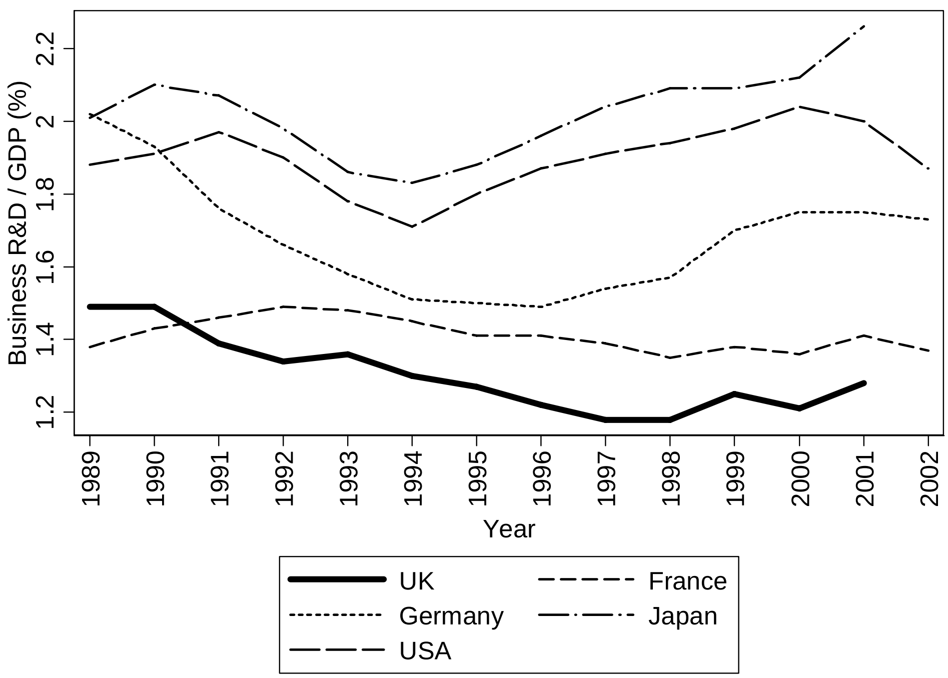
[2] Many other possible reasons for the UK's productivity performance have been suggested, including: lack of access to long term finance, limited supply of skilled and scientific human capital, poor general management, a corporate culture overly focussed on growth through acquisitions, lack of government support and poor university-business links. It is clear that some of these factors also affect R&D expenditure and, for that matter, R&D effectiveness.

2 Business R&D in the UK: what we do and don't know

This section summarises the major issues and results surrounding business R&D in the UK Figure 1 shows the business R&D (BERD) to GDP ratio for five leading economies from 1989-2002. The UK starts this period second from lowest and then its BERD ratio gradually drifts downwards, ending at around 1.2% of GDP and the lowest of the G5 (the ONS data for 2002 also shows the ratio at 1.2%). An initial issue is whether differences in industrial structure account for the level differences between the UK and other countries. Overall, there is little evidence for this being a dominant factor. HM Treasury (2004, p.58) assert that current differences in industry structure account for around half of the difference with the USA, but virtually none of the difference with Germany or France. Van Reenen (1997), in an analysis of trends over the 1974-1991, reaches a similar conclusion: the UK's low BERD is due to within industry factors, rather than industry structure. Griffith and Harrison (2003), in a comparison of UK and USA BERD over the 1981-2000 period, confirm that within industry differences are important, especially in the 1990s. They also find that while much of the fall in BERD intensity in the 1980s was due to a reduction in government funding of BERD, in the 1990s the relative poor performance was due to a fall in internal (business) funding. Further, they find that much of the decline in BERD is due to major falls in machinery, equipment and transportation industries; whereas, they was a strong positive contribution from the pharmaceutical industry.

The above comments suggest that the low levels of BERD in the UK are related to the private choices at the firm-level (or, at the least, at a detailed industry-level not picked up by the structure studies). Although there is a wide literature on the determinants of BERD intensity at the firm- and industry-level (see Cohen, 1995, Symeonidis, 1996, and Rogers, 2002 for recent reviews), there is relatively little for the UK. Bond et al (2003) use data on manufacturing firms in the UK and Germany for 1985-1994 to investigate whether financial constraints affect R&D investment. Using past cash flow as an indicator of access to finance, they find that UK companies are susceptible to financial constraints in the decision to undertake R&D, but past cash flow is not informative on the choice of R&D intensity. Becker and Hall (2004) and Becker and Pain (2003) analyse the level of BERD in 11 UK manufacturing industries for 1993-2000 using a variety of explanatory variables. They find that the 1990s fall was associated with weak output growth, declining government funding and appreciation of sterling since 1996. At the same time, their analysis suggests that low real interest rates, higher import penetration and higher foreign R&D undertaken in the UK all acted to raise BERD. The latter issue – whether increased foreign-funded BERD crowds-in or crowds-out domestic R&D – is also considered by Driffield (2001) for the 1989-92 period using data on 31 industries. He finds the reverse link: higher foreign R&D crowds out domestic R&D, although the elasticity is only 10%.[3]

Figure 1 BERD to GDP ratio, selected countries (OECD data)



Source: Main science and Technology Indicators, OECD. 'Germany' refers to W. Germany until 1990 and to unified Germany from 1991. The Office of National Statistics (ONS) BERD data are slightly different – they indicated the BERD ratio was static at 1.2% from 1995-2002 – but the basic trends shown hold.

The existing literature points to the following differences: (i) the UK BERD ratio is relatively low in comparison to other countries, (ii) this cannot be explained entirely by differences industrial structure, and (iii) the decline in the 1990s has been largely due to firm-level, or at least detailed industry-level, reasons. In addition, financial constraints may account for lower UK BERD, but the only available evidence suggests it affects the decision to do R&D, not

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[3] The share of UK BERD funded from overseas is relatively high (21% in 2000, as opposed to around 3% in Germany). Further, this share has increased from 15% in 1992 (data from ONS, 2001). Whether the increasing share of foreign funded R&D has reduced or increased aggregate BERD to GDP ratio is not something that we analyse here.

the R&D intensity of firms that undertake R&D. Other factors that may contribute to the fall in the 1990s are the high value of sterling post 1996 and reduced government funding.[4]

The formal, econometric analysis of why the BERD ratio is low does provide some insights, but there are no shortages of other possible explanations from the wider literature on UK performance. These include poor management of R&D, including the poor utilisation of the intellectual property system; weak university-business links; limited supplies of scientific and technical labour; lack of fiscal incentives in the 1990s; limited competition in utilities; and the unfavourable tax treatment of intangible assets and high-tech start-ups.[5] There is little direct evidence of the quantitative importance of any of these factors on the BERD ratio.

3 Empirical models of R&D and productivity

3.1. Empirical specifications

The basic relationship of interest is the link between the value added of the firm and its investment in R&D. It is standard to represent these ideas using a production function such as:

$$Y = AN^{\alpha_1}K^{\alpha_2}R^{\alpha_3}\ . \qquad [1]$$

Where Y is some measure of value added, N is labour, K is tangible capital, R represents R&D and A is a parameter representing all the impact of external (to firm) knowledge.[6] Although we have included R in [1] to represent R&D, some authors interpret this term as the firm's 'knowledge stock' and then use R&D as a proxy for this. In order to derive an

[4] These points derive from the analysis in Becker and Hall (2004) and Becker and Pain (2003), although these papers analyse the level of BERD not the BERD/value added ratio.

[5] These are taken from a variety of sources, but summaries are given in HM Treasury (2003, 2004) and DTI (2003).

[6] The presence of A in [1] requires some explanation. In economic growth theory, A represents the level of knowledge or technology of the firm, which would include any contribution from in-house R&D. However, in the empirical R&D productivity literature some authors leave in the A term (e.g. Hall and Mairesse, 1995, although they do not define it), while others omit it entirely (e.g. Bond et al, 2002). Leaving A in [1] makes it clear that there can be external, knowledge related, effects on productivity, perhaps due to spillovers.

empirical specification, take logarithms of [1] which, adding an error term and using i to indicate a firm and t a year, yields

$$y_{it} = \beta_t + a + \alpha_1 n_{it} + \alpha_2 k_{it} + \alpha_3 r_{it} + u_{it} \,. \qquad [2]$$

Where lower case letters represent logarithms, the β_t represent year dummies and u_{it} is the error term. As noted, the term a represents the impact of external knowledge on the firm's productivity (in the empirical analysis below this is proxied by the sum of R&D within the industry). The error term can be thought of as having three components: $\beta_i + \eta_{it} + \varepsilon_{it}$. We define ε_{it} as measurement error in the data (created either by accounting issues or collection errors). The β_i is a time invariant, firm-specific effect, unobserved in the data, but assumed to be known to the firm. Finally, η_{it} is a 'shock' experienced and known to the firm, but not to the econometrician. If not controlled for, the presence of both η_{it} and β_i can bias estimates if they are correlated with the explanatory variables. Interpreting β_i as, say, management ability, indicates the possibility of such a correlation. There is also a literature of the fact that 'shocks' (the η_{it}) may also affect optimal choices of variable inputs.[7]

It is possible to re-write [2] in intensive form. This involves subtracting n from each side, leading to output per worker as dependent variable, and then rearranging the right hand side to yield

$$y_{it} - n_{it} = \beta_i + \beta_t + a + (\phi - 1)n_{it} + \alpha_2 (k_{it} - n_{it}) + \alpha_3 (r_{it} - n_{it}) + u_{it} \,, \qquad [3]$$

where $\phi = \alpha_1 + \alpha_2 + \alpha_3$. Hence this allows a direct test of constant returns to scale (i.e. ϕ-1 should equal zero if constant returns to scale). Hall and Mairese (1995) argue [3] is preferred for 'interpretive reasons', although some authors claim that this specification may also lesson outlier or heterogeneity problems (Los and Verspagen, 2000).

Entering R&D or the stock of R&D for r in [2] or [3] allows an estimate of the elasticity of output with respect to R&D investment (α_3). To be precise, estimating [2] or [3] assumes that

[7] Recent papers dealing explicitly with this issue include Bond and Soderbom (2005) and Ackerberg and Caves (2004). On the whole this literature suggests that labour will be the variable factor, while capital (at time t) will not be influenced by η_t. Whether labour is, in fact, the variable input – especially when labour is measured by employment, and not hours, and capital can be leased – is such to debate.

the elasticity is equal across all firms in the sample. Researchers are also interested in the rate of return to R&D. The gross rate of return to R&D (dY/dR) can be calculated from the elasticity (i.e. $dY/dR=\alpha_3 Y/R$), which implies the rate of return varies inversely with R&D intensity. High R&D intensity firms would be automatically attributed a low marginal rate of return. This is fully compatible with the concavity of the production function but is, of course, not compatible with the idea of a competitive market for R&D, which should equalise marginal returns across firms. In view of this, an alternative estimation method is also used that assumes the rate of return is constant across firms (see, for example, Hall and Mairese, 1995). Taking first differences of [2] yields

$$\Delta y_{it} = \Delta\beta_t + \Delta a + \alpha_1 \Delta n_{it} + \alpha_2 \Delta k_{it} + \alpha_3 \Delta r_{it} + \Delta u_{it} \ , \qquad [4]$$

where r is the log of R&D stock, hence (omitting the i index)

$$\Delta r = r_t - r_{t-1} = \ln\left[\frac{RD_t + (1-\delta)RS_{t-1}}{RS_{t-1}}\right] = \ln\left[\frac{RD_t}{RS_{t-1}} + (1-\delta)\right] \approx \frac{RD_t}{RS_{t-1}} \ , \qquad [5]$$

where RD_{it} is R&D expenditure, RS_{it} is R&D stock and δ is the rate of depreciation of R&D. Under the assumption that δ and RD_{it}/RS_{it-1} are close to zero, the Δr_{it} term is approximately RD_{it}/RS_{it-1}. Since the parameter α_3 is the elasticity of R&D, equation [4] can therefore be re-written as

$$\Delta y_{it} = \Delta\beta_t + \Delta a + \alpha_1 \Delta n_{it} + \alpha_2 \Delta k_{it} + \alpha_4 \frac{RD_{it}}{Y_{it}} + \Delta u_{it} \ . \qquad [6]$$

Hence we can enter the R&D to output ratio in a first difference specification and the coefficient (α_4) will be the (approximate) gross marginal return on R&D. This 'first difference' specification removes the firm-specific effect (β_i) and prevents this possible source of bias. Specification [6] also assumes that the gross marginal return to be constant across all firms in the sample, whereas estimating [2] or [3] forces the elasticity to be constant.

A major issue facing the estimation of [2] or [3] is how to construct R&D stocks. As per equation [5], the standard approach is to calculate R&D stocks by assuming a fixed rate of depreciation (δ) using, for example,

$$RS_t = RD_{t-1} + (1-\delta)RS_{t-1} \ , \qquad [7]$$

where RS_t is the R&D stock at beginning of period t and δ is often assumed to be 0.15, although some sensitivity analysis is sometimes carried out. Hall and Mairese (1995) use this procedure in a study of R&D in French manufacturing firms in 1980s. A further issue is how to generate the first year's stock and the general assumption is that:

$$RS_1 = \frac{RD_0}{g+\delta} \qquad [8]$$

Where g is the (assumed) long run growth rate of R&D. Bond et al (2002) argue that since, in steady state, $RD_t = (g+\delta)\ RS_{t-1}$, and also $RS_t = (1+g)\ RS_{t-1}$, we can write:

$$\frac{RS_t}{(1+g)} = RS_{t-1} = \frac{RD_t}{g+\delta} \Rightarrow RD_t = \frac{g+\delta}{1+g} RS_t \qquad [9]$$

Taking logs of far right we have that $\ln RD_t$ is approximately equal to $\ln RS_t$ (and, of course, is exactly equal in the case of 100% depreciation if $\delta=1$). This prompts them to use (log of) current R&D as a proxy for R&D stock in their analysis. More generally, some papers appeal to the idea that a single year's R&D may be a better proxy for a firm's knowledge stock (e.g. Hall and Mairese, 1995).[8] This also allows for the possibility that a firm's knowledge stock is more than just the (discounted) sum of past R&D; for example, recent R&D may be critical in allowing the absorption of other firms' knowledge.

This short discussion has highlighted that analysing the impact of R&D on output is confronted with a series of difficult issues even at the conceptual stage. Estimating the R&D elasticity assumes that the marginal rates of returns vary across firms and involves approximations for the R&D stock. Estimating the rate of return allows the elasticity to vary across firms, but also involves a series of approximations.

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[8] Note that since regressions enter the log of R&D, the assumption that all firms' R&D stocks are a multiple of current R&D (i.e. $x^*R\&D_t$, with $x>1$), simply means that the coefficient estimate from using log(R&D) or log(stock of R&D) is identical.

3.2. Estimation issues

Although [2], [3] and [6] are widely used estimation equations, it is important to acknowledge there are a range of difficult issues involved in their estimation. These difficulties can be summarised as follows.

Measurement error. Each of the variables can be subject to sizeable measurement error. An issue regarding R&D is the so-called double-counting issue (originally raised by Schankerman, 1981). The issue here is that R&D expenditures will include money spent on employees and capital equipment.[9] Since employees and capital are also entered as explanatory variables, this suggests a measurement issue which, according to Schankerman, will bias estimates of R&D coefficients downwards. Hall and Mairese (1995), who are able to adjust for the double-counting, find support for such a downward bias, although Verspagen (1995) does not find it affects the coefficient substantially. Other variables also suffer from measurement issues. For example, data on tangible capital are often taken from financial accounts and, as such, rely on accounting conventions, which differ from economic conventions. Employment data again come from published accounts and these do not normally distinguish between part- and full-time employees, let alone allowing the researcher to calculate a 'hours' input measure. In general, measurement error in the explanatory variables will cause attenuation bias. Note that this may be more severe in first difference or within deviation models.[10]

Simultaneity. As mentioned above, an issue raised in the literature is that the production function above is a reduced form of a system of equations. Each of these equations can be thought of as jointly determining each of the key variables (i.e. *k*, *l* and *r*). This potentially

[9] In the UK in 2000, wages and salaries accounted for around 40% of total BERD, other variables costs for around 50%, with the rest spent on capital (ONS, 2001).

[10] The basic result that measurement error can attenuate coefficients (cause them to be biased towards zero) is contained in, for example, Greene (1993) or Johnston and Dinardo (1997). In first difference or within deviation models the attenuation is worse if the explanatory variables are correlated over time (Griliches and Hausman, 1986, Baltagi, 1995). In general, measurement error in the dependent variable (i.e. output) is not a concern, however, in the case of a production function there are potential problems. Klette and Griliches (1996) discuss the case where the use of aggregate deflators introduce a firm specific error that can be correlated with growth of inputs.

introduces a correlation between u_{it} and the right hand side variables, which will bias coefficient estimates. Some researchers tackle this issue by assuming right hand side variables are predetermined or endogenous and then using lagged values as instruments; others assume optimising behaviour, and external information (e.g. on investment) to identify the production function (e.g. Olley and Pakes, 1996, see Bond and Soderbom, 2005, for a recent discussion of these issues).

Omitted variables. The fact that the data available never contain all the potential variables of interest generates the possibility of omitted variable bias. As an example, in the analysis below (and many other studies) there is no data on investment in IT. Equally, there is no data on the level of human capital and skills, either in general workforce or in the management team. These types of variables are often thought to be of critical importance in determining productivity outcomes, but it is generally not possible to control for them directly. One solution is to assume that all of these omitted variables are 'picked up' by the firm specific effect (β_i), hence we assume that the effect of these variables is time invariant (over the sample period at any rate). However, this is unlikely to remove the omitted variable bias entirely.

Dynamics. A further issue is the possibility of lag effects in the influence of right hand side variables or, indeed, from omitted variables whose effect is contained in u_{it}. Although many analyses ignore the possibility of dynamic effects, some papers explicitly focus on this issue by estimating lagged dependent variable models, common factor models or error-correction models (Nickell, 1996, Bond et al, 2002, Los and Verspagen, 2000). Related to this issue is how current R&D may impact on both current and future productivity. It seems reasonable to assume that current R&D affects future productivity (as apposed to [1] where the impact is concurrent), hence some form of dynamic model seems justified. More realistically, one might expect the impact of current R&D on future productivity to be conditional on other investments (e.g. marketing investment in the case of product related R&D, or investment in capital or training in the case of process R&D).

The various generic problems discussed above mean that the empirical analysis of firm-level productivity has to be approached with care. Although the existing literature tackles some of these problems, there are no papers that attempt to tackle *all* of these issues. Given the complexity of the issues, and the fact that data are always limited in some respect, this is entirely understandable. Our view is that there is no single estimator that can alleviates all of these problems; rather individual estimators are influenced by different aspects of the above problems.

Returning to the empirical specifications above, clearly [2] and [3] contain firm-specific effects (β_i) hence, if panel data are available, this suggests either first differences (FD) or within estimation (FE). This said, some studies use OLS or between estimates, accepting the possible bias to coefficients. This can be justified if there are concerns that measurement error is severe. Many studies recognise the simultaneity issue and treat labour and capital as 'endogenous' This leads some to use IV techniques (including GMM). However, some studies simply use pre-period values as explanatory variables.[11]

The 'omitted variable' issue raised above clearly presents difficulties for every study. In general data on human capital, training or specific investment are not available, so little can be done. The inclusion of fixed effects and industry dummies is common. In addition, some studies allow the coefficient on R&D to differ across sectors, normally high-tech verses low-tech sectors (e.g. Greenhalgh and Longland, 2002, Los and Verspagen, 2000). Wakelin (2001) has data for whether firm has made a significant innovation in the past and looks at the difference in R&D coefficient between 'innovators' and 'non-innovators'. The issue of 'dynamics' raised above is often not discussed explicitly. An exception is Bond et al (2002), who only estimate a common factor model (i.e. an autoregressive distributed lag model), finding some support for this approach, although results are very sensitive to the estimator used.

A final issue facing empirical studies is whether to filter the data before analysis. Most papers do not discuss this explicitly, although they often have samples of, say, just large firms, which may well remove the smaller firms with extreme R&D values. However, Hall-Mairese 'clean' their data by removing outliers in both growth rates and levels (any level outside median +/-3 x interquartile range; growth of value added <-90% and >300%, and for labour, capital and R&D, <-50% and >200%). They also remove any firms with less than three years

[11] For example, Hall and Mairese, 1995, state, "By using input measures from the beginning of the year for which output is measured, we hope to minimise the effects of simultaneity between factor choice and output, but this could still be a problem" (p.269). Later in their paper they do tackle the simultaneity issue, using a partial factor-choice approach, but they find that it makes little difference in the 'within-firm and first difference' approach.

of data. Similarly, Los and Verspagen (2000) omit any firm with a year-on-year sales growth of greater than 80% (in any year of sample).

3.3. Previous estimation results

The diversity of approaches used to assess the impact of R&D on productivity means that it is difficult to concisely summarise previous findings. Mairese and Mohnen (2003) provide a review of empirical firm-level studies finding that, for US data up to mid-80s, the rate of return on private R&D is between 13% and 25%. Griffith (2000) references other studies and states that the private rates of returns tend to be between 10-15% and that elasticity estimates are around 0.07. In general, the estimates for elasticity tend to be higher from cross-sectional estimators and lower from within estimators. This is consistent with the idea that, given the presence of measurement error, the coefficients are biased downwards in within or first difference estimations. Table 1 summarises some recent empirical studies in more detail. In summary, the UK studies find R&D elasticities of between 0.02-0.07 (although some of these differences may stem from calculating R&D stocks in different ways). The only direct study on rates of return (Wakelin, 2001) estimates it at around 27%, although Griffith et al (2004) calculate a value of 16% for the mean firm in their sample. The Bond et al (2002) paper does not report rate of returns explicitly, but does claim that the UK firms rate of return must be higher than German firms (since elasticity estimates are similar, while UK firms have lower R&D intensities).[12] The table summarises two international studies that are of particular interest: Hall and Mairese (1995) estimate various models in French data (1980-87) and Harhoff (1998) for Germany firms (1979-89). Both these papers use a variety of estimators.

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[12] The Bond et al (2002) abstract states “we find that the R&D output elasticity is approximately the same in both countries [UK and Germany], implying a much larger rate of return on R&D in the UK than in Germany”. They do note that this result requires further testing (their footnote 21) and, specifically, direct estimates of rates of return (as in this paper).

Table 1 Summary of recent empirical studies

Author	R&D variable(s)	Output measure	Country	Sample	Estimator	Elasticity estimate	Rate of return estimate (gross, marginal)
Bond et al (2002)	Ln(R&D)	Ln (sales)	UK	230 large manufacturing firm, 1987-96	Common factor model (dynamic)	0.065 (Gmmsys) 0.044 (OLS)	Only calculated as ratio to German firms
Greenhalgh & Longland (2002)	Ln(R&D/Assets)	Ln(value added)	UK	740 production firms (including non-R&D firms)	FE	0.04 (full sample) 0.07 (high tech) 0.02 (low tech)	Not calculated
Griffith et al (2004)	Ln(R&D stock)	Ln(value added)	UK	188 manufacturing firms	OLS GMM-SYS	0.029 0.026	16% (for mean firm)
Wakelin (2001)	R&D / Sales (average 1988-92)	Growth of sales per employee (1988-1996)	UK	170 large manufacturing firms, 1988-96	OLS		27% (full sample) 26% (innovators)
Ballot et al (2002)	Ln(R&D stock)	Ln(value added)	Sweden	200 firms 1987-1993	OLS GMM-SYS	0.10 – 0.15	
Bond et al (2002)	Ln(R&D)	Ln (sales)	Germany	205 manufacturing firm, 1987-96	Common factor model (dynamic)	0.079 (GMM-SYS) 0.093 (OLS)	
Goto & Suziki (1989)	R&D stock (growth of)	Total factor productivity growth	Japan	40 firms, 1976-84	OLS		40% (full sample) (sector estimates vary between 19% and 81%)
Hall & Mairese (1995)	Ln(R&D stock)	Ln(value added per employee)	France	197 manufacturing firms, 1980-87	OLS, FE, FD	0.18-0.25 (OLS) 0.05-0.07 (FE) 0.02-0.16 (FD)	
	(R&D / value added)$_{t-1}$	Growth of value added per emp.			FD		22% - 34%
Harhoff (1998)	Ln(R&D stock)	Ln(sales)	Germany	443 manufacturing firms, 1979-89	OLS, FE, FD	0.13 (OLS) 0.09 (FE)	
	(R&D / value added)	Growth of value added per emp.			FD		22%
Los & Verspagen (2000)	Ln(R&D stock)	Ln(value added per employee)	USA	485 manufacturing firms, 1974-93 (15 year balanced panel)	Between (BE), Fixed effect (FE) ECM	0.014 (BE/FE) 0.04-0.1 (for high tech sector)	
Tsai and Wang (2004)	Ln(R&D stock)	Ln(value added per unit of capital)	Taiwan	136 firms, 1994-2000	RE	0.18 (full sample) 0.07 (low tech) 0.3 (high tech)	35% (high tech) 9% (low tech)

Notes: OLS = ordinary least squares; FE = fixed effects; RE = random effects; FD = first difference; ECM = error correction model GMMSYS = method of moments-system.

4 Data overview

The database uses firm-level financial information from Company Analysis (Extel Financial, 1996, and Thomson, 2001). The financial data include the usual items, such as sales, profits, wages and salaries, assets, standard industrial classification (SIC), and also R&D expenditure. A major constraint on the size of the sample is the availability of R&D data in financial accounts. The accounting conventions covering disclosure of R&D changed substantially in January 1989 with the introduction of SSAP 13 (which effectively made large and medium sized firms report R&D in their accounts). Given these constraints, and the economic issues of interest, the analysis is confined to the period between 1989 and 2000. A firm is required to have at least three years of data to be included in the analysis (this removes 189 observations (4.3%) of the sample). A balanced panel of 86 firms is also constructed for the period 1990 to 1999.

The primary measure of output in the analysis is value added. Value added is constructed by adding total staff costs, depreciation and profit before tax and then deflating (see Data Appendix for further information). Since the log of value added is always used in the analysis this effectively removes any negative values (this removes 7.8% or 347 observations). The measure of capital is tangible fixed assets as entered in the balance sheet. The measure of labour input is the number of employees. Although the database contains variables for part-time and full-time employees, the coverage for these is minimal, so we are unable to adjust the labour measure to reflect differences across firms in part- and full-time working. All financial data are deflated with using the best available series (see appendix).

Plots of the first difference of the dependent variable (log of value added) against the first difference of the log of assets and employment variables, as well as the ratio of R&D to value added (for period t-1), indicate some outliers. As discussed in the previous section, some researchers to filter the data in various ways. One issue is the presence of high growth rates in the variables, which may be due to firms merging or de-merging, or major adjustments in accounting procedures. To remove the influence of abnormal firms we follow Hall and Mairese (1995) and Harhoff (1998) by creating a sample which removes firms with high (or low) rates of growth of value added, capital, labour or R&D (this removes 465 firms; see data appendix for full details).

The analysis below makes use of both an unbalanced and balanced sample, with both being defined for manufacturing and non-manufacturing firms. Table 2 shows summary statistics for these different samples. Note that in both cases these summary statistics are based on excluding high growth rate firms (see above) and also only includes firms with 3 or more years of data over the sample periods. The manufacturing unbalanced sample has 3,163 observations, which come from 468 unique firms. The median sales revenue is £182 million (the mean is £1.3 billion). There are fewer non-manufacturing firms in the data yielding only 1,288 observations (228 firms) (the median firm has sales of £190 million; mean of £1.1 billion). The non-manufacturing sample contains a wide range of industries. However, the major industries represented are 'business services' with 27% of observations (this includes software and data service firms); the wholesale trade industry (19%); electricity, gas and water utilities (14%); and, oil and gas extraction (8%).

Although the numbers of firms may appear small, these firms account for a substantial proportion of total business R&D (BERD) in the UK. For example, in 2000 the ONS report that total UK BERD was £11.5 billion, while our data sample contains £10.7 billion of R&D. The reason for this is that large firms account for most R&D (and the data here contains most large firms). For example, although the balanced sample of manufacturing firms contains only 66 firms, they accounted for 43% of BERD reported by the ONS.[13] It is worth highlighting that R&D expenditure is highly skewed. For example, in 1999 the top five R&D spending companies accounted for 51% of total BERD in 1999.[14]

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[13] This percentage is calculated by taking the sum of current price R&D in 1999 for balanced sample and dividing by ONS data. The ONS data for calculations in this paragraph come from ONS (2001), which is the Research and Development in UK Businesses, Business Monitor (MA14) publication. The ONS data are estimated from a (stratified) sample survey, which has complete coverage of the (believed) largest 380 R&D firms and then surveys a further 3620 firms. Note that the ONS estimates R&D performed in the UK, while our data includes all R&D investment by firms (whether in the UK or overseas).

[14] These companies are Astra Zeneca PLC (£1.74 bn), Glaxo Welcome PLC (£1.27 bn), SmithKline Beecham PLC (£1.02bn), BAe Systems PLC (£0.87bn) and Unilever (£0.62bn). Note that Astra Zeneca is not in balanced panel since its R&D data – in the database we use – only starts in 1992.

Table 2 Summary statistics for R&D

Manufacturing sample

Year	Obs	Unbalanced sample R&D spend (£bn)	Unbalanced sample R&D/ value added	Unbalanced sample R&D/sales	Balanced sample R&D spend (£bn)	Balanced sample R&D/ value added	Balanced sample R&D/sales
1989	123	5.60	0.065	0.020			
1990	226	7.09	0.068	0.021	3.68	0.068	0.020
1991	292	8.56	0.077	0.023	3.57	0.074	0.021
1992	303	8.81	0.080	0.024	3.90	0.081	0.024
1993	324	9.44	0.081	0.025	4.22	0.080	0.023
1994	335	9.04	0.073	0.022	4.21	0.080	0.024
1995	346	9.10	0.069	0.021	4.38	0.077	0.023
1996	320	7.84	0.059	0.018	4.41	0.072	0.022
1997	290	7.73	0.061	0.019	4.29	0.074	0.023
1998	254	8.77	0.082	0.025	4.53	0.094	0.028
1999	194	9.38	0.092	0.029	4.82	0.089	0.029
2000	156	7.82	0.077	0.021			
Total or mean	3,163	8.45	0.073	0.022	4.20	0.079	0.024

Nonmanufacturing sample

Year	Obs	Unbalanced sample R&D spend (£bn)	Unbalanced sample R&D/ value added	Unbalanced sample R&D/sales	Balanced sample R&D spend (£bn)	Balanced sample R&D/ value added	Balanced sample R&D/sales
1989	36	9.01	0.026	0.011			
1990	72	1.34	0.029	0.012	4.26	0.026	0.016
1991	101	1.45	0.027	0.011	4.04	0.025	0.015
1992	114	1.47	0.026	0.010	3.90	0.025	0.014
1993	122	1.41	0.024	0.010	4.21	0.027	0.015
1994	134	1.53	0.027	0.010	4.44	0.027	0.014
1995	145	1.70	0.029	0.011	4.60	0.028	0.014
1996	138	1.68	0.028	0.010	4.77	0.027	0.014
1997	130	1.43	0.027	0.010	5.13	0.028	0.014
1998	112	1.39	0.028	0.012	5.05	0.025	0.013
1999	100	1.35	0.032	0.014	5.59	0.026	0.012
2000	84	1.26	0.040	0.014			
Total or mean	1,288	1.46	0.028	0.011	4.60	0.026	0.014

Note: R&D spend figures are real in 2000 prices.

5 Preliminary analysis

5.1. Cross sectional analysis

This section presents some preliminary cross-sectional regression analysis to allow a comparison with previous studies. Table 3 presents a series of regression results based on OLS and IV estimators. Manufacturing and non-manufacturing forms are estimated separately and, for both of these sectors, there is a sample of all firms (1989-2000) and a balanced panel of firms (1990-1999).[15] Clearly, the cross-sectional estimators allow the β_i and η_{it} terms to enter the error term, creating potential bias, but the use of panel estimators may also introduce bias by aggravating measurement error issues. For manufacturing, the regression analysis shows that the coefficient on R&D is 0.12 for the unbalanced sample and higher at around 0.15 for the balanced panel. The coefficients on capital and labour appear reasonable from an economic theory perspective; the coefficients on labour, capital and R&D sum to 0.985 in regression [1], although a formal test of constant returns to scale rejects this at the 1% level. The coefficient on industry R&D is insignificant in a majority of regressions, but is predominantly positive and significant in some samples. Our interpretation is that the measure of external R&D stock used here is too crude to capture any spillover effects.

In comparison with other countries the 0.12 to 0.16 elasticity estimate is lower that for French firms in the 1980s (Hall and Mairese, 1995), but similar to the estimates of other countries. Although not shown here, estimates from a fixed effect model tend to yield elasticities of around 0.04 to 0.06; these again are similar to other countries. Hence, for UK manufacturing firms the elasticity estimates for the 1990s do not appear very different from previous studies. For non-manufacturing firms, the estimates for R&D elasticity in Table 3 are also around 0.12 for the unbalanced panel of firms, but higher for the balanced panel of firms. Since the number of firms in this balanced panel is small (n=20), it seems inappropriate to read too much into this result.

The lower rows of Table 3 show the implied gross (marginal) rate of return to R&D (dY/dR). To calculate these rates of return, the stock of R&D is assumed to equal $R\&D_{t-1}/\delta$, where δ is 0.15 (see equation [8] and assume growth is zero). The elasticity is multiplied by Y/R to yield as estimate for dY/dR. Since the level of R&D varies across the sample, the table shows the implied dY/dR at the 25th, median and 75th percentile of the distribution (for each sample). The rate of return for low R&D intensity firms is much higher than normal estimates for rates of return. For the 75th percentile, however, the implied rate of return is between 0.19 to 0.3 for manufacturing firms (i.e. 19% to 30%), which are similar to previous estimates. These

[15] A formal test the hypothesis that manufacturing and non-manufacturing firms can be pooled is rejected (F^{16}_{4435}=23.1) for the OLS estimator.

calculations highlight the conceptual problem with estimating elasticities if the ultimate interest is in assessing the rates of return to R&D.

5.2. First difference specification: estimating rates of return

Table 4 shows results from using the first difference specification from equation [6]. The R&D variable is now the ratio of R&D to value added (lagged one period), hence the coefficient can be interpreted as the (marginal) rate of return to R&D. Before focusing on the R&D variable, the results indicate that coefficient on ln(assets) appears low in most specifications, which is consistent with the possibility that measurement error is aggravated by the first difference estimator. Note also that the coefficients on both labour and capital terms are volatile in the IV estimations, something which appears linked to the fact that only lagged values are available as instruments.[16] Despite the difficultly in accurately estimating the capital and labour coefficients, the coefficient on R&D to value added is remarkably consistent across specifications. For manufacturing firms, the coefficient on R&D in the unbalanced panel implies a rate of return of around 0.17, while the balanced panel has a higher return of 0.25. Returns to R&D for the non-manufacturing firms appear similar at between 0.18 and 0.23.

These estimates of rates of return are similar to studies of French and German firms (see Table 1), and towards the upper end of a range of estimates from US studies (see Mairese and Mohnen, 2003). Therefore, at this stage of the analysis, there appears no evidence that UK returns are relatively high by international standards.

[16] Use of a dynamic panel model, and GMM methods, also yields volatile estimates on coefficients, depending on sample and instruments specified. This is also apparent in Bond et al (2003). Given this, and the fact that very few existing studies use this methodology, the analysis here focuses on first difference estimators. Appendix 2 shows a set of GMM estimations.

Table 3 Elasticity estimations (regression results using cross-sectional estimators)

	OLS				IV			
	Manufacturing		Non-Manufacturing		Manufacturing		Non-Manufacturing	
	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln (assets)	0.278	0.226	0.346	0.557	0.283	0.235	0.353	0.541
	(19.58)***	(9.71)***	(19.76)***	(8.44)***	(18.92)***	(10.27)***	(18.28)***	(8.27)***
ln (employment)	0.585	0.626	0.508	0.266	0.586	0.633	0.515	0.310
	(36.03)***	(25.46)***	(24.03)***	(3.85)***	(35.13)***	(26.40)***	(22.56)***	(4.44)***
ln (R&D spend)	0.123	0.158	0.123	0.234	0.124	0.146	0.120	0.218
	(16.02)***	(11.95)***	(9.51)***	(6.91)***	(14.38)***	(11.34)***	(8.51)***	(6.00)***
ln (industry R&D)	0.001	-0.002	0.001	0.024	0.002	-0.001	0.001	0.019
	(1.34)	(1.38)	(0.25)	(4.29)***	(1.87)*	(0.60)	(0.41)	(3.75)***
Constant	7.348	6.754	6.750	2.392	7.138	6.913	6.859	2.483
	(49.60)***	(31.80)***	(34.23)***	(2.77)***	(46.28)***	(32.88)***	(28.95)***	(3.00)***
Observations	3163	660	1288	200	2732	625	1100	185
R-squared	0.96	0.98	0.95	0.97	0.96	0.99	0.95	0.98
Significance of year dummies	0.00	0.00	0.00	0.60	0.00	0.00	0.00	0.34
Significance of industry dummies	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Constant returns to scale	0.00	0.14	0.02	0.06	0.22	0.04	0.21	0.03
Implied rate of return								
25th Percentile	0.91	1.27	1.59	3.48	0.91	1.15	1.63	3.32
Median	0.40	0.58	0.53	1.08	0.41	0.52	0.52	1.00
75th Percentile	0.19	0.33	0.14	0.51	0.19	0.30	0.14	0.49

Notes: Regressions (1), (2) use t-1 values for ln(assets), ln(employees) and ln(R&D). Regression (1)-(4) show OLS estimates on unbalanced and balanced samples, for manufacturing and non-manufacturing firms with positive R&D. Unbalanced panel is for 1989-2000; the balanced panel for 1990-99. Regression (5)-(8) use IV regression (using t-1 values as IV for ln(assets) and ln(employees) (where these are now the average value of t and t-1) and uses t-2 as instrument for R&D. The brackets contain t-statistics (which are ‘robust’ for OLS). * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4 Rate of return regressions (first difference model)

	First difference (OLS)				First difference (IV)			
	Manufacturing		Non-Manufacturing		Manufacturing		Non-Manufacturing	
	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
FD ln Assets	0.132	0.125	0.153	0.116	0.099	-0.227	1.355	0.300
	(2.98)***	(1.87)*	(2.57)**	(1.18)	(0.16)	(0.61)	(1.22)	(0.76)
FD ln Employment	0.583	0.553	0.508	0.523	0.682	0.621	0.002	0.619
	(11.25)***	(7.65)***	(7.32)***	(6.03)***	(1.67)*	(2.13)**	0.00	(4.02)***
R&D/value added (t-1)	0.178	0.246	0.227	0.215	0.172	0.249	0.184	0.201
	(3.00)***	(1.97)**	(4.01)***	(1.31)	(2.85)***	(2.02)**	(1.86)*	(1.02)
FD log(industry R&D 4sic, t-1)	0.001	0.004	0.001	0.005	0.000	0.005	0.004	0.005
	(0.27)	(1.56)	(0.10)	(2.17)**	(0.17)	(1.78)*	(0.49)	(1.96)*
Constant	0.037	-0.013	-0.055	0.039	0.036	-0.025	-0.090	0.012
	(1.92)*	(0.44)	(1.56)	(1.63)	(1.62)	(0.80)	(1.60)	(0.26)
Observations	2732	624	1100	185	2729	624	1099	185
R-squared	0.25	0.32	0.18	0.37	0.24	0.25	0.00	0.33
F test: Joint sig. of year dummies	16.68	7.02	1.74	1.26	16.09	5.77	1.35	1.36

Notes: Regressions (9)-(12) use first difference of ln(assets) and ln(employees) and R&D to value added ratio (between t and t-1). The samples are for unbalanced and balanced, and for manufacturing and non-manufacturing, where firms have positive R&D. Regressions (13)-(16) use the lagged levels of ln(assets) and ln(employees) (t-1 and t-2) as instruments; the R&D to value added ratio (t-1) is instrumented with itself. The brackets contain t-statistics (which are ‘robust’ for OLS) with * significant at 10%; ** significant at 5%; *** significant at 1%.

5.3. The role of high R&D intensity firms

A feature of R&D data is that it is highly skewed, with a relatively small number of firms having very high R&D intensities. Schankerman (1981) argued that the double counting problem can cause a downward bias in the estimated R&D coefficient and it seems reasonable to assume that double counting is more severe in firms with high R&D intensities. Equally, one could argue that high R&D intensities firms are 'non-standard' (e.g. they may be start-up companies). In both cases the relationship with productivity may be different from the bulk of firms in the data. To investigate this issue we adopt the following procedure. Regression [9] is re-run on successively smaller samples of manufacturing firms, with each sample omitting the largest R&D/value added ratio. In other words, the first regression has n=2731, the second n=2730 and so on until the sample size is n=1932. The coefficient and 95% confidence interval is plotted in the upper diagram in Figure 2. The diagram shows that the coefficient on R&D does vary as the sample changes. While the average value is 0.25 across these 800 regressions, the average coefficient is 0.21 when firms with R&D intensities above 0.15 are included, and 0.30 when such firms are excluded. These results fit with Schankerman's argument, but the variations are relatively small and well within standard confidence intervals. Figure 2 also shows the coefficient on ln(R&D) from the simple OLS specification (1). The coefficient here is very stable at around 0.13 but, as discussed above, the implicit rate of return varies according to the firm's R&D intensity.

Figure 3 shows similar plots for the non-manufacturing sample. These show that the estimated rate of return does rise as high intensity firms are excluded but that this effect is overshadowed by an increase in the confidence interval (which indicates the coefficient is not statistically different from zero for many of the regressions). The estimates for elasticity are more significant and show a gradual rise in the elasticity as the sample excludes more and more high intensity firms.

Figure 2 R&D intensity and R&D coefficient (manufacturing sample)

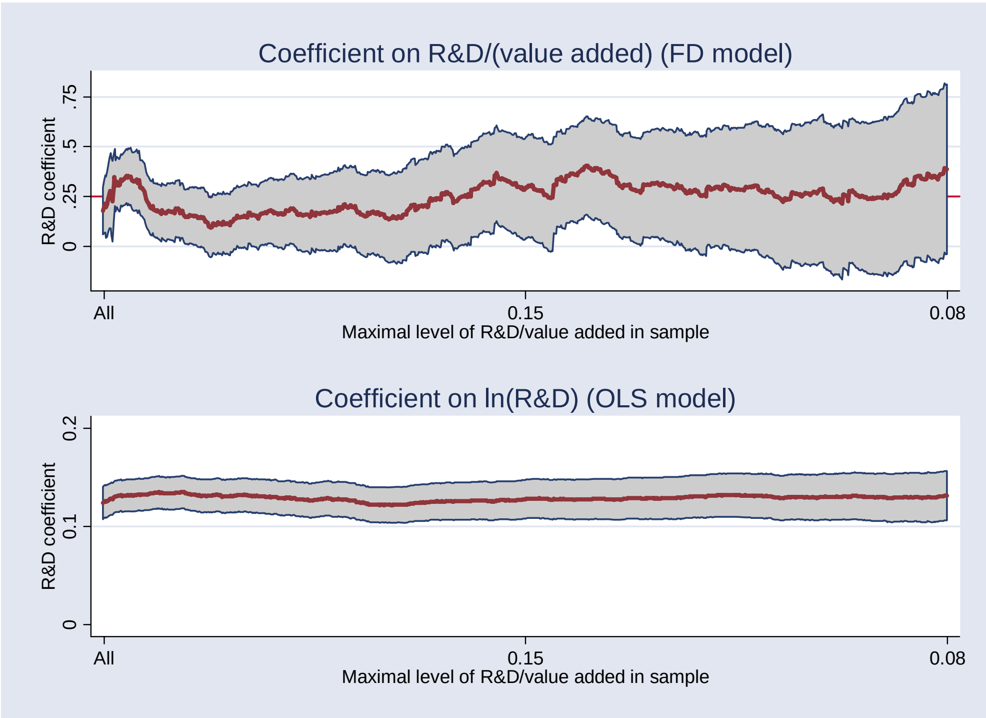
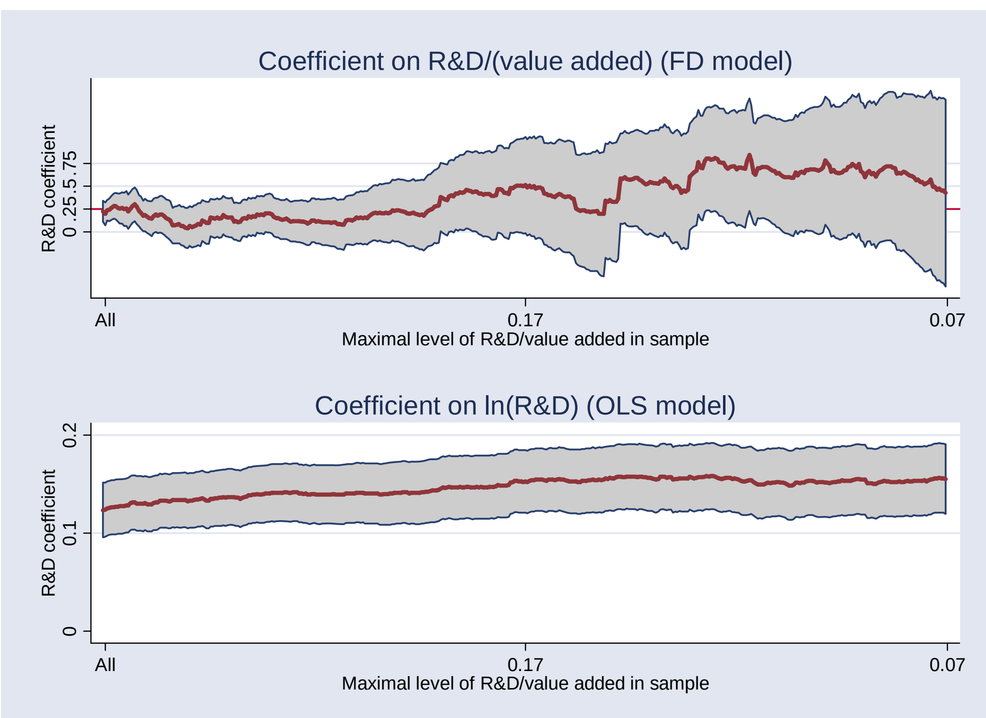


Figure 3 R&D intensity and R&D coefficient (non-manufacturing sample)



6 Variations in the returns to R&D: what can the econometrics tell us?

While it is important to have estimates of the returns to R&D for UK firms, ideally one would like to use the econometric analysis to probe further into the possible reasons for low BERD spending in the UK. Economic theory suggests that (relatively) high rates of return are consistent with firms facing constraints on R&D spending, which could in turn arise from lack of finance or an inability to hire skilled labour. On the other hand, low rates of return or low R&D spending, are consistent with firms' inability to appropriate returns; which may, in turn, be caused by high spillovers or competition, or by poor management of the R&D process or outcomes.

6.1. Has the impact of R&D varied over time?

This section investigates whether the impact of R&D on productivity varied through the 1990s. There are various potential ways of testing this possibility. Here we adopt the simple approach of generating a set of year dummies and inter-acting these with the R&D variable. Entering a set of year dummy-R&D interactions as additional explanators allows a formal test of whether the coefficient on R&D varies in different years. The omitted year dummy is 1989 for the unbalanced sample and 1990 for the balanced sample. Using the simple OLS estimator this procedure shows that the coefficient on log R&D is virtually unchanged through time for the manufacturing sample. The only exception is that there is an increase in the coefficient in 1999 and 2000 of 0.04 (from 0.1 for 1989; 10% significance level); however, the unbalanced nature of the panel and the fall in R&D coverage in these years (see Table 2) makes this result difficult to interpret. For the balanced panel of manufacturing firms there is no statistically significant change in the coefficient on R&D. For the non-manufacturing samples there is also no statistically significant change in coefficient through time. These results are confirmed if we use the first difference estimator: there is no consistent evidence that the coefficient on R&D varies over the time period.[17] The finding that the coefficients on R&D are statistically stable through time suggests that there has been no decline in the productivity of R&D in the 1990s.

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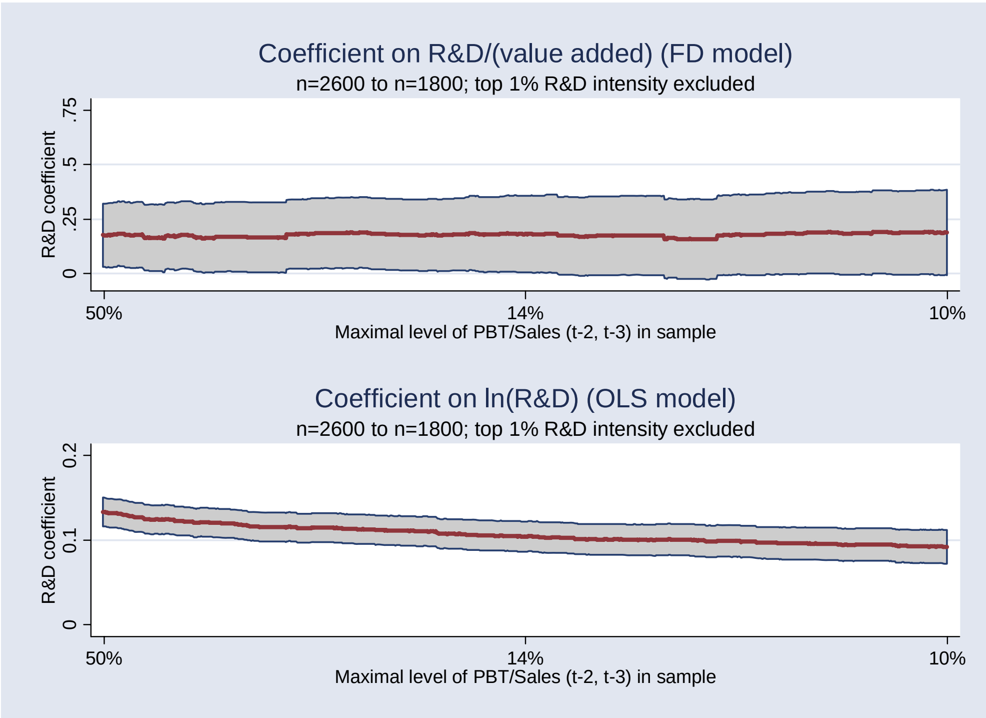
[17] In all estimations a set of year dummies is also included in the regressions. Omitting the year dummies does create some significant coefficient on the R&D and year interaction terms, but this may be capturing aggregate productivity shocks, rather than changes in R&D productivity.

6.2. Access to finance and the returns to R&D

Bond et al (2003) find that the past cash flow of the firm is not a significant predictor of the firm's R&D intensity (although it is a predictor of the choice to undertake R&D). This implies that firms that undertake R&D are not financially constrained. Although the data available here do not contain cash flow, it is possible to provide some further evidence on this issue by using past profitability as a proxy for access to finance.

The ratio of 'net profit before tax' to sales (average of t-2 and t-3) is calculated as the proxy. To assess the relevance of past profitability on rates of return, the sample is ranked from highest to lowest past profitability, and then successive regressions are run omitting the highest profitability firms. In order to prevent extreme values influencing the results, the initial sample excludes high R&D intensity firms (those with R&D to value added ratios above 0.5) and also any firm with profitability greater than 50%. Figure 4 shows how the coefficient on R&D varies as the sample of manufacturing firms becomes smaller (the regressions used are [9] and [1]). The first difference model (top diagram) shows very little change in the coefficient, indicating that over this range of profitability there appears to be no link with rates of return to R&D. The lower diagram shows a slight fall in R&D elasticity but, as discussed above, this result cannot be linked directly to rates of return. The lack of a link to past profitability is consistent with the result from Bond et al (2003): there is no evidence that financial constraints reduces R&D intensity and raises rates of return.

Figure 4 **Profitability and returns to R&D**



A related issue is whether access to stock market funding is important. For manufacturing firms, around 78% of firms in the regression samples are listed on the stock market and these firms have a median R&D to value added ratio of 0.045 (the mean is 0.087). In comparison, non-listed firms have a median value of 0.050 (mean of 0.106). The likelihood of undertaking R&D is much higher for listed firms (using all the data in the OIPRC database, 74% of listed firms report some R&D, while only 28% of non-listed firms do so). Using the first difference specification in regression [9], we analyse whether the returns to R&D are higher for listed or non-listed firms. Using both separate sub-samples and dummy variable techniques, we find no strong evidence that the returns to R&D differ between these groups, suggesting that access to stock market funding is not a factor in R&D investment.[18]

All of the above results are for manufacturing firms only. Analysis of the non-manufacturing firms also indicates no influence of stock market listing on the return to R&D. Analysis of the role of profitability for non-manufacturing firms provides insignificant coefficients on the rate of return to

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[18] There is some initial evidence that returns to R&D are higher for listed, manufacturing firms, but this appears to be driven by a few, high R&D intensity firms that are not listed.

R&D. This is due to the fact that firms with R&D to value added ratios above 0.5 are excluded and, as can be seen from Figure 3, these firms are important in determining a significant coefficient.

6.3. Competition and the returns to R&D

Greenhalgh and Rogers (2004) provide an investigation into competitive conditions and the share market valuation of R&D. They group firms into Pavitt-based sectors, assess the competitive conditions in each sector, and then analyse the share market's valuation of R&D. The results suggest that more intense competition lowers the market's valuation, as would be expected. This section analyses the rate of return to R&D using a similar methodology.

Pavitt (1984) introduced an industrial classification based on technological trajectories. Pavitt's original typology, which has been updated in Tidd et al (2001), can be used to create six different sectors. These are shown in Table 5, along with a brief description of each (further justification can be found in the above references). As can be seen from the last row, the sector that dominates absolute R&D in our data is the science-based sector (51.5% of total R&D spend in the full sample), which includes pharmaceutical firms (28.7% of total R&D spend). In terms of absolute R&D spending it is therefore the science-based sector and, within this, the pharmaceutical firms, that will be critical in driving economy-wide productivity growth originating from R&D.

Table 5 Pavitt sectors

Pavitt sector	Description	SIC (US)	% R&D
(1) Supplier Dominated	Traditional manufacturing. Generally small firms with weak in-house R&D. Innovations come from suppliers.	12, 13, 15, 16, 22-26, 30, 31, 7300/12/36/61	3.5
(2) Production Intensive, Scale Intensive	Large firms producing standard materials or durable goods, inc. cars.	20, 21, 32, 33, 34, 37	22.4
(3) Production Intensive, Specialised Suppliers	Machinery and instruments. Tend to be smaller firms which are technologically specialised.	35, 38, 39	12.9
(4) Science Based	Electronics, electrical and chemicals, inc. pharma. Technology from in-house R&D but based on basic science from elsewhere.	28, 29, 36	51.5
		Pharmaceuticals	28.7
(5) Information-intensive	Includes finance, retail, communications and publishing industries.	27, 48, 50-67, 7313 and 7383 (media)	8.5
(6) Software-related firms	Computer software and services firms.	All SIC 73 sub-codes not above	1.6

There are various ways of assessing competitive conditions, ranging from measures of concentration to direct measures of profitability. Following Greenhalgh and Rogers (2004), the analysis here uses a dynamic measure based on profit persistence. Profit persistence uses the idea that all firms will experience profit shocks and that the intensity of competition determines how long these shock will persist (see Mueller and Cubbin, 1990; Waring, 1996; Glen et al, 2001). For example, a positive profit shock due to an innovation may be short lived if other firms compete effectively. The average degree of profit persistence for a group of firms can be estimated using a standard autoregressive model (i.e. $\pi_{it} = \phi_i + \beta\pi_{it} + \varepsilon_{it}$), where π_{it} is firm *i*'s 'net profit before tax to sales' margin in year *t*, ϕ_i is a firm fixed effect, β represents the persistence to a profit shock and ε_{it} is the standard error term. A β-coefficient close to zero implies little persistence and a highly competitive environment; when $\beta>>0$, profit shocks persist and the implication is that the competitive process is less strong. Profit persistence studies attempt to capture all aspects of competition, whether from rivals within the same domestic industry, overseas firms, or from the threat of new firm entry.

Table 6 shows the Pavitt sectors arranged in order of competitive intensity as assessed by the profit persistence coefficient. As can be seen, the first two Pavitt sectors (Information-intensive and production intensive (scale)) have persistence coefficients close to 0.50. This indicates that half of any profit shock disappears after one year. The subsequent three sectors have a coefficient of around 0.42. The most competitive sector – according to the persistence measure – is the science-based sector, with a coefficient of 0.27.[19] The last row in Table 6 shows the coefficient on R&D to value added from estimating regression [6] on each sector separately. This coefficient therefore represents an estimate of the gross marginal rate of return to R&D. The supplier-dominated sector has the highest estimated rate of return (0.61); however, this sector accounts for only 3.5% of total R&D spend in the sample and is not a R&D intensive sector. The next highest rate of return is Pavitt 2 (0.35), this sector contains traditional, scale intensive firms. The relatively high rate of return suggests that R&D appropriability in this sector may be relatively high. Sectors 3, 5 and 6 have coefficients in the 0.20 – 0.25 range and are, therefore, driving the full sample results show in Table 4. However, the science-based sector – which includes electronics, electrical, chemical and pharmaceutical firms – has a rate of return coefficient of 0.11 (which is not significant at the 10%

[19] These coefficients are taken directly from Greenhalgh and Rogers (2004). They are based on regression analysis of all firms in the OIPRC database for the period 1989-2000.

level).[20] This suggests that returns to R&D in this sector are low. An analysis of the sub-sample of pharmaceutical firms within this sector finds a coefficient of 0.14 (significant at 5% level). However, formally testing the difference in coefficients between pharmaceutical and other firms in the science-based sector, using dummy variable interaction terms, is inconclusive.

In summary, the key finding of this section is that the science-based sector, which includes industries such as electronics, chemicals and pharmaceuticals, has a relatively low rate of return to R&D. This sector is also found to have the highest intensity of competition according to a profit persistence analysis. This cannot be taken as evidence of a causal relationship, but it is consistent with the fundamental economic idea that increased competition will drive down profitability.

Table 6 Competition conditions and rates of return

Based on firms in OIPRC database	Information -intensive (Pavitt 5)	Production intensive (scale) (Pavitt 2)	Production intensive (specialist) (Pavitt 3)	Software firms (Pavitt 6)	Supplier dominated (Pavitt 1)	Science based (Pavitt 4)
Profit persistence (β-coefficient)	0.52	0.49	0.43	0.42	0.42	0.27
Profit before tax / turnover (%)	13.7	7.9	4.5	2.7	6.6	9.4
BERD to value added (%)	3.7	5.2	8.2	7.6	2.0	9.3
R&D active (%)	4.5	34.4	62.4	30.7	17.6	61.2
Median R&D (of those active)	4.1	2.6	7.4	16.7	2.0	6.4
Return to R&D (coefficient on R&D/valued added)	0.20* (1.64)	0.35*** (2.49)	0.25** (2.10)	0.24*** (3.57)	0.61* (1.69(	0.11 (1.48)

7 Conclusions

Using a data set of up to 719 UK firms over the 1990s this paper has analysed the link between R&D and value added. In order to facilitate comparisons with existing studies, this paper uses a

[20] A more formal test of this is conducted by creating a set of Pavitt sector dummy variables and interacting with the R&D to value added ratio. Entering all of these dummies into a regression model, which involves constraining the sum of coefficients to equal zero and omitting the constant term in the regression, shows a negative coefficient (-0.1) on the science-based-R&D interaction term (significant at the 16% level). The coefficient on the R&D to value added variable in this regression is 0.23 (1% significant). All other interaction terms are highly insignificant.

variety of estimators and also distinguishes between manufacturing and non-manufacturing firms. In particular, we use specifications that estimate the elasticity of R&D with respect to value added, as well as specifications that estimate the marginal gross rate of return to R&D. Cross sectional OLS and IV techniques are used to estimate the elasticity of R&D. A first differenced model, which controls for firm-specific effects, is used to estimate the rate of return to R&D. In both cases an unbalanced panel sample (1989-2000) and a balanced panel (1990-1999) is used. The results can be summarised as follows.

First, the coefficients on R&D when the balanced panel of firms is used tend to be slightly higher than the unbalanced panel. One interpretation of this result is that firms that persistently undertake R&D, and who survive over the sample period, are inherently more effective in undertaking R&D. A further result, which reflects the results of previous studies, is that the elasticity of R&D from cross-sectional estimators tends to be higher than from within, or fixed effect, estimations. A standard response to this is that the presence of measurement error biases coefficients downwards, and that magnitude of this bias is greater in the within estimations. Needless to say, such results imply caution in focusing on the exact magnitude of coefficients in such regressions.

A second result of interest concerns the impact of high R&D intensity firms on the coefficient estimates. The productivity-R&D link could differ for high R&D intensity firms either because of measurement issues (e.g. the double counting problem is more severe in high R&D intensity firms) or because high R&D intensity firms are in some sense ‘different’. For manufacturing firms, the results indicate that returns to R&D do appear to rise as high R&D intensity firms are omitted, which is consistent with the double counting problem. However, the differences in coefficients across different samples are well within the 95% confidence interval. Overall, therefore, it appears that the best estimate of the rate of return for manufacturing firms is around 25%. This is similar to estimates of rates of return in France and Germany, and towards the upper range of estimates on US firms.

Three further issues were investigated in section 6. These are intended to probe the reasons for relatively low level of UK R&D. An initial issue investigated is whether the coefficient on R&D has varied across time. By using a set of year dummies interacted with the R&D variable, the analysis indicates that the elasticity of R&D – and the return to R&D – have been roughly constant over the 1990s. The lack of any evidence of variations in returns suggests that the external constraints on firms have not increased during the 1990s. A related issue concerns whether firms are constrained in their ability to finance R&D. If this were the case then one might expect the rate of return to be higher for such firms (since lower R&D, ceteris paribus, implies higher marginal returns). Using past profitability as a proxy for the ability to finance R&D, the analysis finds no evidence that low profitability firms have higher rates of returns in the manufacturing sector. The analysis also finds that firms that are stock market listed do not have different rates of return to R&D from non-listed firms, again suggesting no evidence for financial constraints. A final section takes an initial look at competitive conditions and returns to R&D. The results here suggest that only one sector has a substantially higher level of competition – the science-based sector, which includes electrical, electronics, chemicals and pharmaceuticals – and this sector also has relatively lower returns to R&D.

In summary, this paper finds that the rates of return to R&D for UK firms are broadly similar to other country studies. The fact that we do not find evidence of higher rates of return suggests that these UK firms are not externally constrained in their R&D activities. Hence, commentators that claim that UK firms do not have sufficient access to external finance or skilled labour do not find support here. There are three important caveats to this statement. First, the analysis here looks at firms that undertake R&D and there is some evidence that lack of access to finance may affect the decision to undertake R&D (Bond et al, 2003). Second, in the case of skilled labour, it may be that external constraints raise the cost of R&D, for example by raising salaries of scientists and technicians, and thereby reduce the estimated return to R&D. However, given that there is also a concern that salaries for scientists are *too low*, and that there is an international market in scientists and capital, this argument appears difficult to justify. Third, the analysis here relates to large firms, which may experience fewer financial or other constraints than small and medium-sized enterprises (SMEs). This said, if the objective is to understand why the current BERD ratio is low, the fact that large firms dominate the absolute R&D expenditure means that they *should* be the focus of analysis.[21]

Given all these various findings, the main message of this paper is that large UK firms in the 1990s appeared to choose their R&D budgets on the basis of expected returns, and that these returns are broadly similar to the countries. Moreover, if we ask the question why firms in the science-based sector are not investing more, the econometrics suggests that rates of return are *too low*: UK firms do not invest more since the expected returns are low. Exactly why returns are so low is not clear.

[21] Clearly, this is a ‘static’ argument and ignores the possibility that low (constrained) R&D expenditures made by SMEs in the past has created an economy with fewer large, high intensity firms today.

The analysis does suggest the science-based sector is highly competitive, but this is in all likelihood true in other countries, and sectors within these countries have higher R&D intensity. It may be that the management of the R&D process, including the use of intellectual property, is less effective in the UK than overseas. Investigating this and other possible explanations should be the subject of further research.

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Appendix 1: Data notes on key variables

Value added

Value added is defined as total staff costs plus depreciation plus profit before tax. We have calculated other measures of value added but find this measure, given data constraints, preferable. There is a concern over the inclusion of the book value for depreciation, which may be only weakly related to the true economic rate of depreciation. We have calculated and analysed a measure of value added without depreciation and this is highly correlated t our measure (correlation coefficient 0.99). Also, some studies correct for interest paid and impute a value for the user cost of capital. The data available here do not contain interest paid. Some analysis was undertaken using imputed interest payments (based on debt and market rates of interest) and user cost of capital, but the value added measure obtained was similar to the measure used here.

Omitting high growth firms

A sub-sample of firms that excludes high growth firms was created. This excludes firms with year-on-year growth in value added of greater than 300% and less than -90%. Also, firms with growth rates of labour, capital or R&D of greater than 200% and less than -50% are excluded. This follows Hall and Mairese (1995) criteria and leads to 220 firms being omitted (4.4% of the sample). The main effect of omitting these firms is that the coefficients in the instrumental variable estimates become more significant and closer to theoretical predictions.

Price deflators

The ONS statistics produces industry-level data only for manufacturing industries and only from 1991 onwards. For the 1980s there are no industry-level deflators available. The value added measured is deflated by the overall manufacturing deflator (gross output measure) for 1988-1990 and then industry-level deflators are used (which are at the 2-digit SIC level). These data are on ONS web-site and are listed under producer prices (MM22). For non-manufacturing the GDP deflator is used (ONS, YBFY). All deflators are in constant 2000 prices.

Appendix 2: GMM, dynamic panel estimations

	Manufacturing		Non-Manufacturing	
	Unbalanced	Balanced	Unbalanced	Balanced
Lagged Value Added	0.162	0.420	0.123	0.669
	(8.42)***	(10.29)***	(4.41)***	(13.89)***
ln Assets	0.005	0.129	0.210	0.039
	(0.09)	(2.67)***	(3.04)***	(0.78)
Ln Employment	0.608	0.333	0.175	0.297
	(9.81)***	(5.37)***	(2.60)***	(5.48)***
Lagged R&D/value added ratio	0.123	0.067	0.197	-0.049
	(7.27)***	(2.33)**	(9.21)***	(0.81)
Constant	0.006	0.011	-0.002	0.002
	(2.23)**	(3.74)***	(0.47)	(0.32)
Observations	2720	623	1082	184
Number of firms	466	66	223	20
Long run coefficients				
ln Assets	0.006	0.222	0.239	0.118
ln Employment	0.726	0.574	0.200	0.897
R&D/value added ratio	0.147	0.116	0.225	-0.148
Diagnostics				
Sargan test (over identification)	0.00	0.00	0.00	0.01
Serial Correlation (AR(1): Ho: no serial)	0.00	0.00	0.01	0.01
Serial Correlation (AR(2): Ho: no serial)	0.07	0.46	0.06	0.66

Notes: The above regressions treat labour as endogenous and capital as predetermined. The R&D to value added term (t-1) is treated as an exogenous variable, which is not ideal but estimation of equation [6] in STATA 8.0 or OX/DPD is not flexible enough to specify alternatives (the difficulty is that R&D/Y is entered directly into the first difference model, hence cannot be treated like other explanatory variables). Estimates are for the first step of the procedure.