UNIVERSITY of GREENWICH

FOUNDATION FOR EUROPEAN PROGRESSIVE STUDIES
FONDATION EUROPÉENNE D'ÉTUDES PROGRESSISTES

GPERC

GREENWICH POLITICAL ECONOMY RESEARCH CENTRE

Variations in the effect of R&D investment on firm productivity: UK Evidence *

Edna Solomon
University of Greenwich

Mehmet Ugur
University of Greenwich

Francesco Guidi
Univeristy of Greenwich

And

Esref Trushin
University of Durham

Year: 2015

No: *GPERC30*

GREENWICH PAPERS IN POLITICAL ECONOMY

Abstract: Our research provides novel findings about the heterogenous effects of R&D on UK firm-level productivity. In our comprehensive analysis, the effect of R&D on UK productivity is broken down by type of R&D, sources of R&D funding, sector and Pavitt class. Our sample consists of a panel of 10,920 firms from 1998 to 2012. We find that R&D has a positive and significant effect on labour productivity in the UK. However, there is considerable heterogeneity in the results. The output elasticity of R&D capital is higher for firms in less competitive sectors and in more R&D intensive sectors. Finally, we find that applied R&D, experimental R&D, intramural R&D and R&D from private sources tend to have higher productivity impacts compared with basic R&D, extramural R&D or publicly-funded R&D.

Key words: R&D, knowledge capital, productivity, meta-analysis

JEL Classification: D24, O30, O32, C49, C80

Acknowledgements: Research for this paper has been funded by ESRC under grant reference no ES/K004824/1. We thank our funders for their generous support. We also thank the participants of two workshops for their helpful comments: (i) Evaluation of R&D expenditures, firm survival firm growth and employment: UK Evidence workshop, University of Greenwich, 4 June 2015; and (ii) Advances in Business-Related Scientific Research (ABSRC) 14 October 2015, Rome. The views expressed here are those of the authors, who are responsible for any errors or omissions.

Corresponding author: *Mehmet Ugur, Professor of Economics and Institutions, University of Greenwich Business School, Park Row, London SE10 9LS.*
Email: *M.Ugur@gre.ac.uk*

** This is a first draft. It can be quoted with a proviso to that effect*

1. Introduction

The relationship between research and development (R&D) investment and productivity has been a subject of major interest for researchers and policy makers for a long time. The pioneering work was that of Minasian (1969) and Griliches (1973) on R&D and productivity; and Terleckyj (1974) on rates of return to R&D. The empirical work expanded significantly after Griliches (1979), who has articulated a lasting framework for the range of measurement, modelling and estimation issues encountered in empirical work.

R&D may be defined as “creative work that is undertaken on a systematic basic 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.” (ONS, 2005, p.1). R&D has been identified as a source of growth because it leads to the product and process innovation which increases productivity. Moreover, firms that engage in R&D activity also build up their absorptive capacity which enables them to benefit from knowledge spillovers (Cohen and Levinthal (1989)).

We aim to contribute to existing empirical work along two key dimensions. First, we draw on a number of firm-level UK datasets (the Annual Respondents Database [ARD] and its successor, the Annual Business Survey [ABS], and the Business Expenditures on Research and Development [BERD] to provide up-to-date evidence the relationship between R&D and productivity in the UK from 1998 to 2012.

Second, we aim to account for the sources of heterogeneity by providing estimates by breakdown of R&D and sector. R&D is not a homogeneous phenomenon. It can be broken down by type (basic, applied and experimental), by source of funding (private and public) and by where the research is carried out (intramural and extramural). However, the majority of research in this field examines R&D without distinction about the type of R&D. This is an important omission because different types of R&D have different characteristics that might affect productivity growth. For instance, basic R&D is generally more risky and more easily expropriated than applied or experimental types of R&D (Czarnitzki and Thorwarth, 2012). Hence, there are more private incentives for firms to undertake applied and experimental research compared with basic R&D.

We also examine and provide varied effects of R&D by sector (manufacturing and no manufacturing), level of competition and by Pavitt class. This is important because the type of sector can influence the relationship between R&D productivity. For instance, in sectors where firms have a large market power, an increase in R&D might cause a rise in prices rather than output. Also, firms in highly technological sectors might have more incentives to invest in R&D for their survival compared with firms in other sectors. A majority of studies focus on the manufacturing sector alone since the sector benefits from availability of detailed firm level data. However, in several OECD countries and the UK specifically, it is the non- manufacturing sector that dominates the economy. Hence, focusing on the manufacturing sector alone neglects a large part of the UK economy. To the best of our knowledge, no other study has conducted such a comprehensive investigation on R&D and productivity which takes into account several sources of heterogeneity.

The rest of the paper is organised as follows. In section 2 we provide a brief review of the empirical literature Section 3 introduces the empirical specification and discusses the data and empirical techniques. In section 4 we present descriptive statistics, fixed-effect estimates and the ordered Heckman results on the R&D-productivity relationship. Finally, the conclusions section distils the main findings and elaborates on the strengths and shortcomings of the estimation strategy followed.

2. Literature Review

The literature on the impact of R&D on productivity is large. Several narrative reviews of the literature exist. Of these, Mairesse and Sassenou (1991) and Mairesse and Mohnen (1994) review the literature on R&D and productivity at the firm and industry levels, respectively. Hall (1996) focuses on rates-of-return estimates, differentiating between private and social returns to R&D. A recent and comprehensive review by Hall et al. (2010) provides an authoritative account of the analytical, measurement and estimation issues that characterise the research field. Nevertheless, the reviews of the empirical literature report varied conclusions with estimates of wide ranges of elasticities ranging from -0.262 to 0.810. A recent meta-analysis study by Ugur et al. (2013) revealed that the average elasticity effect of R&D capital on productivity is positive but small ranging from 0.012 to 0.053.

A majority of studies tried R&D capital as homogenous. This is despite the fact that the early work Griliches (1979) welcomed further studies which examined the relative effects of basic vs applied research – and on the relative effects of publicly vs privately funded R&D.

There are three types of research work: basic, applied and experimental. Basic R&D is research conducted at an early stage purely for the advancement of scientific knowledge without any specific application. Applied research is research conducted for a specific application. Experimental research builds on basic and applied research and is directed to the production of new products or processes (ONS, 2005). Czarnitzki and Thorwarth (2012) examined whether the whether the productivity effects of basic R&D differed in low tech and high-tech sectors using Belgian firm level manufacturing data from 2002 to 2007. They found that a high premium effect of basic R&D in high tech sectors but no significant effect in low tech sectors. In fact, the premium effect of basic RD& in high tech sectors was double the premium in the whole sample. The insignificant effect in the low tech sectors was due to the higher risk inherent in basic R&D (such as its lack in specificity and higher tendency for it to be expropriated) which reduced the incentives of firms to engage in R&D in the sector. Nevertheless, basic R&D is essential in in stimulating other types of R&D (Green and Scotchmer, 1995) and in building up the absorptive capacity of firms (Green and Scotchmer, 1995).

Research can be conducted “in-house”, i.e. within the company (intramural R&D) or it can be contracted out by the firm to other entities such as universities, government establishments or other agencies (extramural R&D). Lokshin et al. (2008) examined the impact of internal and external R&D on labour productivity using of dynamic panel of Dutch manufacturing firms from 1996 to 2001. Internal R&D was found to have a positive impact on labour productivity. However, a positive impact of external R&D only existed beyond a minimum threshold of internal R&D. The authors therefore pointed to internal R&D as an important source of absorptive capacity. Similarly, Catozzella and Vivarelli (2014) found that intramural R&D did increase the levels of innovative output between 1998 and 2000 using 3045 Italian firms.

Finally, R&D can be broken down by sources of funding – it can be sourced from either private or public sources. Unfortunately, the literature that examines the relationship between R&D and productivity by source of funding is quite scanty.

3. Methodology and Data

3.1 Empirical framework

We adopt a Cobb-Douglas production function, augmented with R&D capital under the usual assumptions: perfect competition in factor markets, and the separability of factor inputs (capital and labour) from knowledge (R&D) capital

$$Y_{it} = Ae^{\lambda t} C_{it}^{\alpha} L_{it}^{\beta} K_{it}^{\gamma} e^{u_{it}} \quad (1)$$

Where Y is deflated output, C is deflated physical capital stock, K is deflated knowledge capital, L is labour, λ is the rate of disembodied technological change; and *A* is a constant. The subscripts i and t refer to firm and time respectively.

Taking the natural logarithms of both sides, and denoting logs in lower case alphabets yields equation (2a):

$$y_{it} = \eta_i + \lambda t + \alpha c_{it} + \beta l_{it} + \gamma k_{it} + u_{it} \quad (2a)$$

Note that the log of the technical progress term ($Ae^{\lambda t}$) yields a firm specific term (ηi) and a time effect (λt). In (2a), we assume constant returns to scale. However, this assumption can be relaxed and returns to scale can be tested explicitly by subtracting logged labour from both sides of (2a).

$$(y_{it} - l_{it}) = \eta_i + \lambda t + \alpha(c_{it} - l_{it}) + \gamma(k_{it} - l_{it}) + (\mu - 1)l_{it} + u_{it} \quad (2b)$$

Here, $\mu = \alpha+\beta+\gamma$ and implies constant returns to scale if $\mu = 1$; but variable returns to scale otherwise. The coefficient of interest in both (2a) and (2b) is (γ) – the *output elasticity* with respect to knowledge capital.

The estimate equation 3 below

$$(\tilde{y}_{ijt}) = \eta_i + \lambda t + \alpha \tilde{c}_{it} + \gamma \tilde{k}_{it} + (\mu - 1)l_{it} + \emptyset control + \delta_j + u_{ijt} \quad (3)$$

where $\tilde{y} = y_{it} - l_{it}$, $\tilde{c} = c_{it} - l_{it}$, and $\tilde{k} = k_{it} - l_{it}$, i, j and t are firm, two-digit industry and years respectively. Control refers to three other control variables, which include: the log of knowledge spillovers (*S*), UK ownership dummies (*O*) and knowledge gap (*Gap*) as a measure of absorptive capacity.

3.2 Data and Empirical strategy

Data was obtained from two key databases: The Annual Respondents Database (ARD) which was succeeded by the ABS database (ABS) from 2008 and the Business Expenditure on Research and Development (BERD) database. The ARD/ABS database is a census of large UK firms and a sample of smaller ones. Selected firms are sent a detailed annual survey (the *Annual Business Inquiry*) asking about productivity related measures. Hence, the ARD/ABS database contains key data on productivity measures and employment for UK firms. Firms that receive and respond to the survey are regarded as ARD/ABS *selected* firms. Firms who were not sent the survey (i.e. firms who were outside the "selected" sample) or firms who received but did not complete the survey are regarded as ARD/ABS *unselected* firms. We also obtain data from the Business Expenditure on Research and Development (BERD) – this is a repeated annual survey designed to measure R&D expenditure and employment in UK businesses.

After merging the datasets, we dropped firms that were never in the selected ARD database since such firms lacked key productivity measures such as value added. We also dropped firms with a negative capital stock. Finally, we kept firms with data on at least three consecutive periods on the key variables (output, capital stock, employment and R&D capital). Our final panel dataset consists of 10,920 firms and 141, 668 observations from 1998 to 2012.

We measure output (Y) using real gross value added at factor cost. Cunéo and Mairesse (1984) and Mairesse and Hall (1994) report that elasticity estimates based on value-added do not differ from those based on sales without including materials as an additional input. However, Griliches and Mairesse (1981) indicate that elasticity estimates based on value added tend to be smaller than those based on sales without materials. Gross value added was obtained from the ARD/ABS database and deflated using two digit output deflators from the ONS.

We controlled for double counting by adding total current R&D expenditure to gross value added.

Labour (L) is measured using the number of full time equivalent employees. It is constructed by deducting an estimate for 0.5 *part time employees for each firm. Part-time employment is approximated by multiplying the number of full time employees by the number of part time workers by year and two digit sector. Data on Full time (IDBR) employees is obtained from the ARD/ABS database.

Physical capital stock (C) is obtained by applying the perpetual inventory method to real net capital expenditure R&D expenditure using a depreciation rate of 9.3%. The initial capital stock was obtained from ONS estimates. PIM was applied was applied to extrapolated real investment series. Net capital expenditure was first deflated using two digit Gross fixed capital formation (GFCF) from the ONS.

R&D expenditure was obtained from the BERD database and deflated using annual R&D deflators from the ONS. The R&D capital (K) is constructed using the perpetual inventory method that is applied to real R&D expenditure. We assume a growth rate of 5% for R&D investment prior to the start year and a depreciation rate of 15%. The consensus in the literature is that assumed rates of growth or depreciation do not alter the elasticity estimates. We construct separate R&D capital measures they following categories of R&D expenditure: basic R&D, applied R&D, experimental R&D, intramural R&D, and extramural R&D. We also construct R&D capital stocks for privately and publicly funded R&D. We define public R&D funding as sourced from the central government, EC, and extramural R&D outside the UK but bought by Central government funding. We consider all other types of R&D funding as privately sourced.

We control for double counting, which is when R&D expenditure and R&D personnel occur twice – on their own, and as part of input measures when computing physical capital stock (C), Labour (L) and value added respectively. Specifically, we control for double counting in the computation of value added and in the physical capital stock.

The ownership dummy (O) is a variable that takes the value of 1 if the firm is UK owned and 0 if owned by a foreign firm.

Knowledge spillovers (S) is obtained by the unweighted sum of deflated knowledge capital across all firms in each year except firm I at the 3 digit level.

The knowledge gap variable (G) is obtained by the ratio of R&D intensity of firm i in period t to the R&D intensity of the firm with the largest R&D intensity value at the 3 digit sector.

We apply fixed effects estimators to control for unobserved firm effects. Standard errors that are robust to serial correlation and heterogeneity are employed.

We also check whether the effect of R&D varies between firms with different levels of R&D intensity. To address this question, we use an ordered-probit selection model proposed by Chiburis and Lokshin (2007). This model allows for sorting the firms into J+1 classes of 0, 1, 2, … J on the basis of an ordered-probit selection rule where the latent selection variable (z_i*) is not observable but the categorical variable (z_i) is observable and depends on particular realisations of the latent variable. Then, we can specify the selection rule as follows (Chiburis and Lokshin, 2007):

$z^* = \beta' w_i + u_i$; and

$$z_i = \begin{cases} 0 \;\; if -\infty < z_i < \mu_1 \\ 1 \;\; if \quad \mu_1 < z_i < \mu_2 \\ 2 \;\; if \quad \mu_2 < z_i < \mu_3 \\ . \\ . \\ \text{J} \;\; if \quad \mu_J < z_i < \infty \end{cases} \qquad \text{(selection equation)} \qquad (4)$$

and

$$\tilde{y}_{ijt} = \begin{cases} \alpha'_1 \mathrm{x}_i + \varepsilon_{i1} \;\; if \; z_i = 1 \\ \alpha'_2 \mathrm{x}_i + \varepsilon_{i2} \;\; if \; z_i = 2 \\ . \\ . \\ \alpha'_J \mathrm{x}_i + \varepsilon_{iJ} \;\; if \; z_i = J \end{cases} \qquad \text{(outcome equation)} \qquad (5)$$

where the latent variable refers to R&D intensity classes.

The model in (4) and (5) can be estimated through a two-step procedure or via maximum likelihood (ML). The necessary condition for consistent estimation of the model is the same as the selection model in (7) above: the error terms of the selection and outcome equations (ui and εi) must satisfy the condition of joint normality. The two-step procedure is more efficient than ML if normality condition is violated. Therefore, we estimate the model with a two-step consistent estimator.

We define the subsidy intensity classes as follows: zi = 1 is the group consisting of firm/year observations where R&D intensity is less than or equal to the value at the 25th percentile; zi = 2 is the group consisting of firm/year observations where R&D intensity is between the 25th percentile and median; zi = 3 is the group consisting of firm/year observations where R&D intensity is between the median and the 75th percentile; and zi = 4 is the group consisting of firm/year observations where R&D intensity is greater than the value at the 75th percentile.

4. Findings

We begin with an examination of some summary statistics which is shown in Table 1.

Table 1: Summary statistics: 1998- 2012

Variable	Mean	Standard Error
Real value added (£000)	24824.82	226110.2
Employment (FTE) (Headcount)	246.8295	2172.028
Capital stock (£000)	28435.86	379832.1
Knowledge capital (R&D) (£000)	12792.56	134587.4
Knowledge Spillovers (3 digit level) (£000)	1445556	4021704
Knowledge gap	.1438762	.204976
Intramural R&D capital (£000)	10891.98	104488
Extramural R&D capital (£000)	1900.572	41865.07
Basic R&D capital (£000)	633.7377	10435.25
Applied R&D capital (£000)	3669.997	35087.34
Experimental R&D capital (£000)	5662.759	71868.83
Public R&D capital (£000)	1180.822	18473.04
Private R&D capital (£000)	11614.06	127941.1

Table 1 shows summary statistics of the key variables. Average value added across the sample was about £24 million pounds) and the average number of employees was 246 workers. The mean capital stock was 28 million pounds while the R&D knowledge capital stock was about 12.8 million pounds. Average intramural R&D expenditure was considerably higher than average extramural R&D capital. The amount of applied and experimental R&D exceeded basic R&D capital expenditures which is in line with the literature that firms have more incentives to undertake applied and basic R&D as opposed to basic R&D capital. Finally, the amount of R&D capital from private sources exceeded public R&D capital by about 10 fold on average. The large values of standard errors show that there is considerable volatility in the movement of the figures.

Baseline Results

Table 2 presents the baseline results of the effect of R&D capital on productivity (value added per worker). With the OLS estimates, the results indicates that there are increasing returns to labour but when fixed effects are taken into account, there is evidence of decreasing returns to labour.

Capital has a positive and significant effect on productivity and it is within the expected theoretical range. Knowledge spillovers has a positive coefficient – but is only significant in the OLS estimations. The UK ownership dummy is negative, which is in line with the literature that foreign owned firms are more productive than UK owned firms –but again the coefficient is insignificant once fixed effects are accounted for. The knowledge gap coefficient is positive, meaning that the productivity levels of firms increase as their R&D intensity levels approach that of the frontier.

Turning to our variable of interest, our results confirm the hypothesis that there is a positive relationship between R&D and productivity, and that this is significant at the 1% level.

Table 2: Effect of R&D on productivity: OLS and Fixed effects

	OLS	**Fixed Effects**
Returns to scale	0.0214*** *(0.00633)*	-0.325*** *(0.0217)*
Capital	0.237*** *(0.00891)*	0.156*** *(0.0160)*
R&D	0.112*** *(0.00791)*	*0.0779**** *(0.0132)*
Knowledge Spillovers	0.0221*** *(0.0056)*	0.00225 *(0.0063)*
UK ownership dummy	-0.0560*** *(0.0121)*	-0.00412 *(0.0108)*
Knowledge gap	0.0723** *(0.0354)*	0.0660** *(0.0283)*
Number of observations	61244	61244
Number of firms		*9898*

Notes
Standard errors in parentheses
Time dummies and 2 digit sector dummies include; sample with 3 consecutive years of key variables
Standard errors robust to heteroskedasticity and serial correlation
Dependent variable is labl_l_real_gva_fc_cor1_2d
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The differences between the OLS and fixed effect estimates shows the well-known fact that the firm specific factors have a significant effect on productivity, and must be taken into account to avoid spurious results. Hence, in the results that follow, I focus on the fixed effects results only.

Effects of R&D on productivity –by breakdown in R&D capital

To probe further our results, we examine the effect of R&D on capital by type of R&D expenditure. Table 3 focuses on the breakdown of R&D capital into intramural and extramural R&D while Table 4 focuses on the breakdown of R&D capital by source of funding. We consider public sources to be all intramural or extramural R&D funding that are sourced from either the UK government or from EU sources. All other sources of intramural or extramural

R&D (such as own funds, or from private companies, etc) are considered to be from private sources.

Table 3 shows that both intramural and extramural R&D have a positive impact on productivity when they enter into the regression as substitutes– with the elasticity coefficient on intramural R&D much higher than extramural R&D. When both types of R&D are entered into the regression, only intramural R&D remains statistically significant. This shows that in-house R&D has a much larger effect on productivity than R&D contracted out to external sources.

Table 3: Effect of R&D on productivity by intramural and extramural R&D: FIXED EFFECTS ESTIMATES.

	1	**2**	**3**
Returns to scale	-0.321*** (0.0217)	-0.366*** (0.0210)	-0.319*** (0.0227)
Capital	0.190*** (11.72)	0.164*** (0.0166)	0.159*** (0.0166)
Intramural R&D capital	0.0842*** *(0.0130)*		0.0995*** *(0.0143)*
Extramural R&D capital		0.0134*** (0.00575)	0.000641 (0.00562)
Knowledge spillovers	0.00193 (0.00626)	0.0119* (0.00670)	0.00499 (0.00667)
UK ownership dummy	-0.00428 (0.0108)	-0.00227 (0.0113)	-0.00353 (0.0113)
Knowledge gap	0.0617** (0.0282)	0.145*** (0.0302)	0.0713** (0.0298)
Number of observations	61244	55697	55697
Number of firms	9898	9317	9317

Standard errors in parentheses
Time dummies and 2 digit sector dummies include; sample with 3 consec years of key variables
Standard errors robust to heteroskedasticity and serial correlation
*ols=ols; *fe= fixed effects ; *re = random effects,
intram = Intramural R&D capital' extram=Extramural R&D capital' iande=Both intramural & extramural R&D capital
Dependent variable is labl_l_real_gva_fc_cor1_2d
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Both R&D from private sources and public sources have positive effects on productivity when they enter as substitutes (Table 4), but R&D from private sources have a much larger effect – and retain their level of statistical significance when both sources of R&D enter the estimations together.

Table 4: Effect of R&D on productivity: by type of funding: Fixed effects estimates

	Fixed Effects	Fixed Effects	Fixed Effects
Returns to scale	-0357*** (0.0203)	-0.327*** (0.0216)	-0.325*** (0.0221)
Capital	0.165*** (0.0163)	0.156*** (0.0160)	0.160*** (0.0163)
R&D_public	0.154*** (0.00551)		0.00104 (0.00578)
R&D_private		0.0741*** (0.0129)	0.0757*** (0.0142)
Spillovers	0.0101* (0.00604)	0.00240 (0.00627)	0.00467 (0.00608)
UK ownership dummy	0.00121 (0.0108)	-0.00382 (0.0108)	0.000909 (0.0108)
Knowledge gap	0.135*** (0.0281)	0.0690** (0.0282)	0.0786*** (0.0283)
Number of observations	59920	61235	59920
Number of firms	*9790*	*9897*	*9790*

Standard errors in parentheses
Time dummies and 2 digit sector dummies include; sample with 3 consec years of key variables
Standard errors robust to heteroskedasticity and serial correlation
*ols=ols; *fe= fixed effects ; *re = random effects,
fundpub= regressions with public funded R&D; fundpri= regressions with private funded R&D;
fundpubpri= regressions with both public & private funded R&D
Private and public funding is for funding both extramural and intramural R&D
Dependent variable is labl_l_real_gva_fc_cor1_2d
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

When R&D is broken down by type into basic, applied and experimental R&D (Table 5), both applied and experimental R&D capital have positive and significant effects on productivity, by similar magnitudes. However, basic R&D has a negative and significant effect on productivity. This could be because basic R&D is not immediately translatable into sales.

Table 5: Effect of R&D on productivity: by type of R&D: OLS & Fixed effects estimates

	1	2	3	4
Returns to scale	-0369*** (0.0201)	-0.346*** (0.0209)	-0.348*** (0.0208)	-0.342*** (0.0219)
Capital	0.169*** (0.0167)	0.159*** (0.0162)	0.163*** (0.0162)	0.166*** (0.0168)
Basic R&D	-0.00410 (0.00252)			-0.0258*** (0.00554)
Applied R&D		0.0353*** (0.00961)		0.0348*** (0.0102)
Experimental R&D			0.0315*** (0.00849)	0.056*** (5.19)
Spillovers	0.0134** (0.00608)	0.00674 (0.00629)	0.00715 (0.00619)	0.00961 (0.00611)
Knowledge gap	0.146*** (0.0289)	0.116*** (0.0283)	0.111*** (0.0282)	0.107*** (0.0292)
Number of observations	51966	60731	60588	58364
Number of firms	9153	9863	9845	9668

Standard errors in parentheses
Time dummies and 2 digit sector dummies include; sample with 3 consec years of key variables
Standard errors robust to heteroskedasticity and serial correlation
*ols=ols; *fe= fixed effects ; *re = random effects,
intram = Intramural R&D capital' extram=Extramural R&D capital' iande=Both intramural & extramural R&D capital
Dependent variable is labl_l_real_gva_fc_cor1_2d
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Effects of R&D on productivity –by sector

We next turn to whether the effect of R&D on productivity differs by sector. Table 6 provides fixed effects estimates of 4 groups of firms: firms in sectors where the Herfindahl index is above the median (i.e. firms in more concentrated industries) and firms in sectors where the Herfindahl index is less than the median (i.e. in more competitive industries) are respectively in panels 1 and 2 of Table 6. On the other hand, panels 3 and 4 of present results for firms in the manufacturing and non-manufacturing sectors respectively. The coefficient on R&D

regardless of sector remains positive and statistically significant at the 1% level. However, it is clear that firms in more concentrated industries and in the non-manufacturing sectors have higher elasticity coefficients.

Table 6: Effect of R&D on productivity by sector (Fixed effects estimates)

	1	2	3	4
Returns to scale	-0.310^{***} (0.0308)	-0.375^{***} (0.0317)	-0.254^{***} (0.0240)	-0.435^{***} (0.0398)
Capital	0.165^{***} (0.0231)	0.147^{***} (0.0234)	0.164^{***} (0.0205)	0.138^{***} (0.0258)
R&D	0.112*** (0.0206)	0.0374** (0.0161)	0.0672^{***} (0.0143)	0.104^{***} (0.0215)
Spillovers	0.00924 (0.00883)	-0.0123 (0.0111)	0.0123 (0.00785)	-0.0152 (0.0103)
UK ownership dummy	0.0607* (0.0362)	0.0397 (0.0528)	-0.00408 (0.0126)	0.00164 (0.0197)
Knowledge gap	0.00151 (0.0144)	0.00107 (0.0158)	0.109^{***} (0.0307)	-0.0511 (0.0580)
Number of observations	32606	28638	41625	19619
Number of firms	6501	6229	6463	4007
Sector	Less competitive	More competitive	Manufacturing	Non manufacturing

Standard error in parentheses
Time dummies and 2 digit sector dummies include; sample with 3 consec years of key variables
Standard errors robust to heteroskedasticity and serial correlation
*ols=ols; *fe= fixed effects ; *re = random effects,
Dependent variable is labl_l_real_gva_fc_cor1_2d
Panel 1: Sectors in which the Herfindahl index > median. (i.e. more concentrated markets); Panel 2: Sectors in which the Herfindahl index is less than the median (more competitive markets)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
man1= man sector, man2= non man sector

Next, we examine the effect of R&D on productivity by Pavitt class (Table 7). Pavitt class 1 consists of firms in science based industries (e.g., chemicals, office machinery, precision, medical and optical instruments industries, ICT, etc.). Pavitt class 2 consists of industries that are specialized suppliers of technology or capital goods to other industries (e.g., mechanical engineering industries, manufacturers of electrical machinery, equipment hire & lease industries, and business services suppliers, etc.). Pavitt class 3 consists of scale-intensive industries such as pulp & paper, transport vehicles, mineral oil refining industries, financial intermediaries, etc.). Pavitt class 4 consists of technology-supplier-dominated industries such as textiles & clothing, food & drink, fabricated metals, etc.

Across Pavitt classes, the effect of R&D on productivity is positive and significant, but it is clear that the R&D elasticity coefficients are significantly higher in Pavitt class 1, i.e. in the Science based sectors.

Table 7: Fixed Effects estimates of R&D on productivity by Pavitt class

	Pavitt class 1	Pavitt class 2	Pavitt class 3	Pavitt class 4	Pavit class 5
Returns to scale	-0.254*** (0.0431)	-0.419*** (0.0484)	-0.304*** (0.0489)	-0.315*** (0.0395)	-0.420*** (0.0935)
Capital	0.119*** (0.0295)	0.142*** (0.0335)	0.171*** (0.0342)	0.215*** (0.0323)	0.166** (0.0789)
R&D	0.167*** (0.0305)	0.0700** (0.0295)	0.0586** (0.0279)	0.0738*** (0.0225)	0.0590* (0.0333)
Spillovers	0.0260 (0.0174)	-0.0172 (0.0168)	0.0204 (0.0198)	0.0111 (0.0112)	-0.0187 (0.0263)
UK ownership dummy	-0.0400* (0.0237)	-0.0123 (0.0633)	0.116* (0.0597)	0.0401 (0.0474)	-0.140 (0.0873)
Knowledge gap	0.340*** (0.0900)	0.00536 (0.0232)	-0.0115 (0.0260)	0.00775 (0.0174)	-0.0242 (0.0449)
Number of observations	12002	12537	10838	23163	2704
Number of firms	*2086*	*2450*	*1909*	*4341*	*627*

Standard Error in parentheses
Time dummies and 2 digit sector dummies include; sample with 3 consec years of key variables
Standard errors robust to heteroskedasticity and serial correlation
*ols=ols; *fe= fixed effects ; *re = random effects,
Dependent variable is labl_l_real_gva_fc_cor1_2d
Pavitt Class 1= Science based, Pavitt Class 2= specialised suppliers of technology Pavitt Class 3= scale intensive sectors, , Pavitt class 4= Supplier dominated sectors, Pavitt class 5=Others not classifed by Pavit
* p < 0.10, ** p < 0.05, *** p < 0.01

Effect of R&D on productivity: Ordered Heckman Results

The above results show that there is considerable heterogeneity on the effect of R&D on productivity. Therefore, we now examine the effect of R&D on productivity, taking into account firm heterogeneity based on R&D intensity. In other words, does the effect of R&D on productivity differ by R&D intensity classes of firms?

Given the methodological framework described in section 4 above, the selection and outcome models we estimate are as follows:

Sub_RD = β_0 + β_1 $lcap\_RD\_int_{it-1}$ + β_2 $lcap\_RD\_int^2_{it-1}$ + β_3lRD_int$_{it-1}$ + β_4lRD_int$^2_{it-1}$ + $\beta_5 lRD\_pers_{it-1}$ + $\beta_6 lRD\_pers^2_{it-1}$ + $\beta_7$growth$_{it}$ + $\beta_8 lempl_{it-1}$ + $\beta_9 lempl^2_{it-1}$ + β_{10}localunits$_{it}$ + $\beta_{11} Pavitt1_{it}$ + $\beta_{12} Pavitt2_{it}$ + $\beta_{13} Pavitt3_{it}$ + β_{14} $Pavitt4_{it}$ + β_{15} Herf$_{it}$ + β_{16}Herf$^2_{it}$ + uit (6)

(Selection equation)

$$\left(\tilde{y}_{ijt}\right) = \alpha 0 + \alpha 1 \tilde{c}_{it} + \alpha 2 \tilde{k}_{it} + (\mu - 1) l_{it} + \alpha 3 S + \alpha 4 inverse\_Mills$$

(Outcome equation) (7)

where $\tilde{y} = y_{it} - l_{it}$, $\tilde{c} = c_{it} - l_{it}$, and $\tilde{k} = k_{it} - l_{it}$, and S refers to the log of knowledge spillovers (S),

Sub_RD is the dependent variable in the selection model and it is 1 if the firm is in a particular R&D intensity class. On the other hand, $\tilde{y}$ is the dependent variable in the outcome model. It is of a similar specification to equation (3) above except with the inclusion of the inverse Mills ratio.

In the selection model, we assume that firms self -select into latent R&D intensity classes based on certain firm characteristics such as the log of the lagged capital intensity of the firm ($lcap\_RD\_int_{it-1}$), the log of lagged R&D intensity (lRD_int$_{it-1}$), the log of the lagged value of R&D personnel (lRD_pers_{it-1}), the growth of the firm (growth$_{it}$), the size of the firm proxied by the log of employment ($empl_{it-1}$) and the number of plants owned by the firm (localunits$_{it}$). We also include sector level determinants such as the firm's membership of Pavitt technology classes and the Herfindahl index (Herf$_{it}$) as a proxy for the level of competition in the three digit sector of the firm.

Table 8: Ordered Heckman Estimations (First stage Results)

	Dependent variable: R&D intensity classes
Log (Capital R&D intensity$_{it-1}$)	-9.911*** (2.340)
Log (Capital R&D intensity^2$_{it-1}$)	4.915** (1.934)
Log(R&D intensity$_{it-1}$)	5.645*** (0.227)
Log(R&D intensity^2$_{it-1}$)	-0.871***(0.0375)
Log(R&D personnel$_{it-1}$)	0.489*** (0.0229)
Log(R&D personnel^2$_{it-1}$)	0.0406***(0.00416)
Growth	-0.341*** (0.0255)
Log(Employment (FTE)$_{it-1}$)	-0.532*** (0.0672)
Log(Employment (FTE)^2$_{it-1}$)	-0.0108* (0.00597)
Number of live local units$_{it-1}$	0.000293 (0.000188)
Pavitt class 1	0.460*** (6.85)
Pavitt class 2	0.235*** (3.51)
Pavitt class 3	0.111* (1.68)
Pavitt class 4	-0.0799 (-1.22)
Herfindahl index	-0.922*** (-4.45)
Herfindahl index^2	1.205 (0.851)
Cutoffs	
Cutoff 1	-3.093*** (-31.16)
Cutoff 2	-1.981*** (-20.39)
Cutoff 3	-0.843*** (-8.79)

Standard errors in parentheses
Time dummies and 2 digit sector dummies include; sample with 3 consec years of key variables

The first stage estimations in the ordered Heckman procedure examine whether impact of a range of factors on the probability of firms belonging to a particular R&D intensity class (Table 8) . The first part of the table shows that the factors that significantly and positively affect the R&D intensity classes that each firm belong are past levels of: R&D capital expenditure, R&D intensity, R&D personnel (i.e. R&D scientists and technicians employed), The growth of the firm and Pavitt classes of the firms also have a positive effect on the distribution of firms into the R&D intensity classes. The number of employees and the level of competition of the firm also had significant but negative impacts – meaning that smaller sized firms in more competitive markets tended to be in higher R&D intensity classes.

Table 9 shows the effect of R&D (and other inputs) on productivity by R&D intensity class. The R&D elasticity on productivity for R&D intensity classes 1, 2, 3 and 4 respectively are: 0.130, 0.285, 0.308 and 0.529 respectively. In other words, R&D has a higher effect on productivity for firms that belong to higher R&D intensive classes.

Table 9: Impact of R&D on Productivity: 1998-2012: Ordered Heckman Estimator

	R&D intensity class 1	R&D intensity class 2	R&D intensity class 3	R&D intensity class 4
Returns to scale	0.0679*** (0.0160)	0.0103 (0.0130)	0.00115 (0.0115)	0.0108 (0.0104)
Capital	0.248*** (0.0170)	0.174*** (0.0166)	0.137*** (0.0176)	0.0672*** (0.0129)
R&D	0.121*** (0.0180)	0.276*** (0.0218)	0.272*** (0.0218)	0.336*** (0.0187)
Spillovers	0.00722 (0.0120)	0.0309*** (0.0118)	0.0299*** (0.0114)	0.0109 (0.0116)
Lamda	0.00668 (0.0406)	0.0685*** (0.0261)	0.00455 (0.0251)	0.103*** (0.0337)
Number of observations	11,302	11,302	11,302	11,302

Standard error in parentheses
Time dummies and 2 digit sector dummies include; sample with 3 consec years of key variables
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5. Conclusion and Further Work

This paper examined the effect of R&D capital on productivity using detailed UK firm level data from 1998 to 2012. Our results show that R&D has a consistently positive and significant effect on productivity. However, there is considerable heterogeneity with R&D having a higher effect in firms that are in the non-manufacturing sector, with less competition and that are

Science based or specialised suppliers of technology. Also, applied R&D, experimental R&D intramural R&D and R&D from private sources tend to have higher productivity impacts compared with basic R&D, extramural R&D or R&D from public sources.

Further work on the research will involve estimating a dynamic panel model to better control for endogeneity. In particular, there is likely to be simultaneity between output and R&D investment. We will also explore the role of absorptive capacity – whether certain types of R&D lead to higher levels of absorptive capacity in firms. Thirdly, we will examine whether there exists complementarities between the different types of R&D capital. Finally, we will examine whether or not the relationship between R&D and productivity could be non-linear.

References

Catozzella, A. and Vivarelli, M. (2014), 'Beyond absorptive capacity: In-house R&D as a driver of innovative complementarities', Applied Economics Letters, 21(1), pp. 39-42.

Chiburis, R., & Lokshin, M. (2007). Maximum likelihood and two-step estimation of an ordered-probit selection model. Stata Journal, 7(2), 167-182.

Czarnitzki, D. and Thorwarth, S. (2012), Productivity effects of basic research in low-tech and high-tech industries, *Research Policy*, vol. 41, pp. 1555-1564.

Green, J. and Scotchmer, S. (1995). 'On the division of profit in sequential innovation', *RAND Journal of Economics*, vol. 26(1), pp. 20–33.

Griliches, Z. (1973). Research expenditures and growth accounting. In: *Science and Technology in Economic Growth*, R.B. Williams (ed.). John Wiley and Sons, New York.

Griliches, Z. (1979). Issues in assessing the contribution of research and development to productivity growth, *Bell Journal of Economics*, 10(1), 92-116.

Hall, B. H. (1996). The private and social returns to research and development. In Bruce L.R. Smith and Claude E. Barfield (eds.), *Technology, R&D, and the Economy*, Brookings Institution, Washington D.C.

Hall, B. H., J. Mairesse and P. Mohnen (2010). Measuring the returns to R&D. In B. H. Hall and N. Rosenberg (eds.), *Handbook of the Economics of Innovation*, vol. 2, Elsevier, New York.

Lokshin, B. Belderbos, R. and Carree, M. (2008), "The Productivity Effects of Internal and External R&D: evidence from a dynamic panel data model.", *Oxford Bulletin of Economics and Statistics*, 70(3), pp. 399 to 413.

Mairesse, J. and M. Sassenou (1991). R&D and productivity: a survey of econometric studies at the firm level, *STI Review*, OECD, 8, 9-46.

Mairesse, J., and P. Mohnen (1994). R&D and productivity growth: What have we learned from econometric studies?, *Eunetic Conference on Evolutionary Economics of Technological Change: Assessment of Results and New Frontiers*, 817-888, Strasbourg.

Mairesse J., and B. H. Hall (1996). Estimating the productivity of research and development: An exploration of GMM methods using data on French and United States manufacturing firms. NBER *Working Paper Series*. No. 5501.

Minasian, Jora R (1969). Research and development, production functions, and rates of return. *American Economic Review*, 59(2): 80-85.

Office for National Statistics (ONS) (2015). "Business Expenditure on Research and Development userguide", UK Data Service

Terleckyj, N. E. (1974). *Effects of R&D on the productivity growth of industries: An exploratory study* (No. 140). Washington, DC: National Planning Association.

Ugur, M., Solomon, E., Guidi, F. and Trushin, E. (2015), "R&D and productivity in OECD firms and industries: A hierarchical meta-regression analysis"