Types of R&D Investment and Firm Productivity: UK Evidence on Heterogeneity and Complementarity in Rates of Return

Edna Solomon, University of Greenwich.

Abstract

Existing evidence on the impact of R&D on productivity is heterogenous and does not address the question of whether different types of R&D are complements or substitutes. The aim of this research is to open the R&D black box by providing fresh insights about how different R&D types affect productivity in different industrial and technological contexts in the UK. The model adopted allows for non-linearities between R&D and productivity and interactions between R&D types. The analysis makes use of micro data from the Office of National Statistics, comprising 8,284 firms from 1998 to 2012. The results show evidence of diminishing marginal returns to total R&D. This concave relationship also holds for intramural R&D, applied/experimental R&D and private R&D. These findings suggest that studies which do not allow for non-linear relationships between R&D and productivity could suffer from specification bias. The results also indicate complementarity between intramural and extramural R&D and between basic and applied/experimental research. Returns to publicly funded R&D are insignificant and there is neither complementarity nor substitution between publicly and privately funded R&D. The findings strengthen the case for modelling the sources of heterogeneity explicitly by taking account of non-linearities in and interactions between the productivity effects of different R&D types.

Key words: firm productivity, R&D, Pavitt class, basic research, applied research, experimental research, in-house research, extramural research, privately funded R&D, publicly funded R&D.

1. Introduction

The relationship between research and development (R&D) and productivity has been of major interest to researchers and policy makers for several decades. The relevance of R&D is highlighted in a recent study by Pieri, Vecchi, and Venturini (2018) who estimated that R&D and ICT accounted for about 95% of Total Factor Productivity (TFP) growth in 14 OECD countries from 1973 to 2007. 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, 1). R&D has been identified as an important source of firm growth through its contribution to knowledge and innovation (Aiello and Cardamone 2005) and its links with investments in tangible assets (Carboni and Medda 2019). Moreover, R&D enables firms to build their absorptive capacity which is essential for knowledge spillovers to occur (Cohen and Levinthal 1989).

The pioneering works in the literature on R&D and productivity were Minasian (1969), Griliches (1973) and Terleckyj (1974), but empirical studies expanded significantly after Griliches (1979) who articulated a lasting framework for the measurement, modelling and estimation issues in R&D analysis. Despite the vast amount of work in this field, the literature has mixed findings on how R&D affects firm productivity. This is partly because most studies treat R&D as a homogenous activity that is measured by a single variable, usually total R&D intensity or total R&D capital. In reality, R&D is much more complex involving several types (basic, applied, experimental) that can be conducted either in-house (intramural) or contracted to other firms (extramural) and can be funded either privately by the firm/private organisations or from public sources. In addition, the productivity effects of R&D seem to vary widely across different technological sectors and firm sizes (Ortega-Argiles, Piva, and Vivarelli 2015; Spescha 2019)**.** The aim of this research is to open the R&D black box by taking a detailed approach to understanding how different forms of R&D affect productivity in different sectoral and technological contexts. No other study has conducted such a comprehensive investigation on R&D and productivity which considers several sources of heterogeneity.

This paper contributes to the literature along three key dimensions. First, to the best of my knowledge, this is the first study that examines the impact of various types of R&D expenditures (basic, applied/experimental, intramural, extramural, privately funded R&D and publicly funded R&D) on productivity in a single comprehensive study, *and explicitly tests whether there is a nonlinear relationship between each type of R&D and productivity*. Much of the literature treats R&D as a linear function of productivity. However, recent studies have found diminishing marginal returns to R&D due to difficulties in obtaining new ideas and innovative opportunities over time and diseconomies of scale arising from bureaucracy and managerial slack in large firms (Kancs and Silverstovs 2016; Furman, Porter, and Stern 2002; Hagedoorn and Wang 2012). Hence, studies that do not allow for non-linearities in R&D could suffer from specification bias. However, to the best of my knowledge, only three empirical studies have accounted for non-linearities between R&D and productivity: Lokshin, Belderbos, and Carree (2008) and Kancs and Silverstovs (2016) used quadratic R&D terms to capture the non-linear relationship between R&D productivity while Montresor and Vezzani (2015) employed quantile regressions. This study contributes to the limited research on non-linearities in R&D by modelling each R&D type as quadratic functions of productivity.

The second contribution of this study is to examine whether the different R&D types are complements or substitutes in the production process. In other words, *does an increase in one type of R&D increase or reduce the marginal effect of another type of R&D on productivity?* This is important because each R&D type has different characteristics. For instance, basic and intramural research build up the absorptive capacity of firms (Czarnitzki and Thorwarth 2012; Lokshin, Belderbos, and Carree 2008) and extramural R&D enables firms to tap into knowledge from outside the firm (Brossard and Moussa 2016). However, both basic and extramural research are riskier forms of investment (Higon 2016). The rationale for public funding of R&D is to stimulate private R&D spending and hence productivity because market failure leads to underinvestment in R&D (Belitz and Lejpras 2016). While recent research has examined whether R&D types are complementary or substitutes, much is unknown about these relationships. For instance, although studies such as Lokshin, Belderbos, and Carree (2008) have explored whether intramural and extramural R&D are complements, to the best of my knowledge, no study has examined whether basic research is complementary with applied or experimental research. In addition, studies on public R&D mainly focus on whether public R&D funding crowds in or crowds out private R&D but few examine either the impact of privately funded R&D on productivity or whether private and public R&D are complementary or substitutes in affecting productivity. This study extends the literature by investigating whether complementarity exists between basic and applied/experimental research; intramural and extramural research; and privately funded and publicly funded research.

Finally, this research contributes to the literature by *examining whether the non-linearities of each R&D type and the linkages between them are affected by the size and sector of the firm*. R&D intensity is positively related with firm size (Ugur, Solomon, and Trushin 2015) but smaller firms have the advantage of greater efficiency and better incentive structures (Spescha 2019). Recent research shows that large firms benefit from intramural basic research rather than extramural basic research but, for smaller firms, who have less R&D capacity, basic intramural research and basic external R&D involving collaborations with universities are complementary (Higon 2016). Public funding seems to be particularly useful when targeted at small and medium enterprises (SMEs) due to the weaker financial position of these firms (Szucs 2020). With respect to sector, most studies focus on the manufacturing sector due to data availability, an absence of a direct link between research and innovation in the service sector and because fewer firms in the service sector have historically devoted resources to research (Doloreux, Shearmur, and Rodriguez 2016). However, in several OECD countries and the UK specifically, the non-manufacturing sector dominates the economy. Hence, focusing on the manufacturing sector alone neglects a large part of the UK economy. Finally, it is not entirely clear how the level of technology affects the relationship between R&D and productivity. Although several studies show that the marginal effect of R&D on productivity is higher in high-tech manufacturing and knowledge intensive service sectors (e.g. Ortega-Argiles, Piva, and Vivarelli 2015), other studies show that the difference between them is much more muted (Pieri, Vecchi, and Venturini 2018). Moreover, very little is known about whether nonlinearities and the relationships among different types of R&D are affected by the technological intensity of sectors. In this study, the impacts of the different R&D types on productivity are examined in the manufacturing and service sectors, by firm size and Pavitt class.

This research draws from three firm-level UK databases: the *Annual Respondents Database* (ARD) and its successor, the *Annual Business Survey* (ABS), and the *Business Expenditures on Research and Development* (*BERD*) to provide detailed evidence on the relationship between R&D and firm productivity for 8,284 UK firms from 1998 to 2012 using a dynamic panel data model. The findings show strong evidence that the rate of return to total R&D is subject to diseconomies of scale, although the diminishing effect is small. The rates of return of some R&D types (intramural R&D, applied and experimental R&D and private R&D) are also subject to diminishing scale effects. There is evidence of complementarity between certain types of R&D – basic and applied/experimental R&D and between intramural and extramural R&D, but considerable heterogeneity in the results depending on the sector and size of firms.

The rest of the paper is organised as follows. In section 2, the literature is reviewed. Section 3 introduces the empirical specification and discusses the data and empirical technique. In section 4, the results are presented and section 5 concludes.

2. Related Literature

R&D is widely regarded as a key determinant of economic growth. Pieri, Vecchi, and Venturini (2018) identify four mechanisms by which R&D can contribute to productivity growth: capital deepening (i.e. productivity enhancements through investment in knowledge capital), spillovers (through the diffusion of knowledge across firms), shifts in technical change and reducing technical inefficiency. R&D also raises productivity by lowering costs (Lang 2009), increasing the level of innovation output (Raymond et al. 2015) and the stock of knowledge. The literature on the impact of R&D on productivity is large, and several narrative reviews exist (e.g. Mairesse and Mohnen 1994; Hall 1996; Hall, Mairesse, and Mohnen 2010) but report varied conclusions with a wide range of estimated elasticities from -0.262 to 0.810. A recent meta-analysis by Ugur et al. (2016) confirms that R&D has a positive, but small effect on productivity, with an estimated average elasticity of R&D capital on productivity of 0.07, and a gross private rate-of-return from R&D of around 14%.

A major shortcoming of the older R&D literature is that it treats R&D as a homogenous activity but, in reality, R&D is a more complex activity. The more recent literature has begun to examine the impacts of the different aspects of R&D on productivity because each R&D type has distinctive features. Research work can be categorised into 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 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 2015). R&D can be conducted "in-house" (intramural R&D), i.e. within the firm or can be contracted out by firms to other entities such as universities or government establishments (extramural R&D). In addition, R&D can be funded either privately or by governments, usually through subsidies or R&D tax credits.

2.1 R&D and Productivity: Non-linearities

A recent strand of the literature has suggested a non-linear relationship between R&D and productivity. According to Furman, Porter and Stern (2002), current R&D is positively related with the stock of existing knowledge through past R&D investments to increase productivity. This is the "standing-on-shoulders" effect. However, as R&D discovers ideas, it becomes more difficult to discover newer ideas which reduces the marginal effect of R&D on productivity. This is the "fishing out" effect. The combination of the two effects suggests diminishing marginal returns of R&D to productivity. Kancs and Silverstovs (2016) provided evidence of these effects. Among OECD firms from 2006-2007, they found that the relationship between R&D and productivity was insignificant until a minimum level of R&D beyond which productivity increased at a decreasing rate. Hence, a sufficient level of existing knowledge was required by firms to make productive use of new knowledge from R&D (standing-on-shoulders effect) but the marginal effect of R&D on productivity increased at a decreasing rate due to the fishing out effect.

Hagedorn and Wang (2012) found significant diminishing marginal returns to internal R&D on innovation output from a panel of 83 Pharmaceutical firms from 1986-2000. They proposed two explanations for this. The first reason linked to Hitt, Hoskisson, and Ireland (1990) arose from the lower innovative efficiency of larger firms due to bureaucracy and managerial slack. The second reason, drawn from Griliches (1990) and Hausman, Hall and Griliches (1984), was attributed to a decline in innovative output as R&D increased because of a reduction of inventive opportunities over time.

Diseconomies of scale from both internal and external R&D on labour productivity was also discovered by Lokshin, Belderbos, and Carree (2008) for 6 Dutch manufacturing firms from 1996 to 2001 using dynamic panel data modelling. Finally, using quantile regressions on a panel of 1000 top R&D investing firms from the EU between 2002 and 2010, Montresor and Vezzani (2015) provided evidence of non-linear effects between R&D and productivity. They found increasing returns to scale for firms in high and medium high-tech sectors but decreasing returns to scale for the largest firms in low-tech sectors.

2.2 R&D and Productivity: Linkages between R&D types.

2.2.1: Internal and Extramural R&D

Recent research has examined the impact of intramural and extramural R&D on innovation and productivity, and whether intramural and extramural R&D are complements or substitutes. Intramural R&D is regarded as essential for building the knowledge base and absorptive capacity of firms. The impact of extramural R&D is more debatable. On the one hand, extramural R&D is beneficial to firms in reducing costs and for tapping into external knowledge (Brossard and Moussa 2016) but can lead to the appropriation of knowledge assets by rivals (Tamayoa and Huergob 2017) which increases transaction costs (Ceccagnoli et al. 2010). Brossard and Moussa (2016) found that intramural rather than extramural R&D had a significant effect on innovation. Similarly, Bianchini, Pellegrino, and Tamagni (2018) showed that internal R&D had a positive and significant effect on sales growth for Spanish manufacturing firms from 2004 to 2011, due to its complementarity with product and process innovations. These findings led the authors to conclude that knowledge was inherently firm specific and that firms probably faced difficulties in integrating external innovations.

Radicic and Balavic (2019) synthesised the theoretical perspectives that explain complementarity or substitutability between internal and external R&D expenditure. The transaction cost theory suggests that internal and external R&D are substitutes, so firms choose one type or the other depending on which has lower transaction costs. On the other hand, when a firm combines internal R&D with external knowledge sourcing, then the innovation capacity (knowledge-based view) and comparative advantage (Resource based view) of the firm increases leading to complementarities between the two R&D types. In a panel of Spanish manufacturing firms from 2001 to 2011, they found a U-shaped relationship between internal R&D and product innovation. However, only the quadratic term in external R&D was positive and significant, suggesting that significant returns from external R&D only occurred at sufficiently high levels. Complementarity between internal and external R&D was conditional on having a minimum number of cooperative partners.

Complementarity between intramural and extramural R&D in raising the levels of innovative output was found by Catozzella and Vivarelli (2014) for a panel of 3,045 Italian firms between 1998 and 2000. In contrast, Higon (2016) and Ceccagnoli et al. (2010) found intramural and extramural R&D to be substitutes, arguing that firms with stronger internal R&D capabilities were unlikely to pursue external sources of knowledge to prevent knowledge leakages. Other studies show that complementarities between internal and external R&D are conditional upon a minimum level of internal R&D, and emphasise that internal R&D is crucial for developing absorptive capacity in firms to enable them benefit from knowledge sourced from outside the firm (Lokshin, Belderbos, and Carree 2008; Hagedoorn and Wang 2012). In a study of Pharmaceutical companies by Hagedoorn and Wang (2012), the interaction between internal and external R&D was U-shaped in affecting innovation output, with both R&D types substitutes at low levels of internal R&D and complements at higher levels of internal R&D. Finally, internal R&D has been found to be complementary with external R&D involving collaborations with firms and universities rather than the contracting out of research (Higon 2016; Schmiedeberg 2008; Radicic and Balavic 2019).

2.2.2: Basic, applied and Experimental R&D

Basic R&D is important for building the absorptive capacity of firms and contributing to first mover advantages. Higon (2016) found that in-house basic research increased the propensity of firms to pioneer new products in the market by about 5-6 percentage points. Basic research is, however, a risker form of R&D due to its lack of specificity and higher tendency of appropriation (Czarnitzki and Thorwarth 2012). Exploratory research (basic and applied R&D) have been shown to increase the risk of innovative failure, albeit at a diminishing rate as firms learn how to reduce failure over time (D'Este, Marzucchi, and Rentocchini 2018). In a panel of 23 OECD countries from 1996 to 2010, Sun, Wang, and Li (2016) showed that basic, applied and experimental R&D all increased TFP. While applied and experimental R&D had both contemporaneous and lagged effects on TFP, basic R&D had a lagged effect of 2 to 3 years on TFP. Using data envelopment analysis to separate the sources of TFP, they showed that basic R&D had a positive effect on technical change (i.e. shifts in the production frontier) whereas applied and experimental R&D increased technical efficiency change (i.e. enabled firms to catch up with the technological frontier).

2.2.3 Private and Public funded research

R&D can be distinguished by source of funding – either from private or public sources. Public funding of R&D is usually justified because of market failure (See e.g. Gonzalez, Jaumandreu, and Pazo 2005 and Ugur, Solomon, and Trushin 2015). The public good characteristic of knowledge means that it can spillover to other firms which incentivises firms to invest in R&D below the socially optimal level. There is some evidence that private R&D has fallen over time. For instance, although privately funded R&D was found to have a positive effect on productivity in German manufacturing firms, its level had fallen significantly by about 70% between 1960 and 2005. R&D is also a risky type of investment because of uncertainty in the success of generating new knowledge and risk of failure in product and process innovations (D'Este, Marzucchi, and Rentocchini 2018). Public funding is therefore meant to induce private R&D spending to boost innovative output and hence productivity. However, this mechanism cannot be taken for granted (Czarnitzki and Hussinger 2018). First, firms might substitute public funding for private R&D investment, i.e. public funding could crowd out private R&D which would not increase innovative output. Second, firms might choose to fund projects with the highest expected returns privately but use public funding for projects with lower expected returns. Third, public subsidies might go to firms that would have conducted research projects even in the absence of receiving the subsidies (Gonzalez, Jaumandreu, and Pazo 2005), which would lead to a none-sizeable effect of public R&D in stimulating private R&D.

Empirical evidence on the value of public R&D and whether public and private R&D are complementary are mixed. Chen et al. (2020) examined the impact of public R&D on stock returns among US firms from 1987 to 2010 using a matching estimator. Their findings revealed that firms in US states with higher public R&D spending earned higher abnormal stock returns due to reductions in innovation costs and productivity spillovers from public

R&D spending. Although R&D spending tends to be procyclical (Ouyang 2011), Spanish firms that received public funding before a crisis were persistent in intramural R&D spending during crisis periods (Cruz-Castro et al. 2008). Hud and Hussinger (2015) showed that public R&D raised private R&D spending among German SMEs between 2006 and 2010 except during crisis periods where crowding out effects arose as firms relocated normal R&D spending to other business areas. Nevertheless, there has been evidence of crowding out between private R&D and public subsidies for French firms especially among SMEs operating in low R&D intensive industries (Marino et al. 2016). There were no additionality effects from public R&D in a recent study involving the largest R&D performing firms worldwide with average yearly sales of €800 million (Szucs 2020). However, when the sample was split by size and R&D intensity, crowding in of private R&D occurred for smaller sized firms with higher R&D intensity who received smaller grants, but crowding out effects were found for firms with lower R&D intensities. Finally, other studies have linked complementarity to the type of public funding or to the funder. A rise in R&D tax credits by 10% was predicted to increase labour productivity growth by 0.4% per year for US firms between 1975 and 2000, but there were no returns from direct funding of R&D via the Federal funds to R&D (Minniti and Venturini 2017). Among 44,000 research active UK firms from 1998 to 2012, there were additionality effects from EU subsidies on private R&D intensities by about 2% but no additionality effects from UK subsidies (Ugur, Solomon, and Trushin 2015).

2.3 R&D and Productivity: Impact of firm size and sectoral heterogeneities

Apart from differences in the productivity effects of the different R&D types, there is some evidence of heterogeneity in the returns to R&D from the literature, depending on the size of firm and type of industry.

2.3.1 Firm size

The importance of firm size in the relationship between R&D and productivity has been acknowledged by the literature. Smaller firms have greater efficiency, stronger incentive structures and can respond rapidly to market needs, so have an advantage in product innovation (Tsai and Wang 2005; Spescha 2019). On the other hand, large firms have higher productivity levels, bigger R&D resources and can benefit from economies of scale, although the high levels of bureaucracy could reduce the efficiency of R&D (Tsai and Wang 2005). Among 126 Taiwanese manufacturing firms from 1994 to 2000, Tsai and Wang (2005) found that firm size had a U-shaped moderating effect between R&D and TFP, with the marginal effect of R&D on TFP falling for smaller firms but rising for larger firms. Using micro data on large UK establishments from 1997-2008, Bond and Guceri (2017) showed that R&D performing establishments were 14% more productive than non-R&D performing establishments. In contrast, the average difference in mean productivity levels between R&D performing and non-R&D performing manufacturing firms in Spain were higher in SMEs compared with larger firms (Doraszelski and Jaumandreu 2013). Similarly, Spescha (2019) found positive and significant returns from R&D on sales growth for SMEs but insignificant returns from larger firms in Switzerland from 1995 to 2012.

Regarding the R&D types, Higon (2016) argues that large firms benefit more from basic research activities than smaller firms because their larger market shares and greater product diversification improves their ability to exploit the results from basic research. In their study of Spanish manufacturing firms, complementarity between internal and external basic R&D

(through cooperation in basic research with universities) was limited to small firms only. Large firms benefitted from internal basic R&D only, suggesting that internal and extramural R&D were substitutes for larger firms (since these firms have greater internal R&D capability and would want to minimise knowledge leakages). In contrast, Tamayoa and Huergob (2017) found that larger firms, firms that engaged in continuous internal R&D and firms in medium to high-tech sectors were more likely to offshore R&D services. Finally, recent literature has suggested that public subsidies are more effective when targeted at smaller firms (Szucs 2020, Belitz and Leipras (2016) due to financial constraints which hinders their engagement in R&D. Public funding to small firms improves their access to external financing (Meuleman and De Maeseneire 2012)). Using a regression discontinuity method, Bronzini and Piselli (2016) examined the impact of R&D subsidies on innovation in Emilia-Romagna of Northern Italy. R&D subsidies increased the number of patent applications for small firms only. Similarly, Vanino et al. (2019) showed that UK research council grants to participating firms in the UK from 2004 to 2016 had a significant effect on turnover growth for SMEs but not for large firms.

2.3.1 Sectoral heterogeneities

Studies relating R&D to productivity are mostly concentrated in the manufacturing sector where more data exists and the relationship between R&D and firm innovation is stronger (Morris, 2018). However, R&D in service sectors have become more significant. For instance, among Finish firms, Leiponen (2012) found that R&D was as important for service innovation as they were in the manufacturing sector, although the service sector lacked strong R&D management capabilities.

Ortega-Argiles, Piva, and Vivarelli (2015) synthesise the literature on why the technological capacity of industries might influence the impact of R&D on productivity. On the one hand, the productivity effect of R&D is expected to be stronger in high-tech sectors and R&D user services, which are characterised by more technological opportunities, radical innovations, and "innovative complementarities and synergies between R&D, higher skills and organisational change". On the other hand, the latecomer hypothesis suggests that R&D and productivity growth would be stronger in low-tech firms and traditional service sectors with lower R&D and incremental investments due to a "latecomer" advantage. Other reasons for a higher productivity premium from R&D in high-tech sectors are higher persistence in innovative activities and stronger knowledge spillovers (Kancs and Siliverstov 2016).

Ortega-Argiles, Piva, and Vivarelli (2015) examined the impact of intramural R&D on labour productivity in US and European manufacturing and service firms from 1990–2008. The elasticity of labour productivity with respect to knowledge stock per employee in the R&D-user service sector (0.114) was double that of the manufacturing sector (0.073). Also, the productivity impact of R&D was higher in high-tech manufacturing than other manufacturing sectors. A higher productivity premium from R&D in high-tech and knowledge intensive sectors is consistent with several other studies (Doraszelski and Jaumandreu 2013; Kancs and Siliverstov 2016; Baum et al., 2017). In contrast, Pieri, Vecchi, and Venturini (2018) found that R&D had a positive and significant impact on productivity in high and low-tech sectors alike, with only marginal differences between them, because R&D played important, albeit different roles in both sectors. In high-tech sectors, where R&D is geared towards breakthrough innovations, it increased technical change (i.e. led to shifts in the production frontier) but in low-tech sectors where R&D is more incremental and technology adoption rather innovations take place, it increased technical efficiency.

Among Belgian manufacturing firms from 2002 to 2007, Czarnitzki and Thorwarth (2012) found that basic R&D generated a high productivity premium in high-tech sectors but no effect in low-tech sectors because the higher risk inherent in basic R&D disincentivised firms from engaging in basic R&D in low-tech sectors. There are differences in lag structure across sectors between in-house basic R&D and the propensity of firms to pioneer products. Higon (2016) showed that basic research had both immediate and long-term outcomes in enabling firms to introduce new products to the market, but there was a considerable lag of at least five years for firms in high and medium high technology sectors. The delay in realising innovative products from basic research in high-tech sectors was due to the complexity of knowledge in these sectors, whereas basic research in low-tech sectors tended to improve the absorptive capacity of firms to enable them "to be more effective in searching for applied solutions" (Higon 2016, 824).

2.4 Conclusion

The impact of R&D on productivity has been well researched with the general consensus that R&D has a positive effect on growth. However, most studies treat R&D as a homogenous activity and model it as a linear function of productivity. Recent research has begun to address these limitations. This section has undertaken a detailed reviewed of the recent literature on R&D regarding non-linear relationships, the impact of different R&D types and their linkages and how these effects are moderated by firm size and sector.

This study provides additional insights on the R&D-productivity nexus in several ways. First, it examines non-linear effects between different R&D types and productivity. Research on non-linear effects are few and limited to either total R&D or intramural and extramural R&D. In this study, non-linear effects between R&D and productivity are estimated not only for total R&D but also for intramural, extramural, basic, applied/experimental, private and public R&D. Second, it examines whether different R&D types are complementary or substitutes. To the best of my knowledge, no study has examined whether basic and applied/experimental R&D are complementary as other studies have focused on links between intramural and extramural R&D. Also, while much of the literature has examined whether public R&D crowds in or crowds out private R&D, this study contributes to the handful of studies that tests whether public and private R&D are complementarity in affecting firm productivity. Finally, the study examines whether the non-linear effects and interactions between the different R&D types are affected by firm size and sector.

3. Methodology

3.1 Empirical framework and Estimation technique

To investigate the impact of R&D on productivity, the model of Lokshin, Belderbos, and Carree (2008) is adopted as it allows for the testing of economies or diseconomies of scale from R&D and interactions between different types of R&D.

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

$$Q_{it} = \alpha_i L_{it}^{\beta} C_{it}^{\delta} K_{it}^{\gamma} e^{\sigma_{it}} \ \ldots (1)$$

where Q is output, L is labour, C is physical capital stock, K is knowledge stock, $\beta, \delta \ and \ \gamma$ are elasticities with respect to labour, physical capital and knowledge stock respectively. The subscripts i and t refer to firm and time respectively. The parameter σ is a firm specific efficiency parameter.

Dividing both sides by labour, taking the logarithms and first differencing equation (1) yields (2) below:

$$\Delta q_{it} = (\beta - 1)\Delta l_{it} + \delta \Delta c_{it} + \gamma \Delta k_{it} + \Delta \sigma_{it} \ldots (2)$$

To allow for convergence in the efficiency levels between firms, and hence, persistence in productivity (see e.g. Raymond et al. 2015), the changes in firm specific efficiency is modelled as a function of past productivity.

$$\Delta \sigma_{it} = \theta q_{it-1} + \varepsilon_{it} \ldots (3)$$

where θ ranges from 0 (no convergence) to -1 (complete convergence). The error term, ε_{it} consists of a firm specific term (μ_i) to capture firm specific factors that have a permanent impact on productivity such as managerial abilities, a year specific term (λ_t) to capture unobserved time specific shocks to productivity that is common across all firms such as exchange rate shocks, and a serially uncorrelated measurement error (v_{it}):

$$\varepsilon_{it} = \lambda_t + \mu_i + v_{it} \ldots (4)$$

As indicated by Hall et al. (2010), the specification in equation (2) is based on the assumption of factor share equalisation across firms. However, this assumption may be too restrictive if firms adjust their factor use to technological and/or demand conditions in their industries. Therefore, a large body of the R&D-productivity literature adopts the assumption of rate-of-return equalisation. In such specifications, the elasticity of the R&D capital is decomposed in accordance with (5) below.

$$\gamma \Delta k_{it} \approx \frac{\partial Y}{\partial K} \frac{K_{it-1}}{Y_{it-1}} \frac{\Delta K_{it}}{K_{it-1}} \approx \rho \frac{\Delta K_{it}}{Y_{it-1}} \ldots (5)$$

where $\rho = \frac{\partial Y}{\partial K}$ is the rate of return to R&D investment and is the coefficient of interest. Following Lokshin, Belderbos, and Carree (2008), the change in knowledge capital intensity, $\frac{\Delta K_{it}}{Y_{it-1}}$ can be expressed as a function of R&D investment intensity. Four alternative functions are specified to allow for interactions between different R&D types: Hence, changes in knowledge capital stock is a function of: total R&D intensity in (6a), intramural and extramural R&D intensities in (6b); basic and applied/experimental R&D intensities in (6c); and private and public R&D intensities in (6d)[1].

1 Lokshin, Belderbos, and Carree (2008) specified changes in knowledge capital stock as a function of Internal and External R&D only. I expand this to include other types of R&D.

$$\frac{\Delta K_{it}}{Y_{it-1}} = f\left(\frac{R_{it-1}}{Y_{it-1}}\right) = f(r_{it-1}) \dots (6a)$$

$$\frac{\Delta K_{it}}{Y_{it-1}} = f\left(\frac{R_{it-1}^{intra}}{Y_{it-1}}, \frac{R_{it-1}^{extra}}{Y_{it-1}}\right) = f(r_{it-1}^{intra}, r_{it-1}^{extra}) \dots (6b)$$

$$\frac{\Delta K_{it}}{Y_{it-1}} = f\left(\frac{R_{it-1}^{basic}}{Y_{it-1}}, \frac{R_{it-1}^{appexp}}{Y_{it-1}}\right) = f(r_{it-1}^{basic}, r_{it-1}^{appexp}) \dots (6c)$$

$$\frac{\Delta K_{it}}{Y_{it-1}} = f\left(\frac{R_{it-1}^{pri}}{Y_{it-1}}, \frac{R_{it-1}^{pub}}{Y_{it-1}}\right) = f(r_{it-1}^{pri}, r_{it-1}^{pub}) \dots (6d)$$

Finally, as in Lokshin, Belderbos, and Carree (2008), equations $7a$ to $7d$ allow for both complementarity/ substitution between different types of R&D and for non-linearities that may indicate economies or diseconomies of scale. Recent research that control for non-linearities in the relationship between R&D and productivity in a knowledge capital model finds evidence of diseconomies of scale from in-house and external R&D which they ascribe to the cost spreading argument of Cohen and Klepper (1996). In this argument, firms with larger R&D budgets pursue more marginal R&D projects which leads to diminishing scale effects in R&D productivity. In a sample of 1500 top innovating firms in the OECD, Kancs and Siliverstovs (2016) also find evidence of non-linear effects of R&D on productivity. A minimum level of R&D was necessary to reap significant productivity rewards, but after this minimum threshold, the relationship between R&D and productivity became concave. At low levels of R&D, the accumulation of additional knowledge was beneficial for productivity as firms built up absorptive capacity and know-how. However, at higher levels of R&D, the capacity to find new ideas declined and hence the fall in productivity.

$$\gamma \Delta k_{it} = \varphi[\eta_1 r_{it-1} + \eta_2 (r_{it-1})^2] \dots (7a)$$

$$\gamma \Delta k_{it} = \varphi\left[\eta_1 r_{it-1}^{intra} + \eta_2 r_{it-1}^{extra} + \eta_3 (r_{it-1}^{intra})^2 + \eta_4 (r_{it-1}^{extra})^2 + \eta_5 r_{it-1}^{intra} r_{it-1}^{extra}\right] \dots (7b)$$

$$\gamma \Delta k_{it} = \varphi\left[\eta_1 r_{it-1}^{basic} + \eta_2 r_{it-1}^{appexp} + \eta_3 (r_{it-1}^{basic})^2 + \eta_4 (r_{it-1}^{appexp})^2 + \eta_5 r_{it-1}^{basic} r_{it-1}^{appexp}\right] \dots (7c)$$

$$\gamma \Delta k_{it} = \varphi\left[\eta_1 r_{it-1}^{pri} + \eta_2 r_{it-1}^{pub} + \eta_3 (r_{it-1}^{pri})^2 + \eta_4 (r_{it-1}^{pub})^2 + \eta_5 r_{it-1}^{pri} r_{it-1}^{pub}\right] \dots (7d)$$

Apart from allowing for testing of economies/diseconomies of R&D from each type of R&D, equations $7b$ to $7d$ also allow for testing whether different types of R&D are complements or substitutes. Equation $7b$ allows for interactions between intramural and extramural R&D. Investment in intramural R&D builds the absorptive capacity of firms, allowing them to positively exploit external knowledge (Lokshin, Belderbos, and Carree 2008; Catozzella and Vivarelli 2014). Similarly, although the high risk and generality of basic research might not yield immediate productivity returns, investment in basic research stimulates other types of R&D and builds up the absorptive capacity of firms (Green and Scotchmer 1995). Hence, equation $7c$ tests whether basic R&D is complementary with applied and experimental R&D. Lastly, equation $7d$ allows for the testing of complementarity between private and public funding of R&D. Reviews of the literature on whether public R&D have increased private R&D spending are mixed (David, Hall, and Tootle 2000; Dimos and Pugh 2016) but there has been some evidence of additionality between public and private R&D in continental European countries (See, for instance, Hussinger 2008). Among UK firms, Ugur, Solomon, and Trushin

(2015) do not find evidence of additionality between UK subsidies and privately funded R&D but find complementarity between EU subsidies and private R&D spending. Aiello, Albanese, and Piselli (2019) find complementarity between firms that receive public financial support and private R&D spending among Italian manufacturing SMEs, although the complementarity does not translate into higher innovation output. In fact, firms who received public financial support had less innovative output than firms who did not receive such support.

Combining equations 2, 3, 4, 7a-7d, adding control variables and rewriting $\Delta q_{it} = q_{it} - q_{it-1}$ with q_{it-1} moved to the right hand side yields equations 8a to 8d:

$$q_{it} = (1+\theta)q_{it-1} + (\beta - 1)\Delta l_{it} + \delta\Delta c_{it} + \varphi[\eta_1 r_{it-1} + \eta_2 (r_{it-1})^2] + \emptyset controls + \lambda_t + \mu_i + v_{it} \dots (8a)$$

$$q_{it} = (1+\theta)q_{it-1} + (\beta - 1)\Delta l_{it} + \delta\Delta c_{it} + \varphi\left[\eta_1 r_{it-1}^{intra} + \eta_2 r_{it-1}^{extra} + \eta_3 (r_{it-1}^{intra})^2 + \eta_4 (r_{it-1}^{extra})^2 + \eta_5 r_{it-1}^{intra} r_{it-1}^{extra}\right] + \emptyset controls + \lambda_t + \mu_i + v_{it} \dots (8b)$$

$$q_{it} = (1+\theta)q_{it-1} + (\beta - 1)\Delta l_{it} + \delta\Delta c_{it} + \varphi\left[\eta_1 r_{it-1}^{basic} + \eta_2 r_{it-1}^{appexp} + \eta_3 (r_{it-1}^{basic})^2 + \eta_4 (r_{it-1}^{appexp})^2 + \eta_5 r_{it-1}^{basic} r_{it-1}^{appexp}\right] + \emptyset controls + \lambda_t + \mu_i + v_{it} \dots (8c)$$

$$q_{it} = (1+\theta)q_{it-1} + (\beta - 1)\Delta l_{it} + \delta\Delta c_{it} + \varphi\left[\eta_1 r_{it-1}^{pri} + \eta_2 r_{it-1}^{pub} + \eta_3 (r_{it-1}^{pri})^2 + \eta_4 (r_{it-1}^{pub})^2 + \eta_5 r_{it-1}^{pri} r_{it-1}^{pub}\right] + \emptyset controls + \lambda_t + \mu_i + v_{it} \dots (8d)$$

The control variables include: the Herfindahl index computed at the 2-digit level, a UK ownership dummy, wage ratio and the knowledge gap as a measure of absorptive capacity or technological distance.

Equations $8a$ to $8d$ are dynamic panel data models, so are estimated using the System GMM estimator (SYSGMMM) by Arellano and Bover (1995) and Blundell and Bond (1998). The SYSGMM is particularly suitable for estimating short dynamic panels that would render the pooled Ordinary Least squares and fixed effects estimators biased in the presence of the lagged dependent variable (Bond, Hoeffler, and Temple 2001). The SYSGMM has the advantage of controlling for unobserved heterogeneity, endogeneity and measurement error (Blundell & Bond 1998; Bond, Hoeffler, and Temple 2001; Roodman 2009b). There are three conditions to ensure the validity of the SYSGMM: (a) absence of serial correlation in the error term, (b) exogeneity of the instruments and (c) exogeneity of the extra instruments used in the SYSGMM compared with the first-differenced GMM estimator.[2] The first condition is tested using the AR tests for first and second differences of the residuals. There must be a significant negative correlation in the first differences of the residuals but no correlation in the second differences of the residuals. The second condition can be tested using the Hansen test (Bowsher 2002; Parente and Santos Silva 2012). The third condition can be tested using the Difference-in-Hansen test (Roodman 2009b). The null hypothesis for both the Hansen and Difference-in-Hansen tests is exogeneity of the instruments. One problem with the SYSGMM is the

[2] The first-differenced GMM estimator of Arellano and Bond (1991) is constructed by taking the first differences of all variables and instrumenting them using the lagged level values of the series. However, the first differenced estimator suffers from bias in short persistent panel because the lagged values become poor instruments of the first differenced series (Bond, Hoeffler, and Temple 2001). The system GMM estimator was created to overcome this problem. The estimator augments the first differenced series in the first differenced estimator with the original level series instrumented with the lagged first differences of the series. It is the validity of these extra instruments (lagged first differences) that the third condition tests.

proliferation of instruments which can lead to bias and render the specification tests unreliable. Hence, the SYSGMM with a collapsed instrument set is used, as recommended by Roodman (2009a, 2009b).

3.2 Data

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 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, it contains key data on productivity and employment measures for UK firms. The BERD is a repeated annual survey on R&D expenditure and employment from UK businesses.

After merging the datasets, firms that lacked key productivity measures such as value added were dropped. All observations with negative capital stock were also dropped. Only firms with data on at least three consecutive periods on output, capital stock, employment and R&D were kept. Finally, due to the extreme skewness of R&D intensity, the dataset was restricted to observations with R&D intensity less than 1. The final panel dataset consists of 8,284 firms and 27,588 observations from 1998 to 2012.[3]

Table 1 provides a summary of the variables in the model and their definitions.

Table 1: Definitions of Variables

Variable	Definition
	Dependent variable
$\boldsymbol{q}$	Log of gross value added per employee in constant 2008 prices.
	Independent variables
$\boldsymbol{\Delta l}$	Log growth of employment, Full time equivalent (FTE).
$\boldsymbol{\Delta c}$	Log growth of physical capital stock in constant 2008 prices.
$\boldsymbol{r_{it-1}}$	Lagged total R&D intensity (i.e. the lagged value of total R&D expenditure divided by gross value added).
$\boldsymbol{r_{it-1}^{intra}}$	Lagged intramural R&D intensity (i.e. the lagged value of intramural R&D expenditure divided by gross value added).
$\boldsymbol{r_{it-1}^{extra}}$	Lagged extramural R&D intensity (i.e. the lagged value of extramural R&D expenditure divided by gross value added).
$\boldsymbol{r_{it-1}^{intra} r_{it-1}^{extra}}$	$r_{it-1}^{intra} \times r_{it-1}^{extra}$
$\boldsymbol{r_{it-1}^{basic}}$	Lagged basic R&D intensity (i.e. the lagged value of basic R&D expenditure divided by gross value added).
$\boldsymbol{r_{it-1}^{appexp}}$	Lagged applied and experimental R&D intensity (i.e. the lagged value of applied and experimental R&D expenditures divided by gross value added).
$\boldsymbol{r_{it-1}^{basic} r_{it-1}^{appexp}}$	$r_{it-1}^{basic} \times r_{it-1}^{appexp}$

[3] Unfortunately, I was not able to extend the data set due to funding limitations and the prohibitive time cost involved in drawing data from the two sources. In addition, access to the database through the Secure Data Service was disrupted between March and April 2020 which was the period when the paper was being revised. Note that there are several cases in the literature where there is a time lag between the year of publication and the end year of the data. E.g. the sample period of Grillitsch, Schubert, and Srholec (2019) was from 2004 to 2011.

r_{it-1}^{pri}	Lagged private R&D intensity (i.e. the lagged value of privately funded R&D divided by gross value added).
r_{it-1}^{pub}	Lagged public R&D intensity (i.e. the lagged value of publicly funded R&D divided by gross value added).
$r_{it-1}^{pri} r_{it-1}^{pub}$	$r_{it-1}^{pri} \times r_{it-1}^{pub}$
	Control variables
UK ownership dummy	Dummy variable =1 if firm is UK owned; =0 if foreign owned.
Knowledge gap	Ratio of total R&D intensity of each firm to the firm with the largest R&D intensity at the 3-digit sector.
Herfindahl index	the Herfindahl index at the two-digit sector level
Wage ratio	The real average wage for each firm divided by average wage at the 3- digit level.

The dependent variable is labour productivity, which is measured by real gross value added at factor cost per employee. Mairesse and Hall (1996) reports 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 and deflated using two-digit output deflators from the ONS. To control for double counting, total current R&D expenditure was added to gross value added (Hall, Mairesse, and Mohnen 2010).

Labour is measured by the number of full-time equivalent employees. It was constructed by deducting 0.5 *part time employees from the total number of employees for each firm. Part-time employment was approximated by multiplying the number of full-time employees by the proportion of part time workers by year and two-digit sector. Data on full time employees was obtained from the ARD/ABS.

Physical capital stock was computed using the perpetual inventory method (PIM). The initial capital stock was obtained from ONS estimates. For subsequent years, the PIM was applied as follows: $K_t = (1-d)K_{t-1} + I_t$, where d is the depreciation rate of 9.3%[4] and I_t is real investment. Real investment was computed from net capital expenditure[5], deflated using one-digit gross fixed capital formation deflators from the ONS.

R&D expenditure (and its components) were obtained from BERD. In BERD, total R&D expenditure consists of intramural R&D and extramural R&D. Intramural R&D is research carried out within the firm. Extramural R&D is research commissioned by the firm to external organisations either within or outside the UK. Intramural R&D consists of basic R&D (research without specific applications), applied R&D (research towards a particular application) and experimental R&D (research conducted for the development of new or

[4] The depreciation rate of 9.3% is the average depreciation rate of plant and machinery (6%), buildings (2%) and motor vehicles (20%).

[5] To control for double counting, R&D capital expenditure on land and building, and plant & machinery were deducted from net capital expenditure.

substantially improved products, processes, systems or services).[6] Public R&D funding is defined as all intramural or extramural R&D funding that are provided by either the UK government or from EU sources. Private R&D funding refers to all other intramural and extramural R&D funding sourced either by the firm or other organisations from the UK or overseas.

The control variables include: a UK ownership dummy that takes the value of 1 if the firm is UK owned and 0 if owned by a foreign firm, a knowledge gap variable which proxies for technological distance, defined as 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, the Herfindahl index at the two digit sector level and the wage ratio. The wage ratio is defined as real average wage for each firm divided by average wage at the 3- digit level. Nominal wages were deflated using two-digit output deflators.

Table 2: Summary statistics: 1998- 2012

Variable	Mean	Standard Error
Real value added (£ million)	95.27	2451.51
Δ Real value added	2.15	2848.59
Employment: FTE (count)	361.73	3064.87
Δ Employment (FTE)	0.006	0.263
Capital stock (£ million)	36.928	396437.4
Δ Capital stock	-0.020	0.190
Wage ratio	1.01	0.63
Herfindahl index (2 digit)	0.044	0.060
Knowledge gap	0.144	0.203
Intramural R&D intensity	0.073	0.114
Extramural R&D intensity	0.006	0.025
Basic R&D intensity	0.005	0.022
Applied R&D intensity	0.029	0.060
Experimental R&D intensity	0.034	0.066
Public R&D intensity	0.004	0.023
Private R&D intensity	0.074	0.116

Table 2 shows summary statistics of the key variables. Average value added across the sample was about £95.27 million and the average number of full-time employees was 361 workers. The mean capital stock was £36.928 million. More research is undertaken within the firm rather than contracted to external organisations as average intramural R&D intensity exceeded average extramural R&D intensity by about 12-fold. The amount of applied and experimental R&D exceeded basic R&D which is in line with the literature that firms have more incentives to undertake applied and experimental R&D rather than basic R&D. Finally, private R&D intensity exceeded public R&D intensity by 18-fold on average.

[6] See ONS (2005) for more precise definitions.

4 Results

4.1 Main Findings

Table 3 presents the baseline results of the effect of total R&D intensity on labour productivity (measured as value added per worker). It presents estimates from the System GMM (SYSGMM) in column 4 with the pooled OLS (POLS), fixed effects (FE) and first differenced GMM estimator (FDGMM) for comparison. The specification tests show the validity of the SYSGMM. The p-values of the AR(1) and AR(2) tests indicate a significant correlation in the first differences of the error term but no second order correlation showing the absence of serial correlation in the error term. The p-values of the Hansen and difference-Hansen tests (p-values > 0.10) confirm the validity of the instruments. The coefficients on the lagged dependent variable lie between the pooled OLS and fixed effects estimates. This is as expected and shows the reliability of the SYSGMM, since the coefficient of the lagged dependent variable is known to be upwardly biased in POLS models and downwardly biased in FE (Bond, Hoeffler, and Temple 2001). The coefficient of the FDGMM is downwardly biased towards the FE estimates because of the weak instrument problem that the estimator suffers from in short persistent dynamic panels.

Focusing on column 4, the coefficients on total R&D intensity and its square are highly significant and suggest diseconomies of scale. This is in line with several findings (Lokshin, Belderbos, and Carree 2008; Furman, Porter, and Stern 2002; Kancs and Siliverstovs 2016; Hagedoorn and Wang 2012). At lower levels of R&D, ideas and innovations are easier to find and current R&D builds on the stock of knowledge from prior R&D investments to increase productivity (standing-on-shoulder effect). But, at higher levels of R&D, diminishing marginal returns kick in because as ideas and innovations are discovered it becomes more difficult to find newer ideas and innovations (fishing out effect). Also, it is likely that diseconomies of scale from larger firms, who are more R&D intensive, take place so R&D is less efficient due to managerial slack and bureaucratic inefficiencies.

Turning to the other variables, as expected, capital has a positive and significant effect on productivity, but the negative labour coefficient depicts decreasing returns to labour. None of the control variables are significant.

Table 3: Effect of Total R&D intensity on Productivity

(Dependent variable: Log of value added per employee)

	(1) Pooled OLS	(2) Fixed Effects	(3) First Differenced GMM	(4) System GMM
Log (Value added per employee)$_{t-1}$	0.825*** (62.15)	0.344*** (16.09)	0.446*** (5.95)	0.536*** (12.47)
Δ log of Capital stock	0.177*** (9.17)	0.136*** (6.00)	0.456** (2.02)	0.503** (2.53)
Δ log of Employment	-0.645*** (-23.91)	-0.408*** (-12.51)	-0.832*** (-2.77)	-0.689*** (-4.35)
Total R&D intensity	0.222*** (6.49)	0.0731*** (3.78)	0.139** (2.33)	0.110*** (5.15)
Total R&D intensity squared	-0.0012*** (-5.72)	-0.0004*** (-3.05)	-0.0018 (-1.46)	-0.0005*** (-4.14)
UK ownership dummy	-0.0274*** (-4.67)	-0.00741 (-0.64)	0.106 (1.12)	0.0468 (1.43)
Knowledge gap	0.0117 (0.60)	0.0843*** (2.66)	0.169 (1.19)	0.118 (1.02)
Herfindahl index	0.216*** (3.77)	0.273** (2.55)	0.998 (1.30)	-0.145 (-0.65)
Wage ratio	0.118** (2.32)	0.177*** (2.75)	0.271* (1.88)	0.287 (1.61)
Constant	0.514*** (13.72)	2.400*** (26.00)		1.575*** (9.78)
Firm/year observations	27588	27588	16130	27588
Firms		8284	5411	8284
Number of Instruments			125	135
AR(1) test: p-values			0.000***	0.000***
AR(2) test: p-values			0.401	0.350
Hansen test: p-values			0.879	0.447
Difference Hanson test: p-values				0.386

Notes: t statistics in parentheses, time dummies are included in all estimations. Two-digit sector dummies are included in the OLS and Fixed effects estimates. Standard errors robust to heteroskedasticity and serial correlation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 examines the impact of the R&D types on productivity using the SYSGMM with estimates from intramural and extramural R&D in column 1, applied/experimental and basic R&D in column 2 and privately funded and publicly funded R&D in column 3. Column 1 shows diseconomies of scale from intramural R&D, which is in line with Lokshin, Belderbos, and Carree (2008). Extramural R&D is not significant but the interaction term between intramural and extramural R&D is positive and significant, which shows complementarity between them. Investment in intramural R&D builds the absorptive capacity of firms to enable them to benefit from external R&D (Lokshin, Belderbos, and Carree 2008; Catozzella and Vivarelli 2014).

Column 2 depicts diseconomies of scale from applied and experimental R&D, but the quadratic term is not significant on basic R&D. In fact, in terms of magnitude, the returns to applied/experimental R&D exceeds the returns from all other R&D types. However, there are negative returns from basic R&D, which could be because the generality of basic research is not immediately translatable into sales but longer time lags of at least 2 years are needed for basic research to translate into productivity growth. This contrasts with the more immediate benefits from applied research (Sun, Wang, and Li 2016). The interaction term between basic R&D and applied/experimental R&D is positive, showing complementarity between them. This is in line with the literature that basic R&D builds up the absorptive capacity of firms (Czarnitzki and Thorwarth 2012), stimulates other types of research (Green and Scotchmer 1995) and, together with applied research, enables firms to learn from their own innovative failures (D’Este, Marzucchi, and Rentocchini 2018).

Private R&D intensity displays diminishing marginal returns to productivity (column 3). In line with the very scanty literature, privately funded R&D is positively related to productivity (Lang 2009), but, like intramural and applied/experimental R&D, it follows an inverted U-shaped relationship with productivity. Unfortunately, the square of public R&D had to be dropped due to collinearity. Therefore, it is not possible to test whether there are economies or diseconomies of scale on public R&D. However, neither publicly funded R&D nor its interaction with private R&D are significant. The lack of complementarity between public and private R&D is unsurprising since recent research shows no additionality effects between UK public subsidies and private R&D spending among UK firms (Ugur, Solomon, and Trushin 2015).

Table 4: ***Effect of R&D on productivity by type of R&D: (System GMM estimates)***

(Dependent variable: Log of value added per employee)

	(1)	(2)	(3)
Log (Value added per employee)$_{t-1}$	0.712*** (15.26)	0.519*** (8.94)	0.563*** (10.46)
∆ log of Capital stock	0.434** (2.37)	0.0969 (0.38)	0.278 (1.61)
∆ log of Employment	-0.653*** (-2.87)	-0.547** (-2.43)	-0.786*** (-4.07)
Lagged R&D intensity type 1	0.304*** (5.19)	0.464*** (4.31)	0.275*** (3.41)
Lagged R&D intensity type 1 squared	-0.0070*** (-2.92)	-0.0122*** (-3.43)	-0.0046*** (-2.84)
Lagged R&D intensity type 2	0.111 (0.74)	-1.267* (-1.95)	0.0015 (0.38)
Lagged R&D intensity type 2 squared	-0.0074 (-0.73)	0.197 (1.03)	-
Lagged R&D intensity type 1 * Lagged R&D intensity type 2	0.0119** (2.00)	0.132*** (3.33)	0.0421 (0.14)
Constant	1.133*** (5.98)	1.584*** (6.61)	1.514*** (8.31)
Firm/year observations	30446	24029	24970
Firms	8072	7863	8006
Number of Instruments	123	177	177
AR(1) test: p-values	0.0000***	0.0000***	0.0000***
AR(2) test: p-values	0.481	0.134	0.239
Hansen test: p-values	0.715	0.0584*	0.231
Difference Hanson test: p-values	0.260	0.114	0.728

*Notes: Column 1: R&D intensity 1 is intramural R&D and R&D intensity 2 is extramural R&D. Column 2: R&D intensity 1 is applied/experimental R&D and R&D intensity 2 is basic R&D. Column 3: R&D intensity 1 is private R&D and R&D intensity 2 is public R*D. T-statistics in parentheses, time dummies are included in all estimations. Standard errors robust to heteroskedasticity and serial correlation.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *All estimations include the control variables (UK ownership dummy, Knowledge gap, Herfindahl index and wage ratio) but these have not been reported for parsimony.*

4.2 Heterogenous Effects by size of firm, type of sector.

4.2.1 Firm size

The first two columns of Table 5 present results on the effect of total R&D on productivity by firm size and Tables 7 and 8 in the appendix display results by R&D type for SMEs and large firms respectively. The concave relationship between total R&D and productivity holds irrespective of firm size (Table 5) with the returns from total R&D for SMEs slightly stronger than for larger firms. The finding that total R&D is beneficial to both small and large firms is contrary to research such as Tsai and Wang (2005) and Spescha (2019) that predict significantly stronger productivity effects either small or large firms.

When R&D is separated by type, the returns to intramural and extramural R&D, and their interactions are not significant for SMEs (Table 7, column 1). For large firms (Table 8, column 1), only the quadratic terms of intramural and extramural R&D are significant meaning that a minimum level of intramural or extramural R&D is necessary for large firms to reap positive returns from them R&D types. Larger firms tend to offshore R&D services more intensively than smaller firms since they have more contacts (Tamayoa and Huergob 2017). However, the results suggest that intramural and extramural as substitutes which is line with the transaction cost theory that firms choose to engage in either internal or external research depending on which has lower transaction costs (Radicic and Balavic (2019) or might choose intramural rather than extramural R&D to reduce technology leakages (Tamayoa and Huergob 2017).

There are decreasing marginal returns to applied/experimental R&D for SMEs (Table 7, column 2) but for large firms, the quadratic term is insignificant (Table 8, column 2). Basic R&D is insignificant for both SMEs and large firms. Complementarity exists between basic and applied/experimental R&D among SMEs (Table 8, column 2) but unfortunately, collinearity issues make it impossible to test for complementarity in the large firm sample.

Privately funded R&D has an inverted U-shaped relationship with productivity for both SMEs and large firms (Tables 7 and 8, column 3). Among SMEs, public R&D and the interaction terms between private and public R&D are insignificant, even though in the UK, smaller firms are more likely to receive public funding (Ugur, Solomon, and Trushin 2015). The lack of significance on publicly funded R&D among SMEs is surprising and contrary to the recent literature (Szucs 2020; Belitz and Leipras 2016; Vanino, Roper, and Becker 2019) that suggest that public research funding are more fruitful in smaller firms due to their financial constraints. Unfortunately, results relating to public R&D and its interaction with private R&D are very unstable in the large firm sub-sample due to collinearity issues.

Table 5: Effect of Total R&D intensity on Productivity, by size of firm and Pavitt class ***(System GMM estimates)***

(Dependent variable: Log of value added per employee)

	1 **SMEs**	2 **Large firms**	3 **Pavitt class 1**	4 **Pavitt class 2**	5 **Pavitt class 3**	6 **Pavitt class 4**
Log (Value added per employee)$_{t-1}$	0.318*** (6.63)	0.550*** (8.46)	0.773*** (10.02)	0.288*** (3.56)	0.521*** (5.40)	0.519*** (7.67)
Δ log of Capital stock	0.084 (0.58)	0.294 (1.44)	0.801*** (4.12)	-0.013 (-0.08)	-0.371 (-1.06)	0.235 (1.03)
Δ log of Employment	-0.262 (-1.12)	-0.526* (-1.92)	-1.287*** (-4.39)	0.019 (0.09)	-0.191 (-0.60)	-0.470** (-2.11)
Total R&D intensity	0.141*** (2.78)	0.103*** (3.12)	0.377*** (6.11)	0.580** (2.36)	0.639** (2.21)	0.254** (2.39)
Total R&D intensity squared	-0.0023* (-1.78)	-0.0005** (-2.47)	-0.006*** (-4.14)	-0.0248** (-2.18)	-0.013* (-1.73)	-0.0014** (-2.20)
Constant	2.603*** (11.94)	1.807*** (7.71)	0.990*** (2.71)	1.999*** (4.74)	0.955** (2.31)	1.542*** (6.66)
Firm/year observations	11135	11246	5234	5021	5291	10469
Firms	5041	3053	1628	1686	1538	3460
Number of Instruments	136	135	136	126	127	135
AR(1) test: p-values	0.000***	0.000***	0.000***	0.000***	0.0009***	0.000***
AR(2) test: p-values	0.846	0.870	0.883	0.0997	0.561	0.494
Hansen test: p-values	0.679	0.537	0.684	0.685	0.761	0.170
Difference Hanson test: p-values	0.175	0.436	0.592	0.660	0.201	0.114

Notes: Column 1: Estimations for Small and medium sized enterprises (SMEs). SMEs are defined as firm with 250 or less employees. Column 2: Estimations for large firms. Large enterprises are defined as firms with more than 250 employees. Column 3: Estimations for Pavitt class 1, which consists of science-based industries. Column 4: Estimations for Pavitt class 2, which consists of sectors that are specialized suppliers of technology. Column 5: Estimations for Pavitt class 3, which consists of scale-intensive industries. Column 6: Estimations for Pavitt class 4, which consists of industries dominated by technology suppliers. T statistics in parentheses, time dummies are included in all estimations. Standard errors are robust to heteroskedasticity and serial correlation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *All estimations include the control variables (UK ownership dummy, Knowledge gap, Herfindahl index and wage ratio) but these have not been reported for parsimony.*

4.2.2 Sectors

Table 6 in the appendix presents the impact of total R&D intensity by broad sector. The concave relationship between R&D intensity and productivity holds only in the manufacturing sector. In the service sector, the returns to R&D is positive and linear. The results might suggest that firms in the service sector benefit more from R&D than manufacturing sector firms due to the higher rates of return, which supports the finding of Leiponen (2012). Tables 9 and 10 in the appendix display results for the manufacturing and service sectors respectively by type of R&D. Intramural R&D is positive and linear in the manufacturing sector but insignificant in the service sector. Extramural R&D is not significant in either sector, nor is the interaction term between extramural and intramural R&D. Basic R&D is not significant in the service sector but is negative in the manufacturing sector. The negativity of basic R&D could be due to the longer time lag that it takes for basic research to affect innovation and productivity (Sun, Wang, and Li 2016; Higon 2016), Applied/experimental R&D is insignificant in the manufacturing sector and there is no evidence of complementarity between basic and applied/experimental R&D. However, in the service sector, applied and experimental R&D exhibits diseconomies to scale and the quadratic term in basic R&D is positive and significant. Moreover, there is complementarity between basic and applied/experimental R&D. These results lend support to the effect of product innovation being strongest in the service sector (Hall and Sena 2017) but might even be negative in the manufacturing sector (Aboal and Garda 2016). Private R&D exhibits diseconomies of scale in both the manufacturing and service sectors, with public R&D and the interaction term between private and public R&D insignificant.

Columns 3 to 6 of Table 5 present results for the effects of total R&D on productivity by the Pavitt technological classes. The inverted U-shaped relationship between total R&D and productivity holds regardless of Pavitt technological class. The highest returns to R&D are from Pavitt class 3, which consists of scale intensive industries. Hence, the results might suggest that the returns to R&D increases with market power. Tables 11 to 14 in the appendix depicts results of R&D types for Pavitt classes 1 to 4 respectively [7]. Pavitt class 1 for firms in science-based industries (Table 11) consists of large, research intensive, high-tech firms (Pavitt 1984). The quadratic terms of intramural and extramural R&D are both positive, showing that higher levels of intramural and extramural R&D expenditures are necessary to obtain a positive effect on productivity, which is consistent with the standing-on-shoulder effect (Furman, Porter and Stern 2002), where R&D builds on existing knowledge to stimulate output. There does not seem to be any evidence of the fishing-out effect in this Pavitt class. Intramural and extramural R&D are substitutes which is in line with Ceccagnoli et al. (2010) that firms with strong internal R&D capabilities are unlikely to engage in extramural R&D to prevent knowledge leakages. None of the other R&D types are significant (Table 11, columns 2 and 3). Pavitt class 2 (Table 12) consists of specialised suppliers. These are small sized firms that operate in very competitive sectors and rely on firm specific knowledge and quick responses to the needs of customers (Pavitt 1984). Hence, it is unsurprising that intramural and privately funded R&D are important to this class of firms. Results show diminishing marginal returns to intramural R&D but private R&D has a linear effect on productivity. Other R&D types are not significant. Pavitt class 3 (Table 13) are scale-intensive industries that are characterised by economies of scale (Pavitt, 1984). This group consists of low-tech and medium-tech firms. Only the quadratic term of extramural R&D is significant, showing that higher levels of extramural R&D are important for productivity. Intramural R&D is insignificant, and the negative interaction term shows that intramural and extramural R&D are substitutes. This finding supports the fact that larger rather than smaller firms tend to offshore R&D (Tamayoa and Huergob 2017). Given the low technological intensity of these firms, they are likely to have low levels of internal R&D and hence substitute extramural R&D for intramural R&D (Hagedoorn and Wang 2012). Privately funded R&D is characterised by an inverted U-shaped relationship with productivity. Basic, applied/experimental and public R&D are all insignificant. Pavitt class 4 (Table 14) consist of mainly low-tech manufacturing and traditional service sectors. Most of the R&D types are insignificant which is consistent with the literature that suggests that the

[7] There is a fifth Pavitt class consisting of unclassified industries which is not report, but is available upon request .

returns to R&D are less prevalent in low-tech sectors (see e.g. Kancs and Silverstovs 2016; Czarnitzki and Thorwarth 2012). Applied R&D, however, has a significantly positive linear effect, which supports the findings of Pieri, Vecchi, and Venturini (2018) that applied and experimental R&D are important in increasing TFP in lower tech sectors by reducing technical efficiency. Interesting, this sector is the only group where public R&D funding is significant, which might be partly explained by the fact that UK firms with low R&D capital are more likely to attract public subsidies (Ugur, Solomon and Trushin (2015). However, privately funded and publicly funded research are substitutes, which supports the findings of Marino et al. (2016) that public and private R&D are substitutes in low-tech sectors so would not increase innovation output (Czarnitzki and Hussinger 2018) and hence productivity.

5. Conclusion

This research has examined the returns of R&D on labour productivity using detailed UK firm level data from 1998 to 2012. Most of the literature regards R&D as a homogenous activity that is a linear function of productivity, which might explain the very varied results in the literature on the impact of R&D on productivity. This article aimed to provide fresh insights on the R&D-productivity nexus by analysing three key objectives: First, it investigated whether a non-linear relationship existed between R&D (and its various types) and productivity. Second, it examined the impact of the different R&D types on productivity and whether various R&D types were complements or substitutes. Third, it analysed whether the relationship between R&D and productivity was affected by firm size, broad sector (manufacturing or service) and the technological intensity of sectors.

The dynamic panel data model of Lokshin, Belderbos, and Carree (2008) was adopted to allow for non-linearities and interactions between different types of R&D. Estimations were conducted using the system GMM estimator. The main findings and their implications can be summarised as follows:

First, R&D has a positive impact on productivity with strong evidence of diseconomies of scale from total R&D intensity, intramural R&D, applied/experimental R&D and private R&D. The finding of an inverted U-shaped relationship is consistent with the limited literature (Lokshin, Belderbos, and Carree 2008; Kancs and Silverstovs 2016) that have accounted for non-linearities in R&D. This study contributes to the literature by evidencing the existence of diminishing returns to scale for other types of R&D beyond total R&D and intramural R&D. Therefore, an implication for future research is that it is necessary to control for non-linearities in R&D-productivity models to avoid a potential source of omitted variable bias.

Second, the R&D types that are positively linked with productivity in the UK are intramural R&D, applied/experimental R&D and privately funded R&D. These are largely in line with existing literature (Lokshin, Belderbos, and Carree 2008; Sun, Wang, and Li 2016; Czarnitzki and Hussinger 2018; Lang 2009). Intramural R&D, and to some extent, private R&D have been linked positively with innovation output (Higon 2016; Czarnitzki and Hussinger 2018) and building the absorptive capacity of firms (Lokshin et al. 2008) while applied/experimental research are linked to more immediate productivity gains for firms (Sun, Wang, and Li 2016). The lack of significance in basic R&D could be due to the substantial lags that exist between basic R&D and productivity or innovation output (Sun, Wang, and Li 2016; Higon 2016) or the very low investment in basic R&D in the UK. The average basic R&D intensity in the sample was 0.5% with applied and experimental R&D intensity being 2.9% and 3.4% respectively. This is in stark contrast to the mean basic R&D intensity of 2.05% across 23 OECD countries from 1996 to 2010 (See Sun, Wang, and Li 2016). Public R&D is not significantly related to productivity.

Third, consistent with Lokshin, Belderbos, and Carree (2008) and Catozzella and Vivarelli (2014), complementarity exists between intramural and extramural R&D among UK firms. There is also complementarity between basic and applied/experimental R&D. To the best of my knowledge, no other study has tested for interactions between basic and applied/experimental R&D and this finding is therefore a contribution to the literature and a potential area of further research. The interaction between private and public R&D is not significantly related to productivity, which is an implication of the lack of additionality between public and private R&D found in studies such as Szucs (2020). The fact that the various R&D types contribute differently to productivity and that complementarity exists between at least some R&D types implies that R&D should not be treated as a homogenous unit because the returns to productivity depend on the type of R&D. Hence, if different R&D types are treated as substitutes and excluded from the model (which is usually the case), then it is unsurprising that different studies yield very different estimates on the returns to R&D, because their total R&D may consist of different combinations of complementary R&D types.

Fourth, diminishing marginal returns between total R&D intensity and productivity holds regardless of firm size. Moreover, total R&D is important to both SMEs and large firms with similar rates of return which is contrary to studies such as Tsai and Wang (2005) or Spescha (2019) that suggests that the impact of R&D significantly differs by size of firm. However, the results are very heterogenous when R&D is analysed by type. For instance, while intramural and extramural R&D are insignificant for SMEs, only the quadratic terms of both R&D types are significant for large firms. Intramural and extramural R&D are substitutes for large firms only, most probably to reduce the risk of technology leakages (Tamayoa and Huergob 2017).

Fifth, the inverted U-shaped relationship between total R&D and productivity holds in the manufacturing sectors and all Pavitt classes but not in the service sector where R&D has a positive but linear effect on productivity. Nevertheless, there is a lot heterogeneity in the relationship across sectors when R&D is distinguished by type, and a few results are worth emphasising: One finding is that basic and applied/experimental R&D are complementary in the service sector but not in the manufacturing sector. This is an interesting result that deserves further investigation, especially given the limited research of the R&D-productivity relationship in service sectors. A second finding is that R&D has small returns in low-tech industries (Pavitt class 4) as most R&D types were insignificant, which is in accordance with the literature (Kancs and Silverstovs 2016; Czarnitzki and Thorwarth 2012). A third finding is that internal and external R&D are substitutes in technological classes where large firms dominate (i.e. Pavitt classes 1 and 3), which suggests that large firms regard internal and external R&D as substitutes to reduce transaction costs (Radicic and Balavac 2019) especially were the risk of knowledge leakage is high. A fourth finding is that publicly funded R&D is generally insignificant except in low-tech sectors (Pavitt class 4), which might reflect the fact that UK firms with lower R&D capital have a higher propensity of attracting public funding (Ugur, Solomon, and Trushin 2015).

A policy implication of the results is that public funding of R&D in the UK is not effective in increasing productivity even among SMEs that have limited financial resources. Choi and Lee (2017) suggest that public funding is best targeted at projects were market failure is more prevalent, such as sectors with lots of new product innovations (Pavitt classes 1 and 2). Second, there is some evidence that SMEs might be hindered more by non-financial challenges (such as the supply of skilled personnel and competition regulation) than by financing problems (Belitz and Lejpras 2016). This suggests that, in addition to providing subsidies and tax credits, R&D policies should also be targeted at improving the innovation environment for SMEs. Finally, basic R&D in the UK is very low compared with OECD countries and should be increased. Although, basic research is a riskier type of research that does not yield immediate returns, it is vital for growth since it shifts production frontiers (Sun, Wang, and Li 2016).

A caveat of this study is that the timing of the sample (1998 to 2012) includes the period of the global financial crisis in 2008 and initial recovery from it. Ugur, Solomon, and Trushin (2015) show that R&D intensity among UK firms fell during the 2008-2012 period.

Finally, there are two limitations of this study which provide fruitful areas of further research. First, it does not explore the lag structure of the different types of R&D. This is important since certain types of R&D, such as basic research, have longer time lags in affecting productivity. Second, extramural R&D was mainly insignificant, which is in line with several other findings such as Brossard and Moussa (2016). Recent studies suggest that external R&D involving cooperation with other firms and universities is beneficial (Schmiedeberg 2008; Hagedoorn and Wang (2012). However, the dataset used in this study does not allow for identification of external research involving R&D collaborations. A more detailed examination of the impact of R&D cooperation between firms and universities would be insightful.

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Appendix

Table 6: **Effect of Total R&D intensity on Productivity, by broad sector *(System GMM estimates)***

(Dependent variable: Log of value added per employee)

	(1) Manufacturing sector	(2) Service sector
Log (Value added per employee)$_{t-1}$	0.385*** (8.29)	0.565*** (10.76)
Δ log of Capital stock	0.022 (0.09)	0.065 (0.36)
Δ log of Employment	0.051 (0.25)	-0.812*** (-3.67)
Total R&D intensity	0.079*** (4.70)	0.196** (2.48)
Total R&D intensity squared	-0.0004*** (-3.81)	-0.0028 (-1.37)
Constant	1.733*** (9.17)	1.756*** (7.08)
Firm/year observations	20198	6529
Firms	3.650	2592
Number of Instruments	135	135
AR(1) test: p-values	0.000***	0.000***
AR(2) test: p-values	0.273	0.408
Hansen test: p-values	0.121	0.618
Difference Hanson test: p-values	0.131	0.195

*Notes: Column 1: Estimations for the manufacturing sector. Column 2: Estimations for the service sector. T statistics in parentheses, time dummies are included in all estimations. Standard errors are robust to heteroskedasticity and serial correlation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All estimations include the control variables (UK ownership dummy, Knowledge gap, Herfindahl index and wage ratio) but these have not been reported for parsimony.*

Table 7: Effect of R&D by type on productivity: Small and Medium Sized Enterprises (System GMM estimations)

(Dependent variable: Log of value added per employee)

	(1)	(2)	(3)
Log (Value added per employee)$_{t-1}$	0.368*** (3.12)	0.571*** (10.75)	0.583*** (11.03)
Δ log of Capital stock	0.163 (0.82)	0.397** (2.12)	0.240 (1.32)

Δ log of Employment)	0.0742 (0.28)	-0.704*** (-3.45)	-0.697*** (-4.10)
Lagged R&D intensity type 1	0.241 (1.20)	0.158* (1.69)	0.257*** (3.27)
Lagged R&D intensity type 1 squared	-0.0147 (-0.61)	-0.00448* (-1.76)	-0.00528** (-2.05)
Lagged R&D intensity type 2	0.806 (1.52)	-1.271 (-1.47)	0.00551 (0.13)
Lagged R&D intensity type 2 squared	-0.348 (-1.33)	0.0232 (0.07)	-
Lagged R&D intensity type 1 * Lagged R&D intensity type 2	0.124 (0.49)	0.0683* (1.87)	0.964 (0.74)
Constant	2.516*** (4.79)	1.415*** (5.62)	1.530*** (6.77)
Firm/year observations	6070	8771	9266
Firms	2330	2725	2782
Number of Instruments	165	178	164
AR(1) test: p-values	0.000***	0.000***	0.000***
AR(2) test: p-values	0.337	0.928	0.820
Hansen test: p-values	0.633	0.784	0.000***
Difference Hanson test: p-values	0.218	0.115	0.000***

*Notes: SMEs are defined as firm with 250 or less employees. Column 1: R&D intensity 1 is intramural R&D and R&D intensity 2 is extramural R&D. Column 2: R&D intensity 1 is applied/experimental R&D and R&D intensity 2 is basic R&D. Column 3: R&D intensity 1 is private R&D and R&D intensity 2 is public R*D. T statistics in parentheses, time dummies are included in all estimations. Standard errors robust to heteroskedasticity and serial correlation.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Effect of R&D by type on productivity: Large Enterprises
(System GMM estimations)
(Dependent variable: Log of value added per employee)

	(1)	(2)	(3)
Log (Value added per employee)$_{t-1}$	0.368*** (3.12)	0.571*** (10.75)	0.583*** (11.03)
Δ log of Capital stock	0.163 (0.82)	0.397** (2.12)	0.240 (1.32)
Δ log of Employment)	0.0742 (0.28)	-0.704*** (-3.45)	-0.697*** (-4.10)
Lagged R&D intensity type 1	-0.526 (-1.02)	0.716*** (4.02)	0.372** (2.39)
Lagged R&D intensity type 1 squared	0.0609* (1.88)	-0.00507 (-0.94)	-0.00638** (-2.09)
Lagged R&D intensity type 2	0.299 (0.86)	-0.273 (-0.21)	0.0026** (2.12)
Lagged R&D intensity type 2 squared	0.482*** (3.30)	-0.393 (-0.25)	-
Lagged R&D intensity type 1 * Lagged R&D intensity type 2	-0.347*** (-2.64)	0	0
Constant	2.516*** (4.79)	1.415*** (5.62)	1.530*** (6.77)
Firm/year observations	6070	8771	9266
Firms	2330	2725	2782
Number of Instruments	165	178	164
AR(1) test: p-values	0.000***	0.000***	0.000***
AR(2) test: p-values	0.337	0.928	0.820
Hansen test: p-	0.633	0.784	0.000***

values Difference Hanson test: p-values	0.218	0.115	0.000***

*Notes: Large enterprises are defined as firms with more than 250 employees. Column 1: R&D intensity 1 is intramural R&D and R&D intensity 2 is extramural R&D. Column 2: R&D intensity 1 is applied/experimental R&D and R&D intensity 2 is basic R&D. Column 3: R&D intensity 1 is private R&D and R&D intensity 2 is public R*D. T statistics in parentheses, time dummies are included in all estimations. Standard errors robust to heteroskedasticity and serial correlation.* * *$p < 0.10$,* ** *$p < 0.05$,* *** *$p < 0.01$.*

Table 9: Effect of R&D by type on productivity: Manufacturing sector (System GMM estimations) (Dependent variable: Log of value added per employee)

	(1)	**(2)**	**(3)**
Log (Value added per employee)$_{t-1}$	0.367*** (5.54)	0.312*** (3.86)	0.431*** (9.30)
Δ log of Capital stock	-0.588** (-2.01)	-0.189 (-0.88)	0.0400 (0.16)
Δ log of Employment)	0.237 (1.08)	0.173 (0.61)	-0.119 (-0.59)
Lagged R&D intensity type 1	0.377** (2.06)	0.325 (1.60)	0.269*** (4.26)
Lagged R&D intensity type 1 squared	-0.0061 (-0.55)	-0.0089 (-1.34)	-0.0048*** (-3.82)
Lagged R&D intensity type 2	-0.358 (-1.33)	-1.886* (-1.91)	0.00228 (0.56)
Lagged R&D intensity type 2 squared	0.0180 (0.44)	0.0095 (0.03)	-
Lagged R&D intensity type 1 * Lagged R&D intensity type 2	-	0.117 (1.53)	-0.0101 (-0.03)
Constant	1.827*** (7.24)	2.024*** (8.29)	1.637*** (8.04)
Firm/year observations	13821	17874	18526

Firms	2.801	3.371	3.452
Number of Instruments	163	177	163
AR(1) test: p-values	0.000***	0.000***	0.000***
AR(2) test: p-values	0.789	0.467	0.260
Hansen test: p-values	0.496	0.185	0.348
Difference Hanson test: p-values	0.060	0.094	0.101

*Notes: Column 1: R&D intensity 1 is intramural R&D and R&D intensity 2 is extramural R&D. Column 2: R&D intensity 1 is applied/experimental R&D and R&D intensity 2 is basic R&D. Column 3: R&D intensity 1 is private R&D and R&D intensity 2 is public R*D. T statistics in parentheses, time dummies are included in all estimations. Standard errors robust to heteroskedasticity and serial correlation.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Effect of R&D by type on productivity: Service sector
(System GMM estimations)
(Dependent variable: Log of value added per employee)

	(1)	(2)	(3)
Log (Value added per employee)$_{t-1}$	0.542*** (6.80)	0.515*** (10.30)	0.489*** (8.41)
∆ log of Capital stock	0.498* (1.95)	-0.125 (-0.64)	-0.0705 (-0.29)
∆ log of Employment)	-0.874*** (-4.21)	-0.757*** (-3.84)	-0.656*** (-2.66)
Lagged R&D intensity type 1	0.145 (1.26)	0.375*** (3.31)	0.265*** (4.04)
Lagged R&D intensity type 1 squared	-0.0022 (-0.46)	-0.023** (-2.02)	-0.0037*** (-2.68)
Lagged R&D intensity type 2	-0.172 (-0.40)	-0.948 (-1.25)	-0.479 (-1.17)
Lagged R&D intensity type 2 squared	0.029 (0.59)	0.171* (1.74)	-
Lagged R&D intensity type 1 * Lagged R&D	0.012 (1.03)	0.261* (1.69)	0.271 (0.38)

intensity type 2			
Constant	1.790*** (6.10)	1.864*** (8.16)	2.011*** (7.62)
Firm/year observations	3936	5334	5598
Firms	2062	2363	2443
Number of Instruments	177	177	163
AR(1) test: p-values	0.000***	0.000***	0.000***
AR(2) test: p-values	0.941	0.899	0.832
Hansen test: p-values	0.247	0.450	0.407
Difference Hanson test: p-values	0.511	0.133	0.297

*Notes: Column 1: R&D intensity 1 is intramural R&D and R&D intensity 2 is extramural R&D. Column 2: R&D intensity 1 is applied/experimental R&D and R&D intensity 2 is basic R&D. Column 3: R&D intensity 1 is private R&D and R&D intensity 2 is public R*D. T statistics in parentheses, time dummies are included in all estimations. Standard errors robust to heteroskedasticity and serial correlation.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Effect of R&D by type on productivity: Pavitt class 1
(System GMM estimations)
(Dependent variable: Log of value added per employee)

	(1)	(2)	(3)
Log (Value added per employee)$_{t-1}$	0.432*** (3.47)	0.331*** (2.82)	0.494*** (3.15)
Δ log of Capital stock	-0.0707 (-0.24)	0.622*** (2.61)	0.554 (1.16)
Δ log of Employment)	-1.053*** (-2.88)	-0.730*** (-3.05)	-0.916 (-1.06)
Lagged R&D intensity type 1	-0.465 (-1.36)	-0.624 (-1.34)	-0.468 (-0.62)
Lagged R&D intensity type 1 squared	0.061*** (2.70)	0.130 (1.27)	0.0698 (1.17)
Lagged R&D intensity type 2	-1.066 (-0.91)	-1.269 (-0.58)	4.708 (0.48)

Lagged R&D intensity type 2 squared	1.437* (1.92)	6.891 (1.14)	-
Lagged R&D intensity type 1 * Lagged R&D intensity type 2	-0.475*** (-3.15)	-0.724 (-0.25)	-1.487 (-0.22)
Constant	2.332*** (4.40)	2.695*** (5.08)	2.027** (2.54)
Firm/year observations	3256	4332	4483
Firms	1327	1502	1532
Number of Instruments	166	166	153
AR(1) test: p-values	0.000***	0.000***	0.000***
AR(2) test: p-values	0.176	0.526	0.691
Hansen test: p-values	0.807	0.220	0.604
Difference Hanson test: p-values	0.148	0.0032	0.0344

*Notes: Pavitt class 1 consists of firms in science-based industries. Column 1: R&D intensity 1 is intramural R&D and R&D intensity 2 is extramural R&D. Column 2: R&D intensity 1 is applied/experimental R&D and R&D intensity 2 is basic R&D. Column 3: R&D intensity 1 is private R&D and R&D intensity 2 is public R*D. T statistics in parentheses, time dummies are included in all estimations. Standard errors robust to heteroskedasticity and serial correlation.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Effect of R&D by type on productivity: Pavitt class 2 (System GMM estimations) (Dependent variable: Log of value added per employee)

	(1)	**(2)**	**(3)**
Log (Value added per employee)$_{t-1}$	0.563*** (5.42)	0.288*** (3.56)	0.329*** (3.31)
Δ log of Capital stock	0.0399 (0.21)	-0.0128 (-0.08)	0.221 (0.94)
Δ log of Employment)	-0.245 (-1.01)	0.0190 (0.09)	-0.271 (-1.08)
Lagged R&D intensity type 1	1.794*** (3.60)	0.281 (0.84)	1.285*** (2.61)

Lagged R&D intensity type 1 squared	-0.272** (-2.56)	-0.114 (-0.38)	-0.431 (-1.33)
Lagged R&D intensity type 2	-1.046 (-0.50)	1.254 (0.88)	3.473 (0.90)
Lagged R&D intensity type 2 squared	3.062 (1.36)	-1.096 (-0.60)	-
Lagged R&D intensity type 1 * Lagged R&D intensity type 2	-2.066 (-1.11)	1.015 (0.50)	-1.912 (-1.30)
Constant	1.035*** (2.59)	2.647*** (7.46)	2.246*** (5.66)
Firm/year observations	3586	4453	4639
Firms	1569	1599	1644
Number of Instruments	165	165	152
AR(1) test: p-values	0.000***	0.000***	0.000***
AR(2) test: p-values	0.118	0.353	0.411
Hansen test: p-values	0.313	0.824	0.624
Difference Hanson test: p-values	0.247	0.487	0.0537

*Notes: Pavitt class 2 consists sectors that are specialized suppliers of technology. Column 1: R&D intensity 1 is intramural R&D and R&D intensity 2 is extramural R&D. Column 2: R&D intensity 1 is applied/experimental R&D and R&D intensity 2 is basic R&D. Column 3: R&D intensity 1 is private R&D and R&D intensity 2 is public R*D. T statistics in parentheses, time dummies are included in all estimations. Standard errors robust to heteroskedasticity and serial correlation.* * *$p < 0.10$,* ** *$p < 0.05$,* *** *$p < 0.01$.*

Table 13: Effect of R&D by type on productivity: Pavitt class 3 (System GMM estimations) (Dependent variable: Log of value added per employee)

	(1)	(2)	(3)
Log (Value added per employee)$_{t-1}$	0.357*** (3.82)	0.183* (1.76)	0.441*** (4.45)
Δ log of Capital stock	-0.257 (-0.86)	-0.123 (-0.40)	-0.333 (-0.94)
Δ log of Employment)	-0.0612 (-0.21)	0.235 (0.90)	0.104 (0.50)
Lagged R&D intensity type 1	-0.748 (-0.76)	0.259 (0.38)	0.964* (1.91)
Lagged R&D intensity type 1 squared	1.535 (1.64)	0.0497 (0.24)	-0.023** (-2.19)
Lagged R&D intensity type 2	1.628** (1.98)	-12.79 (-1.35)	1.336 (0.54)
Lagged R&D intensity type 2 squared	0.940 (1.47)	56.97 (1.13)	-
Lagged R&D intensity type 1 * Lagged R&D intensity type 2	-3.195* (-1.83)	11.70 (1.09)	0.671 (0.27)
Constant	2.065*** (5.80)	2.400*** (5.58)	1.396*** (3.23)
Firm/year observations	3574	4538	4765
Firms	1334	1445	1479
Number of Instruments	166	166	152
AR(1) test: p-values	0.0049***	0.0003***	0.000***
AR(2) test: p-values	0.449	0.816	0.750
Hansen test: p-values	0.668	0.596	0.320

Difference Hanson test: p-values	0.212	0.399	0.0738*

*Notes: Pavitt class 3 consists of scale-intensive industries. Column 1: R&D intensity 1 is intramural R&D and R&D intensity 2 is extramural R&D. Column 2: R&D intensity 1 is applied/experimental R&D and R&D intensity 2 is basic R&D. Column 3: R&D intensity 1 is private R&D and R&D intensity 2 is public R*D. T statistics in parentheses, time dummies are included in all estimations. Standard errors robust to heteroskedasticity and serial correlation.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Effect of R&D by type on productivity: Pavitt class 4 (System GMM estimations) (Dependent variable: Log of value added per employee)

	(1)	**(2)**	**(3)**
Log (Value added per employee)$_{t-1}$	0.368*** (4.11)	0.479*** (6.38)	0.525*** (6.10)
Δ log of Capital stock	-0.149 (-0.77)	-0.0394 (-0.16)	0.237 (0.93)
Δ log of Employment)	-0.142 (-0.50)	-0.506** (-1.98)	-0.576*** (-2.60)
Lagged R&D intensity type 1	0.137 (0.32)	0.572* (1.88)	0.469 (1.63)
Lagged R&D intensity type 1 squared	-0.0145 (-0.91)	-0.0093 (-0.28)	-0.0116 (-1.33)
Lagged R&D intensity type 2	0.811 (1.50)	-1.750 (-0.50)	0.0143** (2.01)
Lagged R&D intensity type 2 squared	-0.428 (-1.61)	0.081 (0.16)	-
Lagged R&D intensity type 1 * Lagged R&D intensity type 2	0.242 (1.62)	0.039 (0.07)	-0.626** (-2.38)
Constant	1.619*** (3.99)	1.222*** (6.74)	1.578*** (6.15)
	7244	9369	9673
Firm/year observations	3026	3278	3330

Firms	165	165	163
Number of Instruments	0.000***	0.000***	0.000***
AR(1) test: p-values	0.206	0.295	0.463
AR(2) test: p-values	0.370	0.221	0.342
Hansen test: p-values	0.333	0.248	0.281
Difference Hanson test: p-values			

*Notes: Pavitt class 4 includes industries dominated by technology suppliers. Column 1: R&D intensity 1 is intramural R&D and R&D intensity 2 is extramural R&D. Column 2: R&D intensity 1 is applied/experimental R&D and R&D intensity 2 is basic R&D. Column 3: R&D intensity 1 is private R&D and R&D intensity 2 is public R*D. T statistics in parentheses, time dummies are included in all estimations. Standard errors robust to heteroskedasticity and serial correlation.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.