Estimating the impact of R&D on productivity using the BERD-ARD data*

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Executive Summary

Background

The UK has a relatively low ratio of business R&D to GDP (the BERD ratio) compared to other leading economies. There has also been a small decline in UK's BERD ratio in the 1990s, whereas other leading economies have experienced small rises. The relatively low BERD ratio cannot be explained solely by sectoral or industry-level differences between the UK and other countries. There is, therefore, considerable interest in understanding the firm-level determinants of investment in R&D.

This report was commissioned by the DTI to analyse the link between R&D and productivity for a sample of firms derived from merging the ONS's Business Research and Development Database (BERD) and the Annual Respondents Database (ARD). The analysis estimates the *private* rates of returns to R&D, and not the social rates of return, since it is the private returns that should drive firms' decisions. A key objective of this research is to analyse the productivity of R&D in small and medium sized enterprises (SME). The analysis is intended to allow comparisons to the results in Rogers (2005), which uses publicly available data on R&D in medium to large UK firms in the 1990s.

Data

Both the BERD and ARD data sets are derived from random, stratified surveys conducted by the ONS. The BERD data are available for 1996-2003. In 1996 the BERD surveyed around 1,200 firms, although this was increased to around 2,300 from 1999 onwards. While the ARD starts in 1970, the survey size was substantially increased in 1997 (to 50,000 from 15,000). It is necessary to match the two data sets since the ARD contains the value added, capital and employment data necessary for analysing productivity. Matching the two data sets was based on a 'reporting unit' identifier (as recommended by ONS staff). Since both ARD and BERD have low sampling ratios for SME, the matching procedure resulted in about 50% of firms in the BERD having a match with ARD.

As a check on the validity of matching process the ratio of R&D to value added was calculated. In around 5% of cases this ratio exceeded one, which indicates that the reporting units from BERD may not match that from ARD. It is possible that such ratios are valid (i.e. a firm could buy in

R&D, have a low value added, and hence a high ratio), but the scope of this project did not allow for a full investigation of these firms. Hence the empirical analysis reports in detail on how estimates vary as high intensity firms are included in the regression sample. Overall, however, the fact that the regression results are broadly similar to other studies suggests that the matching process was predominantly successful.

Previous results

Previous firm-level, regression analysis of the productivity of R&D in the UK is relatively rare. Three recent papers have found that the rate of return to R&D was between 15% and 25%, which are comparable to estimates from other G5 countries. However, one recent study by Bond, Harhoff and van Reenen (2002) has found that UK rates of return to R&D are much higher than in Germany. A high rate of return is consistent with the idea that UK firms face financial constraints. Rogers (2005) does not find support for a relatively high rate of return to R&D for UK firms in the 1990s. The analysis in this report is intended to provide further evidence in this debate.

Comparing productivity levels (cross-sectional analysis)

The first set of analyses in this report considers the link between the *level* of value added and the *level* of R&D. Specifically, we estimate a standard production function where the log of value added depends on the log of capital, employment and R&D. This method means that the coefficient on R&D represents the *elasticity* of R&D with respect to total factor productivity (the elasticity is the percentage change in productivity for a percentage change in R&D).

The estimates find the elasticity to be between 0.09 and 0.12 for manufacturing firms, and between 0.06 and 0.11 for non-manufacturing firms (Tables 3 and 4). The higher estimates are for the sub-sample of firms with R&D intensity less than one. An estimate of 0.12 implies, for example, that a 10% increase in BERD (around £1 billion) is associated with an increase in productivity of 1.2%. Additional analysis also finds no evidence that intramural R&D is more or less productive than extramural R&D, that foreign firms in the UK have different R&D productivity, or that firms that undertake defence-related R&D have different rates of return.

An analysis of the sub-sample of SMEs in the data set indicates that the elasticity of R&D for manufacturing firms is between 0.11 and 0.14, which is slightly higher than the full sample. For non-manufacturing firms the estimates vary according to whether high R&D intensity firms are included, but the elasticity estimates are between 0.07 and 0.15, which are again slightly higher than the full sample results.

Productivity growth (first difference analysis)

The drawback of cross-sectional analysis is that it assumes that R&D cannot have an effect on the growth rate of productivity. An alternative empirical specification – based on first differencing the data – allows an assessment of the link between the growth of productivity and the R&D intensity of the firm (expressed as R&D to value added). Before reporting the results, it is important to note that this procedure substantially reduces the sample size since a firm must have data from at least two successive years.

For all manufacturing firms the estimated rate of return to R&D is between 19% and 33%, with the higher rates of return derived from samples that include high R&D intensity firms. The returns for non-manufacturing firms tend to be lower – between 0% and 6% - although there appears to be a rate of return of around 18% for foreign-owned, non-manufacturing firms.

For the sub-sample of SMEs, manufacturing firms have estimated rates of return to R&D of between 23% and 58%, with the highest figure coming from the sample that excludes firms with R&D intensity over two. Our preferred estimate is for the sample that excludes firms with R&D intensity above one, which is an estimated rate of return to R&D of 40% to 44% for SMEs in manufacturing. This is higher than the full sample results and provides some support for the view that SMEs may be constrained in R&D expenditures.

The analysis finds no significant returns to R&D for non-manufacturing SMEs but, in our view, the small sample size for the first difference regressions makes this result unreliable.

Summary

The table below summarises the key regression results. Comparing the results in this paper with the parallel paper by Rogers (2005), which uses data on medium to large firms over the period 1989-2000, we find that the full sample rate of return estimates are broadly similar. Here the full sample rates of return are between 19 and 33%, Rogers (2005) finds the best estimate is 25% (with a range between 18 to 30% depending on estimator used). However, the results for SMEs in manufacturing show some evidence of higher rates of return, with around 40% being our preferred estimate. As always in empirical work, there is uncertainty surrounding these estimates, due to standard confidence intervals as well as concerns over the matching procedure. However, the estimates are based on the first analysis of the BERD-ARD data, which are the best data available for such analysis.

Summary table of estimation results

	Elasticity estimates *(Based on cross-sectional, or levels, analysis)*	Private rate of return to R&D (as %) *(Based on first-difference, or growth rates, analysis)*
Full sample		
Manufacturing firms	0.09 to 0.11	19 to 33
Non-manufacturing firms	0.06 to 0.11	0 to 6
Small and medium enterprises only sample		
Manufacturing firms	0.11 to 0.14	23 to 58
Non-manufacturing firms	0.07 to 0.15	0 to 12

1 Introduction

The background to this project is the academic and policy interest surrounding investment in R&D by UK businesses. A key concern is the low ratio of business R&D to GDP in the UK compared to other leading economies. Furthermore, the aggregate statistics show a small decline in the UK's business R&D to GDP ratio in the 1990s, whereas other leading economies have experienced rises. More details of these issues are contained in DTI (2005) and Rogers (2005). In summary, the evidence to date suggests that the relatively low business R&D to GDP ratio is caused by various factors including: differences in industrial structure between UK and other countries; low R&D activity of some firms; and the absence of large UK firms in electronics, motor vehicles and IT.

The paper by Rogers (2005), entitled *R&D and Productivity in the UK: evidence from firm-level data in the 1990s* provides evidence from firm-level data that the rates of return to R&D in the UK are comparable with other leading economies. This is important since Bond et al (2002) have suggested that the rates of return to R&D in the UK are relatively *high*. High rates of return to R&D imply that UK firms are constrained in their investment in R&D (i.e. firms would like to invest more, since R&D projects offer such high returns, but they cannot due to constraints). Capital market (financial) constraints are put forward as the most likely culprit. Rogers (2005) finds no evidence of such constraints in a sample of medium to large UK firms, based on analysis of data from annual financial reports of medium to large UK firms.

The fact that the analysis in Rogers (2005) is conducted on medium to large firms (the median sales of a firm in the sample is around £190 million) suggests care in interpreting this result too widely.[1] This report aims to analyse the link between R&D and productivity on a data set that includes smaller firms. These firms are drawn from the ONS's Business Expenditure on Research and Development Survey (BERD), which is held (securely) at the Business Data Lab at the Office of National Statistics (ONS). In order to obtain the financial data required for the productivity analysis,

[1] Although, if one is solely interested in the BERD to GDP ratio, the fact is that R&D spending by *large* UK firms dominants absolute R&D expenditure. Hence, at a point in time, the R&D activities – and any possible constraints on these – of smaller firms is not critical. However, looked at in a dynamic (intertemporal) framework, any constraints facing smaller firms today may impact on R&D expenditure in the future, *as these firms may grow to be large*. If one takes such a dynamic view of the determinants of the R&D, it is clear that constraints faced by SMEs in the 1980s and 1990s may have determined the current (2005) R&D intensity.

the BERD data are matched to the ONS's ARD (Annual Respondents Database). Further details of these databases, and the matching process, are contained in the next section.

2 Data: BERD and ARD

2.1. BERD

The ONS conducts an annual survey to collect business R&D data (BERD). The definition of R&D comes from the Frascati manual.[2] The survey form sent to businesses states, "the guiding line to distinguish R&D activity from non-research activity is the presence or absence of an appreciable element of novelty or innovation". It is important to understand that the BERD is a stratified, random sample of firms that are considered to do R&D. The sampling frame is derived by the ONS, using their Annual Business Inquiry (ABI), which has a question concerning whether research is done, but also with information from the DTI and the media. The sampling frame is, therefore, those firms that are thought likely to conduct R&D. The data used here are from 1996 to 2003. Although the sampling method was slightly changed in 1998 (an additional 400 firms were surveyed), the basic approach is: a) to completely sample R&D firms that have more than 400 employees; b) to 1:5 sample the size band 100-399 employees; and c) to 1:20 sample the size band 0-99.[3] According to the ONS, in 2003 there were around 400 firms in category a) and the minimum R&D done by these was £2.6 million.

Two different survey forms are used for the BERD: a long form and a short form. The long form is sent to all firms in category a) and some firms in the additional strata. The long form asks for considerable information about R&D, including basic and applied research, intra- and extra-mural, sources of funds and employment. The short form only asks for total R&D, extra-mural R&D and average employment in R&D (although all of these ask for a civil vs. defence split). The Appendix describes in more detail the nature of the BERD data. In summary, the number of firms surveyed in BERD increased from around 1,200 in 1996 to around 2,300 by 1999. Over the entire period 1996-2003, our analysis shows that around 7,000 unique firms have been including in one or more BERD surveys.

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[2] This is "creative work undertaken on a systematic basis in order to increase the stock of knowledge, including the knowledge of man, culture and society, and the use of this stock of knowledge to devise new applications".

[3] These sampling ratios increased slightly after 1998. Also, the ONS vary these ratios across product groups.

2.2. *Annual Response Database (ARD)*

The ARD is an annual data set of firm-level activity compiled by the ONS.[4] Detailed descriptions are available from the ONS and in papers such as Barnes and Martin (2002). In summary, the ARD is a census of large firms (over 250 employees) and a stratified survey of smaller firms, for example, 25% sampling of firms with less than 10 employees. The coverage of the ARD increased from around 15,000 in 1996 to around 50,000 in 1997 (as service sectors were added to the survey and the sampling proportions were also increased). The ARD data used for this project was referenced at the ONS BDL as the 'standard variable files'. These are data files that have been 'cleaned' and composite variables, such as 'value added', have been created.

2.3. *BERD – ARD matched data*

The matching procedure involved taking the 7,000 firms that ever appeared in BERD (1996-2003) and linking these with any data that appeared in the ARD over that period. The data files were linked on the basis of an identifier called *dlink_ref2*, which is an ONS 'reporting unit' reference number. This decision was taken after discussion with ONS staff involved in both BERD and ARD.

Table 1 shows a summary of the matching process. For example, in 1996 the BERD data at the ONS contains 1,186 survey responses from firms (i.e. both long and short form surveys) and 625 of these can be matched with ARD data in 1996. The fourth column in the table shows the percentage matches achieved and, as can be seen, this tends to fall over the period. Note that since the ARD and BERD uses random sampling one should not expect the matching rates to be very high.[5]

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[4] Firm-level activity in the ARD means, almost always, the 'enterprise' level, where enterprise is the smallest group of legal units within a group that have a relative degree of autonomy.

[5] Calculating the exact expected number of matches is non-trivial, since this involves knowing the precise sampling methodology of the ARD and BERD across firm size and industry. However, as a rough indication, let us consider the year 2000. Assume that 400 long forms for BERD were sent out and that all of these are large firms that are present every year in the ARD; hence the remaining BERD data contain 1,879 small firms. The ARD surveys smaller firms with less than 10 employees with a proportion of 0.25 (see Barnes and Martin, 2002, p.36), which would suggest around 470 more matches. The ARD surveys firms with between 10 and 250 employees at around 0.5 probability, suggesting 940 more matches. Hence, the theoretical match number is between 870 and 1340. The actual number of matches is 1036 (see Table 1).

There is always a concern when matching firm-level data from two different sources that the financial data from each may refer to different units (e.g. the R&D could refer to areas A and B of a firm, whereas the ARD value added is only for area A). As a check on this issue, the ratio of R&D to value added is calculated. In around 5% of cases this ratio exceeded one, which indicates that the reporting units from BERD may not match that from ARD. Although it is possible that such ratios are valid (i.e. a firm could buy in R&D, have a low value added, and hence a high ratio), it seems appropriate to analyse the role of these firms in the analysis. To do this the empirical analysis creates two sub-samples of firms: one contains firms with R&D to value added ratios of less than one; the other contains firms with a ratio less than two. This first sub-sample reduces the cross-sectional regression sample from 7172 to 6793 (5%), the second from 7172 to 7051 (2%).

To gain further insight into the matching process, Table 1 shows the total R&D spend for the firms in different sub-samples. The fifth column shows the total R&D spend of the matched firms. For example, in 2000 the total expenditure on R&D was £6.62bn, which compares to the reported £11.5bn spent on R&D within UK businesses in ONS (2003). The sixth column showing the R&D spend for those firms with a R&D to value added ratio of less than one. It is clear that excluding these firms does substantially reduce the coverage of absolute R&D in the sample. It also suggests that the omitted firms are large firms that do substantial R&D and that the use of *dlink_ref2* as an identifier is problematic in these cases. While the omission of some firms that do substantial R&D is unfortunate, it should be noted that these firms only account for a small number of observations. Moreover, the paper by Rogers (2005) contains analysis of R&D and productivity based on (consolidated) firm-level accounts of the largest UK firms and these data are well suited to analysing large firms.

Table 1 Summary of matching success and R&D expenditures in samples

Year	Surveyed firms in BERD	BERD-ARD matches	% match	Total R&D in BERD-ARD matched data (£ billons)	Total R&D (if R&D/value added ratio <1) (£ billons)
1996	1186	625	53%	3.27	2.75
1997	1072	652	61%	6.05	3.74
1998	1332	806	61%	6.43	3.75
1999	2331	1122	48%	7.79	4.6
2000	2279	1083	48%	6.62	4.48
2001	2229	971	44%	6.86	4.38
2002	2236	997	46%	8.51	4.91
2003	2291	916	40%	7.73	4.34

Note: The BERD-ARD match represents the 7172 observations in the full sample OLS regression in Table 4.

3 Empirical models of R&D and productivity[6]

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.[7] 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 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 pure measurement error in the data, created either by accounting issues or collection errors, and is unknown to firm. 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

[6] This section is similar to that in Rogers (2005) since the empirical models are (deliberately) the same.

[7] 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.

correlation. There is also a literature on the possibility that the 'shocks' (the η_{it}) may also affect optimal choices of variable inputs.[8]

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 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)

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

[8] 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.

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] 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 equal to $\ln RS_t$ plus a constant (as long as g and δ are constant across firms; of course, $\ln RD_t$ exactly equals $\ln RS_t$ in the case of 100% depreciation, δ=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).[9] 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.

3.2. Stratified samples and weighting

There is a debate surrounding the use of weights in analysis of random, stratified samples. It is clear that weights should be used if the analysis is concerned with estimates of population characteristics (e.g. the average number of employees in UK firms), but it is less clear if the analysis is investigating underlying mechanisms (e.g. coefficients in regression analysis). Consider our objective of estimating the rate of return to R&D. Weighting the data would give greater importance to those strata that are underrepresented (i.e. smaller firms in this case); in other words, more weight is given to the R&D-productivity relationship for smaller firms. This would make no difference if the rate of return to R&D for all firms is the same. If the rates of return do vary across strata then the correct procedure is to allow the coefficients to vary also (i.e. run regressions on sub-samples of firms), rather than weighting. The basic argument is that weighting only produces different results in cases where the coefficients vary across strata, but if this is the case the researcher should highlight this fact. For these reasons the analysis in this paper does not weight data in regression analysis but we do analyse SMEs separately. Further discussion of these issues can be found in Rogers and Tseng (2000) and Deaton (1997).

3.3. Other 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.

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[9] Note that since regressions use the log of R&D as an explanatory variable, 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.

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.[10] 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) 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.[11]

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 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

[10] 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).

[11] 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.

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.[12]

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 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).

3.4. 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,

[12] 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.

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 2 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).[13] 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.

The previous study most closely linked to this analysis is by Rogers (2005). This paper estimates similar models to those below using a data set of large UK firms for the period 1989 to 2000. The data are derived from publicly available data in annual accounts and are dominated by medium to large firms. The basic results from Rogers (2005) are that the rate of return to R&D to UK-based firms is around 25%, although estimates range between 18 to 30% depending on estimator used. These estimates are similar to some other recent studies and, importantly, suggest that rates of return to R&D in the UK are broadly comparable to other G5 economies.

4 Cross-sectional regression analysis

This section contains a discussion of the regression analysis conducted on the BERD-ARD data. As indicated in section 2, the matched data contain a number of observations where the R&D to value added ratio – *R&D intensity* – is greater than one (and these may be cases where the reporting unit data in BERD does not match the ARD reporting unit). For this reasons the initial analysis in section 4.1 excludes all observations where the R&D to value added ratio is greater than one. The second sub-section reports on the results obtained when the analysis is conducted on the full sample

[13] 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).

(i.e. for any R&D to value added ratio) and when the sample excludes ratios above two. The third section includes some further tests on the role of foreign ownership, defence-related R&D and intra- versus extra-mural R&D. The final section restricts the sample to only small and medium enterprises (SME) (i.e. firms with less than 250 employees), which is a core objective of this research. Summary statistics of R&D intensity and employment of the major samples used are contained in the data appendix.

4.1. Results for sub-sample of firms with R&D intensity less than one

Table 3 shows the regression results from estimating equation [2] on the sub-sample of firms with R&D intensity less than one. This is the empirical specification with the log of value added as the dependent variable and the logs of capital, employment and R&D as explanatory variables. The log of industry level R&D (at the 3 digit SIC level), which does not include firm *i*'s R&D, is also included to proxy any R&D spillovers within the industry. Note that year dummies and industry dummies (2 digit level) are also added to each regression. Each regression uses a pooled, cross-section sample of firms where firms with R&D to value added ratios above one are excluded. To reiterate, the coefficient estimates are based on the difference in productivity *levels* across firms.

Regressions (1) to (4) in Table 3 use the contemporaneous values for the explanatory variables, which may introduce endogeneity bias (the concern is that the regression error may be correlated with explanators). However, the contemporaneous specification is useful for comparison purposes and to show sample sizes available in BERD-ARD data. Regression (1) shows the full sample, regression (2) is a balanced panel of firms that have data over the 1999 to 2003 period. Note that that sample size in regression (2) is dramatically reduced to 894, as opposed to 6793, reflecting the fact that ARD and BERD databases are random surveys.

The regressions shown in columns (5) to (8) use the lagged values (t-1) of the explanatory variables. From an econometric perspective, this should reduce the endogeneity bias (i.e. between error term and explanators), but it is clear that this method also dramatically reduces the sample size by about a half. Note, however, that the coefficients in (5) to (8) are similar to those in (1) to (4), suggesting that endogeneity bias is not a serious problem. Specifically, the coefficient on R&D is unchanged at 0.11 in the full sample regression, and is similar in balanced and manufacturing samples. The only major difference is the non-manufacturing sample where the coefficient is now 0.07.

For the purposes of this paper, the main result from Table 3 is that the coefficient on the log of R&D is generally between 0.11 and 0.13 (the exception being for the non-manufacturing sample with t-1 explanators). A coefficient of 0.12 means that a 1% rise in (real) R&D expenditures is associated with a 0.12% increase in value added. Note that, since the regression is controlling for capital and labour, this association can be thought of as an increase in total factor productivity (TFP). Since this estimate is based on cross-sectional data the association should be thought of as a level effect (i.e. a 10% increase in R&D would increase the *level* of TFP by 1.2%). It is also possible that increasing the level of R&D may increase the *growth* rate of TFP (this is investigated in the next section). Lastly, the implied impact of R&D in these regressions controls for the level of capital. Some economists argue that increased R&D can stimulate greater investment, hence higher capital stock, and thereby higher value added (although TFP would not be affected).

The lower panel of rows in Table 3 show the implied rates of return based on the estimates of elasticity. As discussed in section 3, the rates of return vary according to the ratio of R&D to value added. Specifically, at low levels of R&D intensity the rate of return is (very) high. At the median of the distribution the rate of return is around 0.4, which can be thought of as a rate of return of 40%.[14]

4.2. Robustness of results to the inclusion of high R&D intensity firms

The results in Table 3 are based on the sample of firms with R&D intensity less than one. The regressions shown in Table 3 have also been run for a) the full sample of all firms and b) the sample of firms with R&D intensity less than 2. Table 4 shows the coefficients on the log R&D from these regressions (the coefficients on other variables are omitted for brevity, but are generally similar to those in Table 3). The results in Table 4 indicate that the coefficient on log of R&D tends to fall as the sample includes more high R&D intensity firms. For example, the elasticity on log R&D in the first regression (9) with all firms in the sample is 0.08, this rises to 0.1 if firms with R&D intensity above two are excluded, and to 0.11 if firms with R&D intensity above one are excluded (Table 3).

The implied rates of return based on the elasticity estimates do vary with the sub-samples, as can be seen from Table 4. In this table, the results suggest that the rate of return to R&D is generally lower when more high R&D intensity firms are included in the sample. Also, the differences between balanced and unbalanced panels, and manufacturing and non-manufacturing sub-samples, tends to

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[14] Consider a £1 investment in R&D. The regression estimate implies that this will increase value added by £0.4 in, say, period t+1, and that this level effect is permanent. Using the formula for an infinite series discounted at r, the present value of the £1 investment is 0.4 / r, where r is the internal rate of return.

be greater than in Table 3. Focussing on the rate of return to the median firm, in the sub-sample which excludes firms with R&D intensity greater than two, the results indicate a rate of return of around 37% in manufacturing. For non-manufacturing firms, however, the implied rate of return at the median is lower, with estimates of 8% and 17% depending on the estimator used.

4.3. In-house, foreign and defence R&D

A number of other tests on the role of R&D in cross-sectional regressions were undertaken. These are bulleted pointed below.

- The BERD data contain separate entries for R&D carried out within the company (in-house or intramural) and R&D bought in (extramural). Around 50% of firms in the regression sample do buy in some R&D. Entering the log value of both in-house and external R&D into a regression specification as [1] allows us to test if the impact on either R&D is equivalent. The full sample results show that the coefficient on in-house R&D is slightly higher (0.052) that extra-mural R&D (0.045); however, this difference is not statistically significant. Hence, there is no evidence that returns to R&D vary according to whether it is done in-house or bought in.

- The BERD data contain a variable that defines whether the reporting unit is foreign owned. For the BERD-ARD matched data around 25% are classified as foreign. Testing for whether the impact of R&D is different for foreign owned firms we find no significant results.

- The BERD data also contain data on defence related R&D. Around 9% of firms in the BERD-ARD matched data report some defence related R&D. Omitting these firms from the regression sample, and re-estimating [1], leaves the coefficient on the log of R&D unchanged at 0.11 for the sub-sample of firms with R&D intensity less than one.

4.4. Small and medium sized enterprises (SMEs)

A sub-sample of SMEs was created, which are defined as those firms with less that 250 employees in a given year. The 1996-2003 data contains 2,372 observations on SME (hence they comprise of 33% of BERD-ARD matched data). Table 5 shows the coefficients on log R&D from a set regressions that mirror those in Table 4. Note that only the coefficient on R&D is shown for brevity (the other coefficients are similar to Table 4 and are not central to the analysis here). The table also has no results for the ‘balanced panel’ sample, since there are only 9 SMEs that are present in every year from 1999-2003. For the sample of SME with R&D intensity less than one, the coefficient is between 0.12 and 0.15. These are slightly higher than the regressions in Table 3, suggesting that SME may have higher R&D elasticity. The results from the SME samples that include firms with higher R&D intensity indicate that the elasticity falls slightly as more high R&D intensity firms are included. Overall, however, the results indicate that R&D is an important correlate with productivity for SME with the evidence suggesting that the magnitude of the impact is slightly greater than for larger firms.

As before, it is possible to calculate implied rates of return based on the elasticity estimates. These are calculated for the results from the sample that excludes firms with R&D intensity above one. For a median firm, the results indicate a rate of return of around 37% for SME in manufacturing and around 19 to 26% for SMEs in non-manufacturing.

5 First difference analysis: R&D intensity and productivity growth

This section reports on the results from using the specification shown in equation [6]. This has the first difference in the log of value added as the dependent variable. Since the first difference of the logs is approximately equal to the growth rate (for small values of growth as in these data), the specification can be thought of as investigating the determinants of productivity growth. The explanatory variables are the first difference (growth) of labour and capital, the R&D to value added ratio, and the first difference of industry R&D. The first difference of labour and capital refers to *t* less *t*-1, and the R&D to value added is for *t*-1. The fact that labour and capital are defined in this way could imply an endogeneity bias, but the previous section found this to be limited.[15] Initially, year and industry dummies are also added, although the industry dummies are never significant as a group and are therefore dropped from most of the analysis. This is understandable since the first difference (growth) specification is effectively removing any firm-specific, time invariant effect from the model (such as any unchanging market factors, which had previous been captured by the industry dummies in the cross sectional analysis).

As in the previous section, the analysis is divided into three sub-sections that look at different sub-samples of firms, including SME analysis.

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[15] Note that the econometric solution to endogeneity would normally involve using lagged values as instruments, which would reduce the sample even more given the BERD-ARD data.

5.1. *Results for sub-sample of firms with R&D intensity less than one*

The results of the regression analysis using a sample of firms with R&D intensity less than one are shown in Table 6. The estimation method is OLS. The first regression (25) in Table 6 has 3,402 observations over the 1996 to 2003 period. The use of a first difference specification requires that a firm has at least two successive years of data, and the BERD-ARD data contains fewer cases of such firms (due to sampling methodology used in ARD and BERD). It is clear that this is a potential drawback of this empirical specification since SMEs will tend to be excluded from this analysis. The coefficients are positive and significant for capital, labour and R&D terms. The capital and labour coefficients are too low according to economic theory (and as compared to the cross-sectional results), but this is a common outcome in the first difference specification (Griliches and Mairesse, 1995). The R&D coefficient is 0.20, which can be interpreted as a (gross marginal) rate of return of 20%. Note that the industry dummies are included in regression [25], but are not significant. Regression [26] drops these and the R&D coefficient falls slightly to 0.18. The third regression adds in an interaction term between a foreign ownership dummy and the R&D intensity. This indicates that domestic firms rate of return to R&D is around 0.16, while foreign firms may have a premium although the coefficient is not significant at the 10% level. Looking across the remaining regression results in Table 6 we can see that the returns to R&D tend to be higher for manufacturing firms. Also, any possible foreign premium to R&D is certainly not present in the manufacturing sector, but is in the non-manufacturing sector. In fact, the analysis suggests that domestic firms doing R&D in the non-manufacturing sector do not have a significant, positive return on R&D. This is contrary to the basic, cross-sectional results reported in Table 3, but these did show a lower elasticity for non-manufacturing firms.

The summary of the results in Table 6 is that the rate of return to R&D for manufacturing firms in the UK is between 19% and 23%. For non-manufacturing firms the estimated average return to R&D is lower (maybe only 5%), but foreign owned firms do better (18%), while domestic firms have no (statistically) significant returns.

5.2. *Robustness of results to the inclusion of high R&D intensity firms*

Table 7 shows the results on the R&D variable for the full sample of firms, and also the sub-sample which excludes firms with R&D intensity greater than two. The full sample results show the coefficient on R&D is not significantly different from zero. However, looking across the table we can see that this is driven by poor results for non-manufacturing firms. It is difficult to understand these results without further investigating into the reasons for high R&D intensity firms (i.e. identifying the firms behind the outlier values and whether these are due to matching problems[16]). In contrast, for manufacturing firms the rate of return is around 30%. For the sub-sample that excludes R&D intensity greater than two, the rate of return to R&D in manufacturing is also around 30%. Both these results are slightly higher rates of return than those in Table 6.

5.3. Small and medium sized enterprises (SME)

Table 8 shows a set of results for the sub-sample of SME firms only. The first issue to note is that the sample size is small due to the requirement that a firm must have two consecutive years of data to be included in the first difference estimation. For the full sample of firms that exclude SME with R&D intensity greater than one, the results suggest that rates of return to SME is around 41% when industry dummies are included (regression 41), but 26% when they are not (regression 42). Looking across the table, the results indicate that the rate of return to R&D in the manufacturing sector tends to be around 40%, which is higher than the previous (full sample) estimates for manufacturing (see Table 6). For non-manufacturing SME the results indicate no significant rate of return to R&D, although the sample size for these regressions is low (n=82).

For the sub-sample of firms with R&D intensity less than two (central panel of Table 8), the results indicate even higher returns to R&D for manufacturing firms (around 58%), with non-manufacturing firms having an estimated rate of return of 12%.

Whereas the results for SMEs that have R&D intensity below two suggest higher returns to R&D for manufacturing, this pattern is not confirmed by the regression results for the full sample of SMEs (i.e. any R&D intensity). These results, in the lower panel in Table 8, suggest the rate of return to R&D in manufacturing is around 23% (regression 44), which is below the full sample results (Table 7). Our view is that these results should be given little weight since firms with R&D intensity above two are likely to be either ones for which the BERD-ARD match is inappropriate, or firms that are unusual in having such high R&D expenditures.

[16] Such an investigation could be conducted, subject to ONS confidentiality conditions, but would require additional research time that was not specified for this project.

6 Conclusions

The relatively low ratio of business R&D to GDP (the BERD ratio) in the UK as compared to other leading economies has created academic and policy interest into R&D. The aggregate statistics also show a small decline in UK’s BERD ratio in the 1990s, whereas other leading economies experienced rises. The relatively low BERD ratio cannot be explained solely by sectoral or industry-level differences between the UK and other countries. This report analyses the link between R&D and productivity for a sample of firms derived from merging the ONS’s Business Research and Development database (BERD) and the Annual Respondents Database (ARD). The main aim of this is to allow small and medium sized enterprises (SME) to enter the analysis, as most previous studies have been based on larger firms.

The BERD and ARD data sets are derived from random, stratified surveys conducted by the ONS. The BERD data available are for 1996-2003. In 1996 the BERD surveyed around 1,200 firms, although this was increased to around 2,300 from 1999 onwards. While the ARD starts in 1970, the survey size was substantially increased in 1997 (to 50,000 from 15,000). It is necessary to match the two data sets since ARD contains the value added, capital and employment data necessary for analysing productivity. Matching the two data sets was based on a ‘reporting unit’ identifier (as recommended by ONS staff), and the subsequent regression analysis suggests the matching procedure was largely valid. Since both ARD and BERD have low sampling ratios for SME, the matching procedure resulted in about 50% of firms in the BERD having a match with ARD. An important characteristic of the matched data set is that a number of observations have high R&D intensities (around 5%), defined as R&D to value added ratios greater than one. These observations could be due to a problem in the ‘reporting unit’ match (i.e. the R&D data in BERD do not represent the same unit of reporting as in ARD). Alternatively, these high R&D intensity firms could be ‘true’ in the sense that some firms may have very high R&D expenditures relative to value added. Such firms would be likely to be relatively small firms, perhaps start-up firms or those that provide R&D services for others. An analysis of the absolute amount of R&D expenditure accounted for by the firms with high R&D intensities (see Table 1) suggests that some of these do represent matching problems, since the amounts of R&D are large (e.g. in 2003, omitting the 5% of firms with R&D intensity greater than one, removes over £3 billion of R&D). Given these issues, the regression analysis is conducted on three different sub-samples: the sub-sample of firms with R&D intensity less than one; the sub-sample of firms with R&D intensity less than two; and the sample of all firms.

The cross sectional analysis discussed above considers the link between the *level* of value added and the *level* of R&D. Estimating a standard production function, with the log of value added as the dependent variable, allows an elasticity of R&D with respect to total factor productivity. The estimates consistently find the elasticity to be between 0.09 and 0.12 for manufacturing firms, and between 0.06 and 0.11 for non-manufacturing firms (Tables 3 and 4). The higher estimates are for the sub-sample of firms with R&D intensity less than one. An estimate of 0.12 implies, for example, that a 10% increase in BERD (around £1 billion) is associated with an increase in productivity of 1.2%. Additional analysis also finds no evidence that intramural R&D is more or less productive than extramural R&D, that foreign firms in the UK have different R&D productivity, or that firms that do defence-related R&D have different rates of return.

An analysis of the sub-sample of SMEs in the data set indicates that the elasticity of R&D for manufacturing firms is between 0.11 and 0.14, which is slightly higher than the full sample of all firms. For non-manufacturing firms the estimates vary according to whether high R&D intensity firms are included, but the elasticity estimates are between 0.07 and 0.15, which are again slightly higher than the full sample results.

A drawback of the cross-sectional analysis is that it assumes that R&D cannot have an effect on the growth rate of productivity and also that the marginal rate of return to R&D varies across firms. An alternative empirical specification – based on first differencing the data – allows an assessment of the link between the growth of productivity and the R&D intensity of the firm (expressed as R&D to value added). This method also directly estimates a constant (average) private marginal rate of return to R&D across firms in the sample. Before reporting the results it is important to note that this procedure substantially reduces the sample size since a firm must have data on at least two successive years. Since both the ARD and BERD randomly sample SMEs, while larger firms are always surveyed, this productivity growth estimates are based on a sample dominated by larger firms.

For all manufacturing firms the estimated rate of return to R&D is between 19 and 33%, with the higher rates of return derived from samples that include high R&D intensity firms. The returns for non-manufacturing firms tend to be lower – between 0 and 6% – although there appears to be a rate of return of around 18% for foreign-owned, non-manufacturing firms.

For the sub-sample of SMEs, manufacturing firms have estimated rates of return to R&D of between 23 and 58%, with the highest figure coming from the sample that excludes firms with

R&D intensity over two. The variation in estimates according to whether high R&D intensity firms are included is unfortunate, but it is not something that can be investigated given the scope of this project. Our preferred estimate is from the sample that excludes firms with R&D intensity above one, which is an estimated rate of return to R&D of 40 to 44% for SME in manufacturing. This is higher than the full sample results and provides some support for the view that SME may be constrained in R&D expenditures. The analysis finds no significant returns to R&D for non-manufacturing SMEs, but the small sample size for the first difference regressions makes this result difficult to interpret.

Comparing the results in this paper with the parallel paper by Rogers (2005) that uses data on medium to large firms over the period 1989-2000 we find that the full sample rate of return estimates are broadly similar. Here the full sample rates of return are between 19 and 33%, Rogers (2005) finds the best estimate is 25% (with a range between 18 to 30% depending on estimator used). However, the results above for SME in manufacturing show some evidence for slightly higher rates of return, with around 40% being our preferred estimate. Needless to say, there is uncertainty surrounding these estimates, due to standard confidence intervals as well as concerns over the matching procedure. However, the estimates presented above are based on the first analysis of the BERD-ARD data, which are the best data available for such analysis.

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Data Appendix

BERD

The BERD data at the ONS BDL is organised into files for each year (e.g. BERD_2003.dta). The unit of data is the ONS's 'reporting unit', which refers to the activity of an autonomous part, or the whole, of a firm. For reference the identifier for this is the *Dlink_ref2* variable. Since the objective was to merge these data with the ARD, which contains 'reporting unit' data, the advice from ONS was to use 'reporting unit' (*Dlink_ref2*) as the main identifier.

Each annual BERD dataset appears to contain many thousands of firm-level observations (e.g. in 2003, there are 18,931 observations). However there are two reasons why this figure is so large. First, most of these are imputations carried out by ONS. The actual survey responses in 2003 is much smaller at 2,710 (this is based on a variable in the data that indicates that a long or short form has been sent out). Second, the data contains multiple observations for a single firm; since the ONS splits the information on a survey form into various observations (i.e. one observation for, say, firm *x*, will contain 'civil' R&D, while another will contain 'defence' R&D). This means that the data needs to be consolidated back into a single observation representing the R&D activity of a firm before regression analysis can be undertaken. Once the imputations, and duplicates, are removed the number of actual firms in the data in 2003 falls to 2,291. In 1996 the equivalent figure is 1,186; but from 1999 the figure is around 2,300. Over the entire period 1996-2003 the analysis showed that there were around 7,000 unique firms that appeared in the BERD in at least one year.

ARD

The definition of (factor cost) value added is:

sales of goods and services - amount of VAT
+ total value of all stocks end of yr - Total value of all stocks at the beginning of the period
+ value of insurance claims received - total purchases of goods materials/services

Value added was deflated by producer price (MM22 base year 2000).

Capital is calculated from data on net capital expenditures (capex) in ARD ('net capital expenditures' are gross investment less disposals). Separate capex are available for buildings, vehicles, machines and office equipment. Each of these is deflated using ONS deflators (MM17, base year 2000). If a single year of data is omitted, and data on capex exists before and after this year, an average of the two years is inserted. The initial capital stock (in 1993, or first year of data for the firm) is calculated using capex/(0.047 + 0.02), where 0.047 represents average depreciation rate and 0.02 is average growth rate (both based on sample averages). For constructing the capital stocks, vehicles are depreciated at 20% per year, machinery and equipment at 6% and buildings at 2%. Since leasing of capital is important for many firms, the data on leasing expenditures was capitalised and added to derived capital stock. The capitalising of leasing used the formula leasing expense/(0.1+0.047), where 0.1 represents average return to leasor (10%) and 0.047 is average depreciation rate. Initial analysis suggested that there was little difference between capital stock with and without leasing imputation, but the coefficient on the leasing-adjusted capital stock was slightly more significant.

Summary statistics

	mean	Median	10^{th} percentile	90^{th} percentile
Cross sectional samples				
n=6793 (Table 3)				
R&D / value added (as %)	4.2	10.1	0.5	29.6
Employment	425	1039	81	1556
n=2217 (SME, Table 5)				
R&D / value added (as %)	5.5	12.0	0.1	32.8
Employment	119	123	33	218
First difference samples				
n=3402 (Table 6)	4.0	10.8	0.0	30.0
R&D / value added (as %)	538	1251	150	1833
Employment				
n=607 (SME, Table 8)				
R&D / value added (as %)	5.5	12.1	1.0	33.0
Employment	132	135	59	212

Table 2 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)	
	$(\text{R\&D / value added})_{t-1}$	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.

Table 3 **Cross-sectional estimates for sample with R&D intensity < 1**

	Contemporaneous explanatory variables				Lagged explanatory variables			
	All	Balanced	Manu.	Non-manu	All	Balanced	Manu.	Non-manu
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln (assets)	0.15***	0.20***	0.14***	0.18***	0.18***	0.20***	0.16***	0.25***
	(24.9)	(10.8)	(21.1)	(12.1)	(19.4)	(10.7)	(16.3)	(10.0)
ln (employment)	0.78***	0.71***	0.79***	0.74***	0.73***	0.67***	0.75***	0.68***
	(82.4)	(20.2)	(73.9)	(35.0)	(50.0)	(18.1)	(45.2)	(19.6)
ln (R&D spend)	0.11***	0.13***	0.11***	0.11***	0.11***	0.13***	0.12***	0.07***
	(25.4)	(9.2)	(23.0)	(9.8)	(17.2)	(9.1)	(17.0)	(3.9)
ln (industry R&D, 3 digit level)	0.02***	0.05***	0.01**	0.05***	0.02***	0.03*	0.01**	0.05**
	(4.1)	(2.8)	(2.2)	(3.6)	(2.8)	(1.9)	(1.8)	(1.9)
Constant (included, but not shown here due to ONS confidentiality rules)								
Observations	6793	894	5643	1150	3705	858	3188	517
R-squared	0.88	0.81	0.86	0.90	0.83	0.79	0.81	0.87
F test: Significance of year dummies	0.00	0.16	0.00	0.00	0.02	0.67	0.03	0.74
F test: Sign. of industry dummies (2 digit)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
F test: Constant returns to scale	0.00	0.23	0.00	0.01	0.01	0.72	0.00	0.97
Implied rate of return								
25th Percentile (of R&D/valued added)	1.19	0.99	1.08	1.73	1.17	1.04	1.11	1.46
Median (of R&D/valued added)	0.41	0.40	0.41	0.40	0.41	0.42	0.43	0.30
75th Percentile (of R&D/valued added)	0.15	0.12	0.16	0.08	0.14	0.13	0.16	0.05

Notes: All regressions are OLS. Regressions (1), (2), (3) and (4) use contemporaneous (*t*) values for explanatory variables. Regression (5)-(8) use lagged (t-1) values for the explanatory variables. Balanced panel is for 1999-2003. * significant at 10%; ** significant at 5%; *** significant at 1%. The F-test rows contain the probability of a type II error.

Table 4 Cross-sectional estimates for full sample and R&D intensity < 2

	Contemporaneous explanatory variables				Lagged explanatory variables			
	All	Balanced	Manu.	Non-manu	All	Balanced	Manu.	Non-manu
Full sample of firms	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
ln (R&D spend)	0.08***	0.07***	0.09***	0.06***	0.06***	0.07***	0.10***	0.02*
	(17.4)	(4.9)	(17.1)	(5.3)	(11.6)	(5.0)	(13.0)	(1.9)
Observations	7172	938	5759	1413	3919	906	3256	663
Implied rate of return								
25th Percentile (of R&D/valued added)	0.80	0.50	0.85	0.74	0.78	0.53	0.90	0.29
Median (of R&D/valued added)	0.27	0.19	0.32	0.10	0.27	0.20	0.34	0.03
75th Percentile (of R&D/valued added)	0.09	0.05	0.12	0.01	0.08	0.05	0.12	0.00
Sample of firms with R&D intensity <2								
ln (R&D spend)	0.10***	0.07***	0.11***	0.08***	0.10***	0.08***	0.11***	0.04***
	(22.3)	(5.5)	(20.6)	(8.2)	(14.8)	(5.4)	(15.3)	(2.6)
Observations	7051	938	5718	1333	3850	899	3236	614
Implied rate of return								
25th Percentile (of R&D/valued added)	0.99	0.54	0.97	1.07	0.94	0.57	1.01	0.862
Median (of R&D/valued added)	0.34	0.21	0.37	0.17	0.33	0.22	0.39	0.08
75th Percentile (of R&D/valued added)	0.11	0.06	0.14	0.03	0.11	0.06	0.14	0.01

Notes: All regressions are OLS. The coefficients on the other explanatory variables, which are the same as in Table 3, are omitted. Regressions (9) to (12) use contemporaneous (*t*) values for explanatory variables. Regression (13)-(16) use lagged (t-1) values for the explanatory variables. Balanced panel is for 1999-2003. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5 Cross-sectional estimates for sample of small and medium sized enterprises (SME)

	Contemporaneous explanatory variables				Lagged explanatory variables			
	All	Balanced	Manu.	Non-manu	All	Balanced	Manu.	Non-manu
	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Sample of firms with R&D intensity <1								
ln (R&D spend)	0.13***		0.12***	0.15***	0.14***		0.14***	0.13**
	(15.6)		(13.4)	(7.4)	(8.5)		(8.4)	(2.8)
Observations	2217	n/a	1785	432	709	n/a	587	122
Implied rate of return								
25th Percentile (of R&D/valued added)	0.98		0.93	0.93	0.97		0.99	0.97
Median (of R&D/valued added)	0.36		0.37	0.26	0.35		0.39	0.19
75th Percentile (of R&D/valued added)	0.14		0.17	0.08	0.14		0.17	0.04
Full sample of firms								
ln (R&D spend)	0.10***		0.11***	0.07***	0.11***		0.13***	0.08
	(10.4)		(11.1)	(3.2)	(5.8)		(7.3)	(1.4)
Sample of firms with R&D intensity <2								
ln (R&D spend)	0.12***		0.11***	0.12***	0.13***		0.13***	0.13***
	(13.9)		(12.1)	(6.7)	(7.7)		(7.8)	(3.1)

Notes: All regressions are OLS and for the sample of SME only. The coefficients on the other explanatory variables, which are the same as in Table 3, are omitted. The balanced panel for 1999-2003 cannot be estimated due to insufficient observations. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6 Rate of return regressions (first difference model) for R&D intensity < 1

	First difference (OLS)							
	Full sample	Full sample	Full sample	Manufact.	Manufact.	Manufact. Balanced	Non-manu	Non-manu
	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)
FD ln Assets	0.07***	0.08***	0.08***	0.09***	0.09***	0.06	-0.01	-0.00
	(2.7)	(2.9)	(2.9)	(3.2)	(3.2)	(0.7)	(0.1)	(0.0)
FD ln Employment	0.63***	0.64***	0.64***	0.63***	0.63***	0.60***	0.64***	0.64***
	(18.7)	(19.2)	(19.2)	(17.4)	(17.4)	(8.9)	(7.5)	(7.5)
R&D/value added (t-1)	0.20***	0.18***	0.16***	0.23***	0.23***	0.19***	0.05***	-0.02
	(5.2)	(5.5)	(4.0)	(5.9)	(4.8)	(3.1)	(0.8)	(0.2)
FD log(industry R&D 4sic, t-1)	0.01	0.00	0.00	0.00	0.00	-0.04	0.01	0.01
	(0.6)	(0.4)	(0.4)	(0.0)	(0.0)	(1.2)	(0.3)	(0.4)
foreign dummy x R&D/value added (t-1)			0.07		0.02			0.18**
			(1.2)		(0.3)			(1.7)
Constant	-0.45	0.00	0.00	-0.00	-0.00	0.04*	0.07	0.06
	(1.4)	(0.0)	(0.0)	(0.2)	(0.2)	(1.7)	(0.3)	(0.3)
Observations	3402	3402	3402	2965	2965	687	437	437
R-squared (adjusted)	0.11	0.12	0.12	0.12	0.12	0.13	0.12	0.14
F test: Joint sig. of industry dummies	0.32	Na	Na	Na	Na	Na	Na	Na
F test: Joint sig. of year dummies	0.08	0.05	0.06.	0.01	0.01	0.73	0.24	0.24

Notes: Regressions (25)-(32) use first difference of ln(assets) and ln(employees) and R&D to value added ratio (t-1). All samples are unbalanced except for regression (30). Regressions (28) to (30) only include manufacturing firms; regressions (31) and (32) only non-manufacturing firms. The brackets contain t-statistics. * significant at 10%; ** significant at 5%; *** significant at 1%. The F-test rows contain the probability of a type II error.

Table 7 Rate of return regressions (first difference model) for full sample and R&D intensity < 1

	First difference (OLS)							
	Full sample	Full sample	Full sample	Manufact.	Manufact.	Manufact. Balanced	Non-manu	Non-manu
	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
Full sample								
R&D/value added (t-1)	0.01	0.01*	0.00	0.32***	0.29***	0.22***	-0.00	-0.00
	(1.6)	(1.9)	(0.4)	(15.9)	(11.1)	(5.7)	(0.9)	(1.1)
foreign dummy x R&D/value added (t-1)			0.11***		0.06			0.03*
			(6.9)		(1.5)			(1.6)
Observations	3585	3585	3585	3018	3018	698	567	567
R-squared (adjusted)	0.09	0.09	0.10	0.16	0.16	0.14	0.09	0.09
R&D intensity < 2 sample								
R&D/value added (t-1)	0.24***	0.16***	0.16***	0.31***	0.33***	0.13**	0.06**	0.04
	(9.6)	(8.7)	(7.0)	(10.6)	(9.2)	(2.4)	(2.1)	(1.2)
foreign dummy x R&D/value added (t-1)			0.02		-0.05			0.07
			(0.7)		(1.0)			(1.4)
Observations	3536	3536	3536	3002	3002	694	534	534
R-squared (adjusted)	0.12	0.11	0.11	0.13	0.13	0.10	0.11	0.11

Notes: The table shows the coefficient estimates for the R&D intensity from a first difference OLS specification that contains the sample explanatory variables as in Table 6 (other coefficients are omitted for brevity). The ‘full sample’ of firms is all firms in the matched BERD-ARD regardless of value of R&D intensity. The second sample excludes firms with an R&D intensity above 2. The brackets contain t-statistics. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8 Rate of return regressions (first difference model) for sample of SME only

	First difference (OLS)							
	SME sample	SME sample	SME sample	SME Manufact.	SME Manufact.	SME Manufact. Balanced	SME Non-manu	SME Non-manu
	(41)	(42)	(43)	(44)	(45)	(46)	(47)	(48)
SME with R&D intensity < 1 sample								
R&D/value added (t-1)	0.41***	0.26***	0.22***	0.44***	0.40***		0.07	0.04
	(4.2)	(3.2)	(2.5)	(4.0)	(3.3)		(0.4)	(0.3)
foreign dummy x R&D/value added (t-1)			0.15		0.11			0.16
			(1.0)		(0.6)			(0.5)
Observations	607	607	607	525	525		82	82
R-squared (adjusted)	0.20	0.20	0.20	0.21	0.21		0.14	0.14
SME with R&D intensity < 2 sample								
R&D/value added (t-1)	0.43***	0.23***	0.26***	0.58***	0.58***		0.12*	0.13*
	(7.6)	(5.8)	(5.8)	(8.1)	(7.8)		(1.9)	(1.7)
			-0.11		-0.03			-0.02
			(1.4)		(0.2)			(0.2)
All SME								
R&D/value added (t-1)	0.20***	0.18***	0.16***	0.23***	0.23***		0.05***	-0.02
	(5.2)	(9.0)	(3.9)	(5.9)	(4.8)		(0.8)	(0.2)
foreign dummy x R&D/value added (t-1)			-0.1**		-0.09			-0.00
			(2.6)		(0.8)			(0.00)

Notes: The table shows the coefficient estimates for the R&D intensity from samples of only SME firms. These are defined as having employment (in a given year) of less than 250. As in Table 6 and 7, the estimator is a first difference, OLS specification, and each regression has the same set of explanatory variables as in Table 6 (other coefficients are omitted for brevity). The brackets contain t-statistics. * significant at 10%; ** significant at 5%; *** significant at 1%.