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The Impact of Research and Development (R&D) Expenditure on Productivity Growth: A Panel Data Evidence from the UK Manufacturing Sector

Sixtus Cyprian Onyekwere

Department of Economics and Finance, University of Portsmouth, UK.
Email: sixtusonyekwere@gmail.com

Abstract

This study focuses on the impact of Research and Development (R&D) expenditure on productivity growth for a panel of 13 UK manufacturing industries, using dataset from 1997 to 2014. The paper used the extended Cobb-Douglas production function, where R&D expenditure is included as one of the factor inputs, just like labour and capital. The study employs the fixed effects method for the panel data analysis and found R&D coefficient of 0.07, significant at 1%. The finding implies that, consistent with previous papers done for the UK manufacturing sector, R&D expenditure still has a positive relationship with productivity growth at panel industry level. However, the estimate 0.07 lends support to the argument of small coefficient for R&D, unlike other papers arguing for higher coefficient. Thus, we align with the argument that R&D has a small positive impact on productivity growth. Theoretical implication of this finding is that technological advancement which contributes to productivity growth is not exogenous; it can be determined by R&D decisions in firms and in industries. Thus, policy recommendation of this research is for the UK government to provide incentives to increase innovation in the UK manufacturing industries by increasing research grants and subsidies given to firms. Finaly, evidence from the result of this paper has shown that firms who wish to increase labour productivity should include R&D investment as one of their strategies.

Keywords: R&D, Productivity, Cobb-Douglas production function, Panel data, Fixed effects, UK manufacturing industry.
JEL Classification: L00.

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Contents

Contribution of this paper to the literature
This study contributes to the existing literature by examining the impact of Research and Development (R&D) expenditure on productivity growth for a panel of 13 UK manufacturing industries, using dataset from 1997 to 2014.

1. Introduction

Harari (2015) defines productivity growth as the increase in output per employee. It is generally believed among economics endogenous growth theorists such as Romer (1986); Romer (1990) and Lucas (1988) that, one of the obvious ways to achieve productivity growth is through technological advancement, which they argue can result from investments in R&D (Moen and Burchardt, 2009). This is in contrast to previous exogenous growth theory proposed by Solow (1956) which rather saw technological advancement as a factor outside the control of agents. Since the work of Romer (1986) an ample amount of research has been undertaken on this topic mostly in the USA, to understand the nature of the impact of technological advancement through R&D on productivity growth. Researchers arguing on this topic adopt different R&D data for investigation such as, R&D expenditure, R&D Patents and embodied R&D (intermediate and investment goods), depending on data availability. For this current research, the widely available R&D expenditure data is used as depicted on the title, to contribute to the arguments.

The choice of focus on the UK manufacturing sector for this research is due to huge investments in R&D which flow from this sector. According to Keen (2015) the four major business industries in 2013 which contributed to over 64% of the gross expenditure on R&D (GERD) in the UK all come from the manufacturing sector. They are; Pharmaceutical industry 22%, Motor vehicles and Parts 11%, Computer programming and information services 11%, and Aerospace 9%. In addition,Warwick (2010) reports that 75% of total expenditure on R&D in UK business came from the manufacturing sector in 2008. By implication, the manufacturing sector can be said to be the sector with the highest business R&D expenditure in the UK. This research therefore pays attention to this sector of the economy, using econometric valuation of R&D, which is in line with the economics endogenous growth theory.

Although previous studies confirm a positive impact of R&D on productivity growth, there are still ongoing arguments on the exact impact of R&D investments on productivity growth, with most arguments arising between time-series studies and cross-section studies. Interests on this topic span from country level to industry level, down to firm level. Most of these arguments started after the productivity slowdown in the 1970s in USA and UK industries, despite investments in R&D (Cameron, 2003). Holtz-Eakin (2005) states that this productivity growth which slowed down in the 1970s led to a massive econometric analysis of the impact of R&D investment on productivity growth. According to Holtz-Eakin (2005) while some researchers report a zero R&D contribution to productivity growth, others report a massive contribution and the rest lie somewhere in-between the two extremes. Thus, these contradictions poses a problem that need addressing. Again, Kafouros (2005) laments that the adoption of econometric valuation for R&D (as used in this present paper) which attracted much attention in USA, France and Germany, has received less attention in the UK and therefore calls for more research.

Following the gaps identified in literature and the problems noted, this present study has set out the following objectives:

- To ascertain the nature of the relationship between R&D expenditure and productivity growth in UK manufacturing industries.
- To highlight the exact impact of R&D expenditure on productivity growth in UK manufacturing industries.

2. Significance of Study

The aim of this research is to contribute to the existing body of literature, on the exact impact of R&D investments on productivity growth. This will help firms and government policy makers to make rational decisions on the most efficient way to allocate scarce resources towards the production of goods and services. Again, the paper also contributes to the argument surrounding the endogenous growth theory.

3. Review of Related Literature

The importance of technology, innovation activities, and productivity growth are heavily emphasised in many academic papers. Nevertheless, different papers focus on different aspects of the topic. Studies at industry and firm level shows there are two most influential categories of papers found. They are those which argue for large coefficient for R&D and those which argue for small coefficient. Those studies arguing for large coefficients for R&D are usually those using cross-section data while those which argue for small coefficient are those using time-series data. The most recent emerging sets of papers are those which use panel data.

According to Holtz-Eakin (2005) the elasticity of R&D for studies that use cross-section data at firm level range from 0.05 to 0.60 while those on industry level range from 0 to 0.50. This shows that industry level studies and firm level studies have so much in common in terms of R&D coefficient estimates. In support of this, Cameron (1998) adds that, their literature search did not find any substantial difference between R&D estimates from studies at the firm level and those at the industry level, even when a normal thinking should be that industry level studies should have higher elasticity as a result of knowledge spill over. Due to the close estimates between industry and firm level studies, our research did not see it necessary to discuss these papers separately instead; it pays more attention to whether it is a time-series or cross-section study, where there is serious contention on the size of the impact of R&D expenditure on productivity growth, as identified in Holtz-Eakin (2005). However, to be able to cover these papers in a broad sweep, there is a need for a table presentation. This will enable a clearer observation of results at a glance, as full details of papers are presented alongside findings.

3.1. Arguments for Large Impact from Cross-Section Studies

These papers as stated on the previous section generally report high coefficients for R&D. They are presented in Table 1 and 2, putting industry level and firm level papers on different tables to observe if there is a pattern or not.

Table-1. Industry level papers for selected estimates of the elasticity of Private R&D from cross-sectional studies.

Paper	Country/level	Sample	Approach	Model/ Variables	R&D elasticity
Englander *et al.* (1988)	6 countries/ Industry level	16 industries across six countries; 1970 to1983	Cob-Douglas production function	**OLS/** TFP , R&D	0.16 -0.50
Mansfield (1988)	Japan/ Industry level	17 Japanese manufacturing industries	Cob-Douglas production function	**OLS/** TFP, R&D	0.42
Sterlacchini (1989)	UK/ Industry	15 industries from 1945-83	Cobb-Douglass production function	**OLS/** TFP , R&D	0.12 to 0.2
Czarnitzki and Thorwarth (2012)	UK/ Industry	UK Industries from 2002 until 2007	Cobb-Douglass production function	**OLS/** TFP, L, k ,R&D	0.13

Table-2. Firm level papers for selected estimates of the elasticity of Private R&D from cross-sectional studies.

Paper	Country/level	Sample	Approach	Model/Variables	R&D elasticity
Minasian (1969)	US/ Firm level	17 U.S. firms (chemical industry); 1948 to 1957	Cob-Douglas production function	**OLS/** GVA, L, K, R&D	0.11 - 0.26
Cuneo and Mairesse (1984)	France/ Firm level	182 firms; 1972 to 1977	Cob-Douglas production function	**OLS/** GVA, L, K, R&D	0.20
Griliches and Mairesse (1990)	US / Firm level	525 U.S. manufacturing firms; 1973 to 1980	Cob-Douglas production function	**OLS/** TFP, L, K, R&D	0.25
Griliches and Mairesse (1990)	Japan/ Firm level	Japanese manufacturing firms; 1973 to 1980	Cob-Douglas production function	**OLS/** TFP,L, K, R&D	0.20 - 0.56
Hall and Mairesse (1995)	France/ Firm level	197 French firms; 1980 to 1987	Cob-Douglas production function	OLS/ LP K, R&D	0.05 - 0.25
Wang and Tsai (2003)	Taiwan/ Firm level	136 Taiwanese manufacturing firms; 1994 to 2000	Cob-Douglas production function	OLS / Output, R&D, with control variables	0.19
Kafouros (2005)	UK/ Industry	firm-level data (78 firms, 1989–2002), 205 UK manufacturing	Cobb-Douglass production function	**OLS/** Output (sales), L, K, R&D	0.04

From the Table 1 and 2 the first observation is that there is no clear pattern in R&D elasticity estimates, to be able to differentiate firm level studies from industry level studies, just as Cameron (2003) also claims. Secondly, it can be observed that coefficients for R&D are very high, especially those of Griliches and Mairesse (1990); Englander *et al.* (1988); Mansfield (1988) and Minasian (1969). Except for Kafouros (2005) who reports very low coefficient for R&D, others as seen in the table report very high R&D coefficient between 0.11 and 0.50. However, Hall and Mairesse (1995) argue against the result in Kafouros (2005) pointing out that the use of sales to proxy for GVA leads to bias R&D coefficient. Nonetheless, it can also be observed that although estimates are consistently high, there are little variations. However, because these papers are conducted in different countries, different time periods, with little different specifications, authors such as Hall and Mairesse (1995); Holtz-Eakin (2005) and Moen and Burchardt (2010) sustain that the little differences in coefficients are inevitable.

3.2. Arguments for Small Impact from Time-Series Studies

Moving on to time-series studies, there appears to be a significant difference from the cross-section studies in Table 1 above. As stated earlier, the elasticity estimates from time-series studies are generally much lower than those obtained from cross-sectional studies. Holtz-Eakin (2005) further states that, some studies that use time-series estimates of R&D find elasticity that are insignificant, which weakens their argument of small contribution. Example of such statistically insignificant time-series studies are Mairesse and Sassenou (1991) Australian Industry Commission (1995) and Hall and Mairesse (1995). Nevertheless, Holtz-Eakin (2005) explains that in statistical sense, the insignificance often encountered in time-series data is not surprising because the R&D data varies more in the cross-section dimension than in the time-series dimension which by implication, suggests that firms or industries with high R&D expenditures have higher levels of productivity than those with less R&D expenditures. See Table 3 and 4 for findings from some time-series studies.

Table-3. Industry level papers for estimates of the elasticity of private R&D from time-series studies.

Paper	Country/level	Sample	Approach	Method/ Variables	R&D Elasticity
Griliches and Lichtenberg (1984b)	US/ Industry level	27 U.S. manufacturing industries; 1959	Cob-Douglas production function	OLS/ TFP, R&D	0.04
Cameron and Muellbauer (1996)	UK/ Industry	Manufacturing industries from 1962-92	Cobb-Douglass production function	OLS/ TFP , R&D	0.15 to 0.37
Cameron (2003)	UK/ Industry	Manufacturing industry from 1960-1995	Cobb-Douglass P-function	VAR/ TFP, R&D	0.29
Hubert and Pain (2001)	UK/ Industry	15 Industries from 1983-92	Cobb-Douglass production function	OLS/ LP, K, R&D	0.029
Griliches (1980a)	US/ Industry	39 2- and 3-digit manufacturing industries 1959-1977	Cobb-Douglass production function	OLS/ TFP, R&D	0.06

Table-4. Firm level papers for estimates of the elasticity of private R&D from time-series studies.

Paper	Country/level	Sample	Approach	Method/Variables	R&D Elasticity
Minasian (1969)	US/ Firm level	17 U.S. firms; 1948 to 1957	Cob-Douglas production function	OLS/ GVA, L, K, R&D	0.08
Griliches (1980b)	US/ Firm level	883 U.S. firms; 1957 to 1965	Cob-Douglas production function	OLS/ TFP, R&D	0.08
Cuneo and Mairesse (1984)	France/ Firm level	182 French manufacturing firms; 1972 to 1977	Cob-Douglas production function	OLS/ GVA, L, K, R&D	0.05
Griliches and Lichtenberg (1984)	US/ Firm level	133 U.S. firms; 1966 to 1977	Cob-Douglas production function	OLS/ TFP, R&D	0.09
Griliches (1986)	US/ Firm level	652 U.S. firms; 1966 to 1977	Cob-Douglas production function	OLS/ TFP, R&D	0.12
Hall and Mairesse (1995)	France/ Firm level	197 French firms; 1980 to 1987	Cob-Douglas production function	OLS/ LP, K, R&D	0.07

Firstly, it can be observed from Table 3 and 4 that just like the cross-section studies, there is no clear difference between the size of R&D coefficients from industry level and that of firm level is found. The only clear pattern is the huge reduction in R&D compared to those in Table 1- 2. As can be observed again, just like in cross-section studies, there are two papers found among time-series papers in Table 3 which report surprising results. They are Cameron (2003) and Cameron and Muellbauer (1996) that report very high coefficients for R&D, similar to those of cross-section studies. However, because Cameron (2003) is the only paper which adopts a VAR method of estimation, it is a bit difficult to compare this with the rest of the papers using OLS estimation method. According to Holtz-Eakin (2005) a method of estimation a researcher chooses also influences the findings.On the other hand, it is difficult to explain why Cameron and Muellbauer (1996) report such as high estimate which violates conventional findings for other time-series papers. More surprisingly, Cameron and Muellbauer (1996) also uses almost the same observation periods for the UK with that of Hubert and Pain (2001) which reports a much lower coefficient.Thus, it becomes very difficult to decide whose estimate to accept.

Moreover, one general observation from these cross-section and time-series papers is that arguments do not only arise between them but also within them. As can be seen on Table 1- 2 and Table 3-4 cross-section and time-series studies generally report different estimates for R&D, which also leads to another aspect of inconclusive arguments on the exact elasticity of productivity with respect to R&D expenditure.

3.3. Arguments from Panel Data Studies

To settle these arguments arising between time-series and cross-section studies, the immerging set of papers adopt a broader approach. These papers are those which try to carry the two dimensions of studies (time-series and cross-section) along at the same time during econometric design. These types of studies are generally referred to as panel data studies (Asteriou and Hall, 2011). Good examples of such studies are Grossman and Helpman (1991) McVicar (2002) and Kafouros (2008). Although Wakelin (2001) and Higon (2007) also adopts panel data but as stated earlier, this present research is neither interested in the rate of return studies nor interested in elasticity studies solely based on spillover effects, which those two papers study. Thus, close attention is only given to Grossman and Helpman (1991) McVicar (2002) and Kafouros (2008) which study direct elasticity of private R&D for the UK.

First of all, Grossman and Helpman (1991) uses panel data for 79 UK industries from 1976-79 using the fixed effects model to estimate R&D coefficient of 0.015. On the other hand, McVicar (2002) uses the same approach but with different dataset for 7 industries from 1973-92 to report same coefficient of 0.015. Although a little higher coefficient was rather found in Kafouros (2008) which uses dataset for 89 firms between 1989 and 2002, also adopting the fixed-effects model and finds elasticity estimate of around 0.10 and 0.16. See detail of papers on Table 5:

Table-5. Selected elasticity estimates of private R&D from panel data studies.

Paper	Country/level	Data	Approach	Method/ Variables	R&D coefficient
Geroski (1991)	UK/ Industry	79 industries from 1976-79	Cobb-Douglass production function	Fixed effects/ LP, K, R&D	0.015
McVicar (2002)	UK/ Industry	7 industries from 1973-92	Cobb-Douglass production function	Fixed effects/ TFP, R&D	0.015
Cameron *et al.* (2005)	UK/ Industry	13 manufacturing industries from 1971–1992	Cobb-Douglass production function	ECM/ TFP, R&D, CU, controls	0.09-0.16
Kafouros (2008)	UK/ Industry	89 firms between 1989 and 2002 aggregated to industry level	Cobb-Douglass production function	Fixed effects/ Output, L, K, R&D	0.10-0.16

As seen on Table 5, it can be observed that these papers provide support for time-series papers which are presented on Table 3-4 by reporting small coefficients for R&D. Thus, the areguments on the size of the impact of R&D on productivity is therefore drifting in favour of time-series studies. These imply that perhaps, the impact of R&D on productivity growth is not as large as cross-section studies normally reports. Nevertheless, this conclusion cannot be made untill there is a greater number of panel data studies which provide support for small coefficient, which is why the first research question for this research is highly important. Recall that the first question seeks to know the extent of the impact of R&D expenditure on productivity growth.

Furthermore, there is an additional interest to also carry out individual time-series analysis for the industries in the UK manufacturing sector.This is to get a wider understanding of the nature of elasticity of productivity growth with respect to R&D expenditure within the industries. To address this, there is a need to call up previous papers done for the UK on this context, to understand what is already going on in these industries.

3.4. Conclusion on Literature Review

It is necessary to summarise the arguments after an extensive critical study of various views of authors on this topic. Firstly, studies on this topic have either used Error Correction Model (ECM), OLS or fixed effects method for their research. However, every paper follows the extended Cobb-Douglas production function framework. Those which study time-series and cross-section dimension generally apply OLS estimation, while those which use panel data generally use fixed effects model or ECM. Nevertheless, the general conclusion is that R&D has a positive relationship with productivity growth at all levels of aggregation, which confirms the endogenous growth theory. Nonetheless, the arguments on the exact size of R&D coefficient is still inconclusive, with cross-section studies arguing for very high coefficients for R&D expenditure and time-series together with panel data studies arguing for small coefficient.

Two major gaps identified in this literature which needs filling are the minimal amount of panel data studies which investigate this specific topic to help address the problem; and the time lag since the last research was done for the UK using panel data. As observed in the study, the most recent panel data paper for the UK is Kafouros (2008) whose observation period ended in 2002. Therefore, between 2002 and 2015, economic events like the 2008 financial crisis would have impacted on the nature of the relationship between R&D expenditure and productivity growth in the UK manufacturing industries.

4. Methodology and Data

4.1. Data

The data for this research were chosen to be consistent with the data needed to successfully estimate the Cobb-Douglas production function for the UK manufacturing industries. The data used throughout this study is obtained from Office for National Statistics website which supplies data to Eurostat[1]. They include, number of employees by industry, net physical capital by industry in chained volume measure (cvm) and output measured in gross value added (GVA) by industry also in cvm. GVA is simply calculated by subtracting the consumption of intermediate inputs[2] from the output, which was calculated by Office for National Statistics (Statistical, 2015).

The choice of using Net physical capital over gross physical capital is because in calculating Net physical capital, yearly depreciation as a result of wear and tear is subtracted from the actual value thus, reflecting the yearly worth of the assets (Statistical, 2015). Additionally, the data for R&D expenditure (which proxies' knowledge gain from innovation) is also obtained from ONS as net R&D stock in cvm. Many papers argue that R&D has some depreciation[3]. Some authors use 10% and some use 15% but Hall and Mairesse (1995) argue that this has negligible impact on estimates. Nevertheless, we also resort to net R&D data, depreciated by ONS. See Table 6 for the industries of interest. Nevertheless, because the actual share of labour and capital inputs in total

[1]Eurostat is the statistical office of the European Union situated in Luxembourg. Its task is to provide the European Union with statistics at European level that enable comparisons between countries and regions Eurostat (2015).

[2] Intermediate consumption consists of the value of those goods and services consumed as inputs by the process of production, excluding fixed assets whose consumption are recorded as the consumption of fixed capita Statistical (2015).

[3] The premise for their argument is based on the fact that knowledge gain from R&D becomes obsolete at some point in time or new inventions are made to replace the old ones. Thus, it becomes appropriate to subtract a certain depreciation rate from the R&D data.

cost for R&D is not found, the double counting problem emphasised in Hall and Mairesse (1995) is not corrected in R&D data.

Table-6. The 13 broad UK manufacturing industry classifications as defined by ONS (2015).

Tabulation of industry SIC_CODE
Sample: 1997 2014
Included observations: 234
Number of categories: 13

SIC code	Count	Title
C10T12	18	Manufacturing - Food Products, Beverages and Tobacco
C13T15	18	Manufacture of textiles, wearing apparel, leather and leather products
C16T18	18	Manufacture of wood and paper products, and printing
C19	18	Manufacture of coke and refined petroleum products
C20	18	Manufacture of chemicals and chemical products
C21	18	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22_23	18	Manufacture of rubber and plastics products, and other non-metallic mineral
C24_25	18	Manufacture of basic metals and fabricated metal products, except machinery and equipment
C26	18	Manufacture of computer, electronic and optical products
C27	18	Manufacture of electrical equipment
C28	18	Manufacture of machinery and equipment n.e.c.
C29_30	18	Manufacture of transport equipment
C31T33	18	Manufacture of furniture; other manufacturing; repair and installation of machinery and equipment
Total	234	

Table-7. Descriptive statistics.

Sample: 1997 2014			
	DLNQ/L	DLNRD	DLNK
Mean	0.004964	-0.004790	-0.005385
Median	0.005835	-0.005362	-0.007517
Maximum	0.053280	0.182322	0.394096
Minimum	-0.064515	-0.234401	-0.059976
Std. Dev.	0.014609	0.048597	0.038481
Skewness	-0.877042	-0.033505	5.274432
Kurtosis	6.629870	6.641905	54.07541
Jarque-Bera	149.6609	122.1758	25046.45
Probability	0.000000	0.000000	0.000000
Sum	1.097058	-1.058538	-1.190118
Sum Sq. Dev.	0.046955	0.519577	0.325780
Observations	221	221	221

From the negative skewness of labour productivity and R&D expenditure in Table 7, it is obvious that there are few industries with high growth in productivity and R&D expenditure over time. It is an expectation that such industries possessing high productivity growth would have invested heavily in R&D (Kafouros, 2005). Again, the mean value for R&D expenditure is negative, further indicating that growth in R&D expenditure has been slower in most industries than the rest over time. With these insights, it is certain that our data does not follow normal distribution. That is, skewness is less than zero, kurtosis is greater than 3 and probability is significant at 0.05 thus, regression results are likely not to show the true picture (Gujarati and Porter, 2010). However, the central limit theorem still permits the use of the data even when they are not normally distributed as normal distribution depends on the type of sample one obtains (Gujarati and Porter, 2010).

Table-8. Correlations table.

Variables	DLNQ/L	DLNRD	DLNK
DLNQ/L	1.000000	0.097032	0.031428
DLNRD	0.097032	1.000000	0.350891
DLNK	0.031428	0.350891	1.000000

As seen on Table 8, the correlations analysis show that growth in R&D expenditure is positively correlated with productivity growth up to 0.097%, which accords with our expectations of positive relationship between R&D expenditure and productivity growth (Romer, 1986). Another interesting fact is that capital investments appear to have lower correlation with productivity growth (that is, 0.031%) than R&D expenditure which implies that, investments in R&D yields more to productivity growth than investments in capital for the UK manufacturing industries. In addition, it is also observed that R&D expenditure is correlated with capital only up to 35%, which is not very high (that is, not up to 90%) therefore there is no problem of multicollinearity between explanatory variables (Gujarati and Porter, 2010).

4.2. Methodology

Consistent with other papers reviewed in this study, with similar objective of investigating the impact of R&D on productivity growth, this paper also starts off the investigation with the conventional production function, which is also the starting point for Wakelin (2001); Geroski (1991); Higon (2007) and many others.

$$Q = F(L, K) \qquad (1)$$

The function on equation 1 above represents the relationship between output and factor inputs

Where,
Q = is the quantity of output.
L= the quantity of labour used in the production process.
K= the amount of physical capital.

This theory or function is constantly used in economics to represent the relationship between the output Q and the combination of the production inputs L, K, and other inputs.

For the purpose of our research objectives which is to investigate the impact of R&D expenditure, an extended form of the Cobb-Douglas production function which favour the endogenous growth theory introduced in Romer (1986); Romer (1990) and Lucas (1988) is utilized, where R&D expenditure is incorporated into the regression as one of the factor inputs, just like labour and physical capital. This relationship is widely presented as follows:

$$Q_{it} = AK_{it}^{B1} L_{it}^{B2} RD_{it}^{B3} \quad (2)$$

Where:
it = industry i at time t.
Q_{it} = Output in industry i at time t, measured in gross value added (GVA).
A = Constant or state of technology.
K_{it} = Net physical capital stock.
L_{it} = Labour employed.
RD_{it} = Knowledge stock (Net R&D capital stock).
B_1 = the partial elasticity of output with respect to capital.
B_2 = partial elasticity of output with respect to Labour.
B_3 = partial elasticity of output with respect to R&D.

However, for estimation purposes, there is a need for an equation which is linear in its parameters (Gujarati and Porter, 2010). This implies that the application of logarithmic transformation to Equation 2 which is the same approach adopted in Griliches and Lichtenberg (1984) becomes neccessarry. Following this, while allowing for random influence in the industries U_{it}, Equation 2 is transformed as follows:

$$\text{Log}(Q_{it})=\log(AK_{it}^{B1}L_{it}^{B2}RD_{it}^{B3}) \quad (3)$$

$$\log(Q_{it}) = \log(A) + \log(K^{B1})_{it} + \log(L^{B2})_{it} + \log(RD^{B3})_{it} + U_{it} \quad (4)$$

$$\text{Log}(Q_{it}) = \text{Log}(A) + B_1\log(K)_{it} + B_2\log(L)_{it} + B_3\log(RD)_{it} + U_{it} \quad (5)$$

Equation 5 is now linear in terms of the parameters B_1, B_2 and B_3.

The sum of the exponents (B_1 B_2 and B_3) indicates returns to scale:

If $B_1+B_2+B_3=1$, it implies constant returns to scale for all the production inputs L, K, RD.

If $B_1+B_2+B_3<1$, it implies decreasing returns to scale.

If $B_1+B_2+B_3>1$, it implies increasing returns to scale.

Nevertheless, the interpretation given to Equation 5 according to Czarnitzki and Thorwarth (2012) is the partial elasticity of output Log (Q_{it}) with respect to R&D expenditure log(RD_{it}).This is different from our research interest, which is to investigate the elasticity of productivity with respect to R&D expenditure and not the actual output. However, in using the productivity approach, the question of what appropriate measure of productivity to adopt arises, which has posed serious arguments among early researchers according to Kafouros (2008). While some reseachers adopt labour productivity as the desired measure, others have resorted to estimating total factor productivity (TFP).

According to Kafouros (2008) it was previously believed that TFP was a better measure because it incorporates all production inputs. However, recent findings in Sargent and Rodriguez (2000) cited in Kafouros (2008) suggests that both measures have their place and that, none of them even shows the whole picture. The results of Sargent and Rodriguez (2000) suggest that the measure of productivity to be used should depend on factors such as the time period the researcher is interested in studying and the comparability of capital stock data. In their analysis, they suggest that if the time being studied is over a period of a decade or so, then the appropriate measure of productivity would be labour productivity. In contrast, if the interest is in long run trends of several decades, then TFP should be used. In addition, Sargent and Rodriguez (2000) opine that if the measures of capital stock are not comparable, then again labour productivity should be used. Thus, giving that our research does not cover many decades, this research adopts the labour productivity measure as its measure of productivity. Another benefit of using the labour productivity approach according to Sargent and Rodriguez (2000) is that, the Labour productivity (LP) framework allows for easy comparision of returns from R&D investments with that of capital investments, which the TFP approach does not allow for as it eliminates capital input from the right hand side of the regression.

That is,

$$\text{TFP}[\log(Q)_{it} - B_1\log(k)_{it} - B_2\log(L)_{it}] = \text{Log}(A) + B_3\log(RD)_{it} + U_{it}, \quad (6)$$

The expression on Equation 6 above gives the derivation of total factor productivity by eliminating the presense of capital and labour inputs from the equation. Consequently, the labour productivity approach retains the individual factor inputs (labour and capital)as shown on Equation 7 below:

$$\text{LP}[\log(Q/L)_{it}] = \log(A) + B_1\log(K)_{it} + B_3\log(RD)_{it} + U_{it} \quad (7)$$

This labour productivity approach is the same productivity measure adopted in Wakelin (2001); Hubert and Pain (2001); Geroski (1991) also used in Hall and Mairesse (1995). Nevertheless, there was no signicant difference found between TFP and LP studies in our literature review.

Respect that in adopting the the LP apporach, Hall and Mairesse (1995) state that the idea is simultaneously imposing that partial elasticity of output with respect to labour equals one for constant returns to scale to exist (That is, $B_2 = 1$) although this is not tested in this study. For convenience, we rearrange Equation 7 as follows:

$$\text{Log}(Q/L)_{it} = \text{Log}(A) + B_1\log(K)_{it} + B_3\log(RD)_{it} + U_{it} \quad (8)$$

The expression on the left hand side log(Q/L) clearly defines labout productivity as the change in output per employee at a particular industry and specific time period, which is explained by capital log(K_{it}) and R&D expenditure log(RD_{it}). Many authors, including Wakelin (2001) maintain that Equation 8 reduces the problem of multicollinearity present in Equation 5 by removing one explanatory variable.

According to Moen and Burchardt (2009) estimating Equation 8 at its present state will yield unreliable results and therefore R&D needs to be lagged. Moen and Burchardt (2009), stating that, R&D is found to take an average of 6 to 18 months to reach the finished development. This implies that a minimum lag of 1 year can be added to our R&D variable in Equation 8 to adjust for the time it takes for R&D to start yielding results in the industries. According to Nishioka and Ripoll (2012) lagging R&D variable also goes to solve the endogeneity problem which could be present in Equation 8 between R&D expenditure and productivity growth.

Additionally, in order to use variables in their rate of change form (that is, making variables stationary), which completely eliminates the problem of spurious regression, we apply first difference transformation to the log variables as advised in Wakelin (2001). Panel unit root test outputs are found in appendix 1, using IM Pesaran and Shin W-stat, ADF-Fisher Chi-square, PP-Fisher Chi-square and Levin,Lin &Chu t. The results indicate that at level with individual industry intercept and trend, log variables still possess unit root, as we fail to reject this null hypothesis because of insignificant probability values at 0.05, coming from majority of the tests listed above. Meanwhile at first difference, null hypothesis of unit root is confidently rejected because of significant probability values at 0.05 from all the tests. This leads to the final specification:

$$\Delta \text{Log}\ (Q/L)_{it} = \text{Log}\ (A) + B_1\, \Delta \text{log}\ (K)_{it} + B_3\, \Delta \text{log}\ (RD)_{it} + B_4\, \Delta \text{log}\ (RD\,(-\,1))_{it} + U_{it} \quad (9)$$

Thus, Equation 9 above can be best interpreted as observing long-run elasticity of labour productivity with respect to R&D expenditure, denoted by B_4. Equation 9 thus becomes the final specification. The equation was therefore estimated using both fixed effects and random effects methods, and the Hausman test was used to determine the appropriate method that produced a more desirable result.

5. Empirical Results

The purpose of this section is to provide answer to research questions therefore; we start with regression results for Equation 9 at a panel level for the industries.

Table-9. Pooled OLS.

Variable	Coefficient	Std. error	t-Statistic	Prob.
C	0.005527	0.001041	5.307143	0.0000
DLNK	-0.010417	0.028752	-0.362289	0.7175
DLNRD	0.012915	0.022969	0.562267	0.5746
DLNRD(-1)	0.060162	0.022202	2.709792	0.0073

Table-10. Fixed effects.

Variable	Coefficient	Std. error	t-Statistic	Prob.	R^2 0.121965
C	0.005890	0.001039	5.669168	0.0000	
DLNK	0.021117	0.031876	0.662470	0.5085	
DLNRD	0.022798	0.023052	0.988967	0.3239	
DLNRD(-1)	0.070136	0.022279	3.148095	0.0019	

Table-11. Random effects.

Variable	Coefficient	Std. error	t-Statistic	Prob.
C	0.005527	0.001030	5.368104	0.0000
DLNK	-0.010417	0.028426	-0.366450	0.7144
DLNRD	0.012915	0.022708	0.568725	0.5702
DLNRD(-1)	0.060162	0.021950	2.740918	0.0067

As explained in the methodology section, the acceptance of result from the random or fixed effect method would require the use of Hausman Test. Note that, because the interest is in acknowledging differences within the industries, the pooled OLS result which does not account for this, is disregarded in this research.

Table-12. Hausman Test: Test for the appropriate method of estimation between fixed and random effects.

Correlated random effects - Hausman test
Equation: EQ01
Test cross-section random effects

Test summary	Chi-Sq. statistic	Chi-Sq. d.f.	Prob.
Cross-section random	8.699107	3	0.0336

As briefly mentioned earlier, the Hausman Test is a test which decides whether the fixed effects or random effects method is appropriate, based on differences in the correlation of the error terms with explanatory variables (Gujarati and Porter, 2009). The null hypotheses H0 is that the error terms are uncorrelated with explanatory variables and thus random effects method is appropriate, while the alternative Ha is that error terms are correlated with explanatory variables and therefore fixed effects method is appropriate (Gujarati and Porter, 2009). Because the p-value is significant at 5%, we reject the null hypothesis of uncorrelated error terms therefore, we proceed with results from the fixed effects method which are:

B_0= 0.006860 = Intercept or productivity growth unattributed to explanatory variables.

B_1=0.021117= Elasticity of productivity growth with respect to capital investment.

B_3=0.022798 = Contemporaneous (Immediate) effect of R&D on productivity growth.

B_4=0.070136 = Long-run elasticity of productivity growth with respect to R&D expenditure.

Recall that interest is not in the contemporaneous effect of R&D. That is, the R&D without the one-year lag (B_3). Rather, we are interested in long-run effect (B_4).

Although the R^2 of 0.12 seems small, it is similar to that reported in Cameron *et al.* (2005) which is around 0.06. Moreover, with the low p-value for the long-run R&D coefficient (less than 0.05) from the fixed effect method, we can infer that, if R&D expenditure increases by 1%, productivity will increase by 0.07%.

6. Discussion

The result reveal that, the extent of the impact of R&D on productivity growth in the UK manufacturing sector is about 0.07% for every 1 % rise in R&D expenditure. Because this result is statistically significant at 10%, there is a confidence to compare it with other papers from the literature review.

Recall that the panel data studies are those which are placed on Table 5. However, only those which also estimated fixed effect from the table are called up for comparison. They include Geroski (1991); McVicar (2002) and Kafouros (2008). These three papers are the three most significant papers to this study. Reasons being that they also study the UK at industry level, using the fixed effects method and a panel data. See Table 13 to observe how our result compare with that of other panel data studies.

Table-13. Comparisons with closest papers at panel level.

Paper	Country	Level	Type of data	Approach	Method/Variables	R&D coefficient
Geroski (1991)	UK	Industry	Panel	Cobb-Douglas production function	Fixed effects/ LP, K, R&D	0.015
McVicar (2002)	UK	Industry	Panel	Cobb-Douglas production function	Fixed effects/ TFP, R&D	0.015
Kafouros and Wang (2008)	UK	Firm level data aggregated to Industry level	Panel	Cobb-Douglas production function	Fixed effects/ Output, L, K, R&D	0.10-0.16

Allthough the result from this current study is a little different from those of other papers as seen on Table 13 above, this is totally explanable. There are two general reasons identified in literature review to cause these minor differences in results. The first reason has to do with different research objectives and type of data for the different papers as highlited in Hall and Mairesse (1995) and Holtz-Eakin (2005) and the other has to do with fluctuations in the external business environment in different time periods being observed, highlighted in Moen and Burchardt (2010). Judging from the angle of the type of data and research objectives, there are a number of interpretation as to why our study produces a slightly different estimate for the UK with regards to earlier papers. Firstly, Geroski (1991) employs a slightly different type of R&D expenditure dataset in their study, separating domestic from foreign R&D expenditure data to assess the impact of each type[4] which means that their result has the tendency to be a little lower than that of this study. Secondly, McVicar (2002) only estimates for 7 UK manufacturing industries thus, it is possible that the inclusion of more industries in the study, as done in this paper should produce a slightly higher estimate. Lastly, the huge difference between the result in Kafouros and Wang (2008) and that of this present research, is somewhat surprising. However, Kafouros and Wang (2008) is the only paper in this category which uses sales to proxy for output. They maintain that because gross value added was not available at the time of the research, the only option was to resort to sales.This means that their result is not expected to be precise with that of this paper. In fact, Hall and Mairesse (1995) argue against the use of sales to proxy for output sustaining that it leads to biased results. In a ddition, the 2008 financial crises created a hole in the data used for this study which means that perhaps, the coefficient of long-run R&D expenditure for this research would have probably been higher than it is, moving closer to that of Kafouros and Wang (2008).

Finally, by observing Table 3 and 4 in literature review, one can appreciate that the long-run R&D coefficient for this present research is very similar to those reported in the tables. In fact, the impact of 0.07 found on this present paper is exactly the same size found for France by Hall and Mairesse (1995) while using time-series data. This implies that this study also joins other panel data studies to provide support for small coefficient for R&D, consistent with the arguments of time-series studies. However, there is still a need for further investigation at individual industry level using time-series data, to assess whether this is also the same picture dipicted.

7. Conclusion

The purpose of this study has been to investigate the impact of R&D expenditure on productivity growth using panel data. Our general conclusion is that there is still a positive relationship between R&D expenditure and productivity growth for the UK manufacturing industries, with R&D elasticity of about 0.07% at panel level and significant at 1 %.

The main implication of these findings is that technological advancement which contributes to productivity growth is not exogenous, contrary to Solow (1956). That is, it can be determined by R&D decisions in firms and in industries, which is in favour of Romer (1986); Romer (1990) and Lucas (1988). Nevertheless, there are also some rare circumstances where this endogenous growth theory does not hold. For instance, Kafouros and Wang (2008) also confirm as well as this study that some industries do possess negative signs. In addition, this study clearly prefers investment in R&D to capital investments, as capital was generally found to contribute less to productivity growth compared to R&D investments. Furthermore, the estimate for R&D coefficient found at the panel level provides support for the argument of small coefficient for studies using time-series data. Thus, we can align with

[4] Domestic R&D is the R&D expenditure undertaken in the industry, while foreign R&D is usually that embodied in purchased capital goods Higon (2007).

the argument of such studies on Table 3-4 that R&D has a lesser impact on productivity growth than those coming from cross-section studies on Table 1-2.

The policy implication for this research is for the UK government to to provide incentives to increase innovation in the UK manufacturing industries. Furthermore, the UK government also needs to design policies which encourage more of R&D investments in firms than capital investments. In addition, since an increase in R&D expenditure has the tendency to increase productivity which in-turn leads to improvement in living standards (Harari, 2015) it is advised that the UK government provides R&D subsidies to struggling manufacturing industries, most of which are in the low-tech category, as this will contribute to economic growth.

7.1. Limitations of Study and Recommendations for Future Research

The major limitation is that, the double counting of labour and capital inputs in R&D is not corrected in our data. Thus, it is likely that our results are bias. Finally, our observation period is only for 18 years and because R&D expenditire does not vary much over time, the research requires longer observation period to be able to reach stronger conclusions. Two important recommendations for improvements and further study on this research topic are one, to carry out more panel data studies using longer observation period of over 30 years and apply higher lags, as this will capture higher variations in R&D expenditure over time thus producing more reliable estimates. The last recommendation is to represent energy input in the Cobb-Douglass production function framework for the industries, to improve the specification.

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