Innovation Caucus

INNOVATE UK GRANTS AND R&D RETURNS:

IMPACT ON BUSINESS AND ECONOMY

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About the Innovation Caucus

The Innovation Caucus supports sustainable innovation-led growth by promoting engagement between the social sciences and the innovation ecosystem. Our members are leading academics from across the social science community, who are engaged in different aspects of innovation research. We connect the social sciences, Innovate UK and the Economic and Social Research Council (ESRC), by providing research insights to inform policy and practice. Professor Tim Vorley is the Academic Lead. The initiative is funded and co-developed by the ESRC and Innovate UK, part of UK Research and Innovation (UKRI). The support of the funders is acknowledged. The views expressed in this piece are those of the authors and do not necessarily represent those of the funders.

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EXECUTIVE SUMMARY

Context and rationale

Understanding the returns linked to pursuing innovation and investing in R&D is important to both businesses and policy makers. Businesses view R&D and innovation as a strategic investment through which they can achieve competitive advantage and increase their market share and/or performance. However, R&D and innovation activities are costly and understanding their rate of return is crucial for businesses to make decisions on their R&D investment strategy. Significant R&D returns would encourage businesses to allocate more resources in R&D/innovation to leverage their gains. Smaller returns may question the ability of the business to translate R&D and innovation into tangible outcomes and may initiate an internal assessment of its R&D strategy.

On the other hand, policy makers are interested in the “gap” between private and social returns on R&D investment, i.e., the benefits appropriated by the business vis the benefits accruing to other businesses in the economy. The inability of businesses to fully appropriate the outcomes of their R&D and innovation activities constitutes a disincentive for businesses to invest in R&D. The core of this is often attributed to the public good characteristics of new knowledge creation and/or innovation activities reflected in the inability of the R&D performing business to exclude other users from ‘consuming’ or benefitting from the outcomes of its R&D and innovation activities. Difficulties in securing external private financing for business R&D and innovation activities pose an additional obstacle for businesses to invest in R&D.

Public support for business R&D aims at mitigating the market failure of underinvestment in R&D by incentivising businesses to invest more in R&D and innovation. In the UK, public spending on R&D was £10.45 billion in 2019 with most of the spending originating from the Department of Business, Energy and Industrial Strategy (BEIS). The greatest part of these funds is allocated to the UK Research and Innovation (UKRI) and its research councils including Innovate UK, the UK’s national innovation agency supporting business innovation. Indeed, since 2004 Innovate UK has injected more than £2.5bn to support business R&D/innovation in the form of grants, leveraging at least £4.3bn of associated private sector investment. Innovate UK has therefore a critical role to play in increasing the overall level of R&D investment in the economy and fulfilling the Government’s target of raising R&D expenditure as a percentage of GDP to 2.4% by 2027 and 3.0% in the longer term.

An assessment of the returns of Innovate UK grants is therefore of pivotal importance not only to Innovate UK and BEIS but also to the HM Treasury, which also has a vested interest in understanding the returns on public investments in supporting business R&D and innovation. Significant returns would further justify the role of public R&D support programmes and could even trigger an increase in the governmental budget allocated to public R&D support.

OBJECTIVES

This study provides an assessment of the ability of Innovate UK grants to generate returns for businesses, developing new insights on the role of public R&D support for beneficiary businesses. More specifically, the study seeks to answer the following questions:

a. What are the returns on total R&D investment for UK businesses? In other words, what is the return of £1 of total R&D investment?

b. How do these returns vary between different types of businesses in terms of size, origin of ownership, knowledge stock, industry and region?

c. Does the provision of Innovate UK grants influence the private R&D investment of businesses? In other words, do Innovate UK grants leverage any additional spending on behalf of recipient businesses – i.e., over-and-above what they would spend in the absence of the grants?

d. What is the return on R&D investment of Innovate UK grants for businesses? In other words, what is the return of £1 of Innovate UK grants within the business?

e. How do these effects potentially vary between different types of businesses based on size, origin of ownership and industry?

f. How do these effects potentially vary between different types of Innovate UK products? Being the most frequently used products, the Collaborative R&D and Feasibility Studies products constitute the focus of this investigation.

g. What is the wider impact of Innovate UK grants for the UK economy? In estimating this impact, direct, indirect and leveraged effects are considered.

By investigating the impact of Innovate UK grants not only on recipient businesses but also on the wider economy, we contribute towards more holistically understanding the impact of Innovate UK grants and their ability to 'boost' the UK economy.

Our Approach

To answer these questions, microdata at the business level are used from two annual surveys conducted by the Office for National Statistics (ONS): the Annual Business Survey (ABS), which is the largest business survey conducted by the ONS in terms of the combined number of respondents and variables it covers, and the Business Enterprise Research and Development (BERD) survey, which captures the R&D expenditure and R&D employment of UK businesses. The dataset resulting from the two ONS datasets offers a large coverage of the UK business sector covering more than 35,000 businesses over the 2008-2019 period. We further link this dataset to data published by Innovate UK which contain information on projects funded by Innovate UK since 2004.

In calculating an overall impact (return) of the Innovate UK grants we take into account the impact from: (a) the public funds invested in the business, i.e., the grant-based impact and (b) the additional private funds invested in the recipient business due to grant receipt, i.e., the additionality-based impact. From an analytical perspective, we employ an extended version of the traditional framework of production function estimation. In doing so, besides capital and labour we additionally model R&D as a determinant of output (value added). Econometric estimation issues are addressed by using appropriate methods that account for a simultaneous relationship between output and inputs. In estimating the returns of Innovate UK grants for recipient businesses we construct the R&D capital stock stemming from the investment of Innovate UK in recipient businesses through R&D grants. In determining whether Innovate UK grants can also generate returns for recipient businesses through inducing additional private spending in R&D, we employ methods that can simulate what would have happened in the absence of Innovate UK grants. The construction of a valid counterfactual therefore enables the identification of causal effects of Innovate UK grants.

Main Findings

The estimated R&D returns for UK businesses are found to be large: for every £1 of investment in R&D, there is approximately a 68p increase in business GVA in the year the investment is made. This implies that, overall, UK businesses have been successful in exploiting their R&D investments to a great extent. However, we find these returns to vary across different types of businesses defined by their size, origin of ownership, industry and region.

We find a positive return of Innovate UK grants: for each £1 invested in businesses in the form of grants, there is a 73p increase in the GVA of the recipient business (immediate impact). However, there is significant return heterogeneity relating to business characteristics (size and industry affiliation). In addition, the returns on Innovate UK grants are also conditional on the Innovate UK product type with “Collaborative R&D” yielding considerably higher returns than “Feasibility Studies” or “Other” products.

Counterfactual analysis revealed that Innovate UK grants can also increase the private R&D investment of supported businesses over and above what their investment would have been had they not received public funds. This provides evidence that Innovate UK funds are effective in mitigating market failures relating to the R&D underinvestment of the private sector. On average, for each £1 of Innovate UK grants invested in businesses led to an increase in business R&D spending of approximately 34p which, in turn, translated into 14p of additional GVA.

By considering both channels of Innovate UK grant impact, i.e., the grant-based impact and the additionality-based impact, while accounting for the wider positive impacts on business-to-business spending along the supply chain (indirect effects) and the wider positive impacts on household income (leveraged effects), we calculate the aggregate returns for each £1 of Innovate UK grants to amount to £6.21 of GVA over the course of 7 years.

1. BACKGROUND

R&D and innovation have been shown to be of fundamental importance in raising per capita income therefore making our societies more prosperous. Hence, it comes to no surprise that governments worldwide have placed R&D and innovation at the top of their agendas in achieving sustainable economic growth. In the UK, the government in its published Industrial Strategy (HM Government, 2017) sets out its ambitious target of increasing investment in R&D to 2.4% of the UK's GDP by 2027 and to 3% in the longer term. Such an increase in R&D investment is hoped to be translated into higher productivity and more well-paid jobs for everyone.

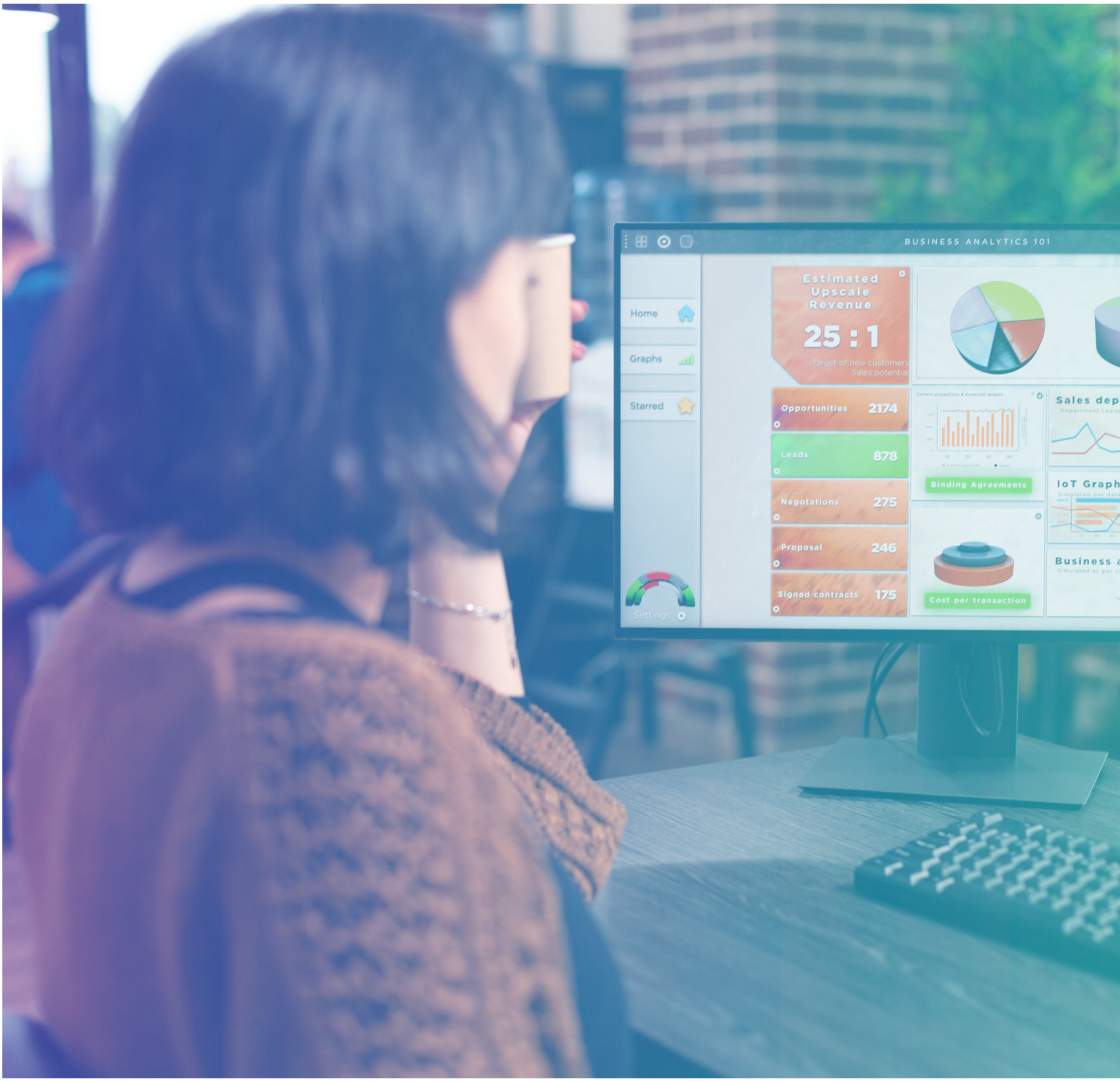
Besides public sector R&D and innovation, the government is committed to invest more in private sector R&D mainly through its research councils with Innovate UK being the organisation that engages with businesses and other organisations (such as universities) with the aim of supporting and nurturing innovation. Innovate UK, the successor of the Technology Strategy Board, directly supports businesses through R&D grants by assessing the quality of proposals based on their feasibility and potential value. The rationale for public intervention lies in failures in the R&D market where limited appropriability of R&D returns and imperfect capital markets provide a disincentive to businesses in investing in R&D and innovation activities.

However, R&D and innovation are of pivotal importance to the private sector and businesses embrace R&D and innovation activities as the means to achieve competitive advantage. R&D and innovation activities help businesses learn how to improve their products and services, their production processes, as well as their organisational and marketing methods. All of these can be translated into more revenue, profits and/or market share and make the business more resilient in facing competition especially during economic downturns. However, R&D and innovation activities require significant resources. R&D equipment operated by technically trained staff, facilities dedicated to R&D and innovation activities, highly specialised instruments and highly qualified R&D staff and researchers constitute a significant expenditure for the business that may serve as a deterrent to businesses to undertake (formal) R&D and innovation activities.

As R&D and innovation activities are costly, businesses are always interested in understanding the returns on their investment in such activities. Significant R&D returns would encourage businesses to allocate more resources in R&D/innovation to leverage their gains. Smaller returns may question the ability of the business to translate R&D and innovation into tangible outcomes and may initiate an internal assessment of its R&D strategy. But it is not only the private sector that is interested in understanding R&D returns. The HM Treasury, the Department for Business, Energy and Industrial Strategy, and Innovate UK all have a vested interest in understanding the returns on public investments in supporting business R&D and innovation. Significant returns would further justify the role of public R&D support programmes and could even trigger an increase in the governmental budget allocated to public R&D support.

Although there is a large body of the literature investigating the ability of public R&D support to increase businesses' private R&D investment and innovation [see (Dimos and Pugh, 2016) for a meta-regression analysis of the corresponding literature] the evidence on the returns of public R&D support is scarce. In the absence of such evidence, we cannot have any expectations of whether Innovate UK grants are translated into tangible outcomes (GVA) for businesses. Therefore, an assessment of the returns of Innovate UK grants for beneficiary businesses is essential in more holistically understanding the impact of public funds. In addition, by further estimating the wider impacts of Innovate UK grants for the UK economy will shed more light on how Innovate UK funding can boost the UK economy.

This study is organised as follows. Section 2 briefly presents the related empirical evidence on measuring R&D returns and the role of public R&D support. Section 3 presents the methodological framework adopted to measure total R&D returns and the returns of Innovate UK grants. Section 4 presents the data and discusses how the variables used were constructed. Section 5 presents the results in measuring R&D returns and the wider impact of Innovate UK grants.



2. PREVIOUS STUDIES

2.1 R&D Returns at the Business Level

At the macro-level, research and development (R&D) has been long documented to be a significant determinant of sustainable per capita income growth (Solow, 1956). At the micro-level, R&D has been shown to have a positive influence on businesses' performance (Aw et al., 2007), productivity (Griliches and Mairesse, 1984; Mansfield, 1988; Griliches and Mairesse, 1990; Hall, 1993) and stock market value (Brockman et al., 2017). However, knowledge creation has public good characteristics, namely non-rivalry – where the use of knowledge by a business does not reduce its amount to be used by another business – and non-excludability – where it is costly or not feasible for a business to exclude other businesses from using knowledge (Nelson, 1959; Arrow, 1962). This implies that besides returns appropriated by the R&D conducting business (i.e., private returns), investment in R&D also yields benefits to the wider industry and society (i.e., social returns).

There is a large body of literature on measuring private and social R&D returns at the country level (Mohnen et al., 1986; Lichtenberg, 1993; Coe et al., 1997), industry level (Griliches and Lichtenberg, 1984; Bernstein and Mohnen, 1998; Griffith et al., 2004; Frontier Economics, 2014) and business level (Griliches, 1980a; Adams and Jaffe, 1996; Doraszelski and Jaumandreu, 2013). [For a detailed review of the literature, see Hall et al. (2010).] However, the focus of this study lies on business-level R&D returns which is a topic of increasing importance as microdata become more widely available.

The seminal study in the field of R&D returns was the work of Zvi Griliches in 1979 who set out the methodological framework and identified related measurement problems (see Section 3 below). Griliches (1979) introduced the production function approach in estimating R&D returns, which allows for a joint estimation of private and social returns by independently modelling the knowledge stock of the R&D performer and the knowledge stock of competitors through the use of technological spillovers. In addition, Griliches (1979) highlighted the issues of multicollinearity and simultaneity in the estimation of the production function – two issues routinely encountered in econometric estimation.

Hall et al. (2010) in their survey of studies measuring R&D returns concluded that private R&D returns for businesses in developed economies mainly range between 20% and 30%. They also found that returns having been estimated from industry-level data were generally close to returns having been estimated from business-level data. However, they emphasised that there is space for improvement in measuring spillovers and social rates of R&D returns.

Griliches (1980a) investigated private R&D returns for a sample of large R&D performing US businesses during the 1957-1965 period. Whereas the author found that the average private R&D return was 27% in 1963, he found that returns were volatile across industries. More specifically, private R&D returns varied from 3% in the electrical equipment and communication industries to 103% in the chemicals and petroleum industry. The author did not find any evidence to support that large businesses appropriate higher R&D returns than those appropriated by small businesses.

By using establishment data from the US chemical sector for the 1974-1988 period, Adams and Jaffe (1996) estimated an output elasticity for own R&D and external R&D of 0.05 and 0.07, respectively.

In addition, they found that spillovers from technologically adjacent businesses depend on R&D intensity and not on the industry's total R&D. Clark and Griliches (1984) also used US data from the manufacturing sector and for the 1970-1980 period. The authors found a significant effect of R&D investment on Total Factor Productivity (TFP) and their estimates of private R&D returns were approximately 20%. According to the authors, this result may explain the observed slowdown on productivity growth in the 1970s since there was a contemporaneous decrease in R&D throughout the same period. The same conclusion was also reached in Griliches (1980b) who show that the observed productivity slowdown of the 1970s was partially due to smaller investments in R&D.

Antonelli (1994) examined spillover effects across large Italian businesses in 1986. Although the sample size of the study was small (94 businesses), the businesses in the sample were investing more than four fifths of total private R&D in Italy for the period under investigation. The study found significant spillover effects but negligible direct R&D expenditure effects on productivity growth when these are considered in isolation (i.e., net of the spillover effect).

By using data from 12,000 Chinese manufacturing businesses for the 2002-2004 period, Goh et al. (2016) found that R&D returns in state-owned businesses are smaller than R&D returns in domestic privately-owned businesses (26% vs. 96%). According to the authors, what can explain this result is that privately-owned businesses are closer to the market and have stronger incentives to make a better allocation and use of their limited resources. However, the authors also found that privately-owned and foreign businesses appropriated lower returns than privately-owned but domestic businesses (23% vs. 26%). This finding led the authors to suggest that financial constraints may also play a crucial role in the sense that financially constrained businesses, such as domestic and privately-owned businesses, may require higher rates of return compared to businesses with less pronounced financial constraints, such as state-owned and foreign businesses. This line of reasoning is also consistent with another finding of the authors where businesses based in less affluent regions appropriate lower rates of return. Similar evidence was provided by Hu (2001) where the output elasticity with respect to R&D for privately-owned businesses (0.46) was found to be larger than for state-owned businesses (0.26). When Goh et al. (2016) investigated the extent of spillovers, they found significant spillover effects for businesses within the same industry.

Apart from business size, financial constraints and location, R&D returns may be conditioned by whether R&D is privately or publicly financed. Indeed, Griliches (1986) found that privately financed R&D yielded larger (private) R&D returns than federally funded R&D in the US. The author further found that although R&D contributed to productivity gains, it was its basic research component that had a stronger effect.

Harhoff (1998) used data from German R&D performing businesses for the 1977-1989 period and found that R&D had a positive effect on businesses' productivity. The author estimated an overall private rate of return of 0.66. However, this return was not uniform across businesses of different technological capabilities. High-technology businesses were found to have a rate of return (0.77) twice as big the return of low-technology businesses (0.38). The effects of R&D spillovers on productivity and the corresponding social rates of return for the businesses in the sample were investigated by Harhoff (2000). Whereas the author found strong spillover effects, it was high-tech businesses that were more exposed to them. The findings also supported the “absorptive capacity” hypothesis (Cohen and Levinthal, 1990) since it was found that more R&D intensive businesses (i.e., businesses with higher R&D capital) were more likely to benefit from positive knowledge externalities.

Besides the technology level of businesses, R&D returns may also vary across industries. By using data from Spanish manufacturing businesses for the 1990-1999 period, Doraszelski and Jaumandreu (2013) found an average rate of return of 1.5% which varied across the manufacturing industries the authors examined.

Bartelsman et al. (1996) used Dutch business data for the 1985-1993 period and estimated a private R&D return of 12% for gross output and 30% for value added. However, when the authors did not depreciate R&D, they found private R&D returns not statistically different from zero for gross output and private R&D returns smaller by one fifth for value added.

Bond et al. (2003) compared large R&D performing businesses based in the UK and Germany for the 1987-1996 period. The authors found that although German businesses invested more in R&D, the elasticity of R&D was the same in both economies. This implied that private R&D returns tended to be larger in the UK. The authors attributed this to differences in the financing of R&D, financial constraints (more pronounced for UK businesses) and corporate governance between the businesses in the two economies which require higher private R&D returns in the UK.

Capron and Cincera (1998) used a sample of international businesses for the 1987-1994 period. The businesses, which were all R&D performers and from the manufacturing sector, were drawn from Australia, Canada, the EU, the USA and Japan. The authors found significant spillover effects on productivity. Whereas US businesses tended to exploit their national R&D knowledge stock, Japanese businesses tended to exploit more the international knowledge stock. The EU followed a similar pattern to the US where EU businesses were mainly exploiting the knowledge stock of the EU (i.e. cross-country but within the EU).

Bloom et al. (2013) by using data from US businesses for the 1963-2001 period found that social returns are at least double when compared to private R&D returns. The authors also found that small businesses tend to generate fewer positive spillover effects for other businesses because they tend to operate in sectors where technologically adjacent businesses are limited. Their work was extended by Bloom et al. (2018) who not only added 15 years of data (and therefore covered the 1963-2015 period) but also updated the interactions of businesses in the technology/market space (and therefore altered their association and subsequent spillovers). Bloom et al. (2018) found similar spillover effects to the ones estimated by Bloom et al. (2013) which remained relatively stable throughout the examined period. However, Bloom et al. (2018) found that the gap between social and private R&D returns was more pronounced between 2005 and 2015 when compared to the 1980s: a ratio of 4 to 1. Given this discrepancy, the role of public R&D support remains important in incentivising businesses to invest more in R&D and innovation activities (Dimos and Pugh, 2016).

R&D returns do not have to be positive but negative R&D returns are also a possibility. Negative private R&D returns may be an outcome of R&D indivisibility (Arrow, 1962), unsuccessful R&D or even an outcome of business imitation (Doraszelski and Jaumandreu, 2013). The latter is the case when businesses merely imitate competitors' R&D without expectations of positive R&D returns in the short-term but because they regard this as a necessary step to catch up with competitors (i.e., businesses act as followers and upgrade their R&D). Obviously, in the long-term businesses should anticipate positive R&D returns from their future (upgraded) R&D activities.

However, the traditional framework does not receive ubiquitous support. Arqué-Castells and Spulber (2019) criticised the established production function model in estimating R&D returns. In particular, the authors questioned the validity of modelling spillovers to jointly estimate private and social returns since the role of spillovers may be limited due to the existence of IP protection policies. Accordingly, they proposed the use of an extended framework where besides traditional spillovers, market-mediated R&D transfers are also accounted for. By using data from publicly listed US businesses for the 1990-2014 period and applying their extended framework, Arqué-Castells and Spulber (2019) found that technology transferred through the market plays a significant role and needs not to be neglected when estimating R&D returns. When compared to the traditional framework, their extended framework yielded larger private R&D returns and accordingly narrowed the gap between social and private returns.

Given the lack of sufficient evidence for the UK economy, our estimation of R&D returns for UK businesses becomes even more important in understanding not only the overall returns on R&D investment but also how these vary across different business types, industries and regions.

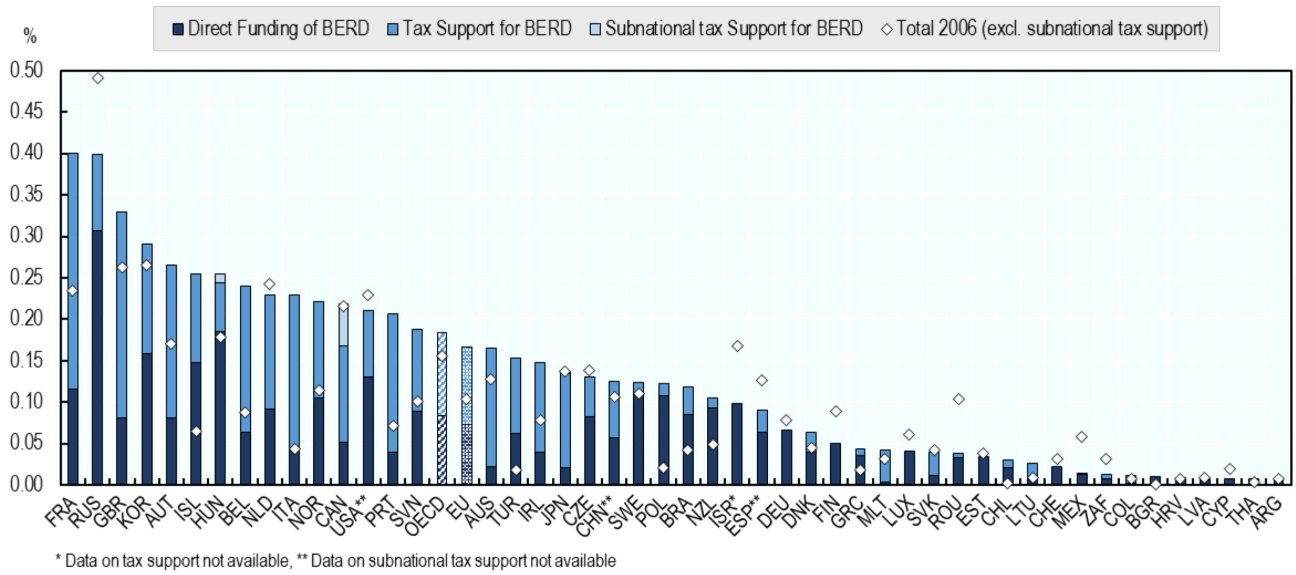
2.2 Public R&D Support and Business R&D Returns

Public R&D support and in particular R&D subsidies can reduce the unit cost of R&D and encourage businesses to spend more on R&D than what they would have done in the absence of support (David et al., 2000). There is a large body of empirical literature that investigates whether public R&D support can induce more private R&D spending at the business level (Klette et al., 2000; Zúňiga-Vicente et al., 2014; Dimos and Pugh, 2016). Although there are heterogeneous effects of R&D subsidies on private R&D spending (Dimos and Pugh, 2016), recent research has identified an average marginal effect of R&D subsidies on R&D expenditure of 0.075 (Dimos et al., 2022). This means that for each additional £1 received by businesses in the form of R&D grants, businesses additionally invest 7.5p. However, there is scarce evidence on the returns of R&D grants for recipient businesses.

Baghana (2010) employed a production function to estimate the returns on R&D grants investment for recipient businesses in Canada. Whereas the treatment group was consisting of businesses that had received R&D grants and the control group of businesses that had not, all businesses from both groups were also recipients of fiscal incentives for R&D. The author found that an additional $1 in R&D grant investment yielded an additional $0.134 in value-added, therefore a return on R&D grant investment of 13.4%. However, the author acknowledged that inappropriate data to proxy the capital stock and knowledge stock may question these findings.

Estimating the effects of R&D grants on business productivity is an equivalent framework to estimating the effects of R&D grants on a measure of output. Although there are some studies that investigate the impact of R&D grants on business productivity (Girma et al., 2007; Karhunen and Huovari, 2015; Cin et al., 2017; Howell, 2017), measured by either total factor productivity or labour productivity, none of them explicitly quantifies the additional returns on public R&D support investment or provide the necessary information to calculate them. This is because of either the absence of information on the value of R&D grants or the adoption of binary indicators to capture receipt of R&D support where the estimation of marginal effects is not possible.

Figure 1. Direct government funding and tax support for business R&D in 2018 (% GDP). Source: OECD R&D Tax Incentives Database, March 2021.



3. ANALYTICAL FRAMEWORK

3.1 Extended Production Function

The returns from knowledge can be measured as the contribution of businesses' knowledge stock to their output (Griliches, 1979). Therefore, appropriate econometric modelling is employed that can treat the knowledge of the businesses as an input of the production process – besides capital and labour which are the key inputs. To this end, it is essential to calculate the cumulative over time knowledge of businesses which stems from their R&D investments, i.e., their R&D stocks.

To estimate the returns of R&D investment, we employ the production function approach which is widely used in the literature [for a survey of studies, see (Hall et al., 2010)]. More specifically, we use an extended version of the Cobb-Douglas production function where, besides the classical inputs of capital and labour, it additionally includes knowledge capital. We proxy knowledge capital by the accumulation of investment in R&D over the years and we differentiate between businesses' own and external knowledge capital. Whereas the former refers to the knowledge stock of the individual business proxied by its R&D capital stock, the latter refers to the knowledge stock of the industry the business operates into and is proxied by the R&D capital stock of other businesses in the industry. The two terms enable the identification of private and social R&D returns respectively with the latter stemming from the presence of (positive) external knowledge spillovers taking place within the industry. Although the interest lies in private R&D returns, knowledge spillover effects should not be neglected in estimating private R&D returns. Indeed, not accounting for knowledge spillover effects (and, hence not estimating social R&D returns) may overestimate private R&D returns (Eberhardt et al., 2013).

From an econometric perspective, the extended production function equation is expressed as:

$$y_{it} = \lambda_t + \alpha L_{it} + \beta C_{it} + \gamma K_{it}^{int} + \mu K_{it}^{ext} + \varepsilon_{it} \quad (1)$$

where y_{it} it is the logarithm of value added, λ_t is the time effect, L_{it} is the logarithm of the labour input, α is the elasticity of value added with respect to labour L_{it}, C_{it} is the logarithm of the (tangible) capital input, β is the elasticity of value added with respect to capital C_{it}, K_{it}^{int} is the logarithm of own R&D capital, γ is the elasticity of value added with respect to internal knowledge K_{it}^{int}, K_{it}^{ext} is the logarithm of other businesses' R&D capital, μ is the elasticity of value added with respect to external knowledge K_{it}^{ext} and ε_{it} is the usual error term.

The elasticity of output (GVA) with respect to internal knowledge γ is a measure of the effect of own R&D capital on output and therefore captures the contribution of R&D to the growth of output. However, the elasticity effects do not constitute an easily interpretable measure of returns because it is expressed in percentage changes in R&D capital rather than changes in levels. To obtain a more interpretable measure of returns, we calculate the marginal effects based on the median of output (GVA) and R&D capital which are equivalent to rates of R&D return. We use the median as it more accurately corresponds to the typical (or 'middle') business in the sample as, contrary to the mean, it is not sensitive to the presence of very large values of R&D expenditures for large businesses. To calculate the rate of private (social) R&D returns we multiply γ(μ) by the ratio of median GVA to median own (external) R&D capital. These effects can be calculated by using the formulae:

$$Private\ R\&D\ returns = \gamma \frac{median\ output}{median\ own\ R\&D\ capital} \quad (2)$$

$$Social\ R\&D\ returns = \mu \frac{median\ output}{median\ external\ R\&D\ capital} \quad (3)$$

3.2 Econometric Estimation Issues

Difficulties in measuring R&D returns have been long documented since the seminal work of Griliches (1979) who stressed econometric issues in the estimation of the extended production function. There are two main reasons why estimation of the extended production function in Eq.(1) may lead to biased estimates of the model's coefficients.

First, measurement issues relating to the double-counting of R&D. The figures of labour (i.e., total employment) and capital include an R&D component as R&D employees are recorded in total employment figures and (part of) R&D expenses is recorded as capital expenditure. Therefore, the figures of labour and capital are not net of the R&D component and if we additionally include the R&D capital in the model specification we will double-count R&D. This could lead to the underestimation of R&D returns and the estimation of only an "excess" rate of return and not a "total" rate of return (Hall and Mairesse, 1995). Indeed, after Hall and Mairesse (1995) corrected for the double-counting of R&D in their study on French manufacturing businesses for the 1980-1987 period, the rate of private R&D returns increased from 23% to 27% whereas the coefficient on labour decreased by approximately the same amount (i.e., 4 percentage points). To address this issue, we remove the number of R&D employees from total employment and also remove the part of R&D expenditure that is capitalised from the measurement of the capital stocks (see below).

Second, simultaneity issues may bias the estimates of the model's coefficients. The simultaneity issues arise from the potentially simultaneous relationship between the inputs of production and output. Whereas higher amounts of inputs are expected to lead to more output, unobservable positive productivity shocks (that are accompanied with an increase in output, ceteris paribus) may, in turn, encourage businesses to use more inputs as a response to output increases. In other words, there may be a two-way causality which, within an econometric context, gives rise to endogeneity. To correct for this, we follow an instrumental variable approach in estimation as set out in Levinsohn and Petrin (2003). The authors propose the use of intermediate input data to address simultaneity as they are correlated with the productivity shocks. An alternative to this approach is to employ the Generalised Method of Moments (GMM) estimator developed by Blundell and Bond (1998). This estimator, which is also known as simply the system GMM estimator, tackles endogeneity by using lagged terms of the dependent variable and exogenously determined independent variables as instruments. The model expresses the first difference of the dependent variable as a function of the differenced lags of independent variables which are believed to be endogenous. We use the two-step estimator variant which can address the simultaneity in the model. [For an application in the R&D support literature, see Yang et al. (2012).]

3.3 Innovate UK Funding Returns

We identify two channels through which Innovate UK grants can yield returns for recipient businesses. The first channel captures the direct impact of grants on business GVA as public funds can directly affect GVA, i.e., the channel of "grant-based returns". The second channel is through inducing additional investment on behalf of the funded business, i.e., the channel of "additionality-based returns" where additionality refers to an increase in private R&D spending over and above of what would have happened in the absence of the grants. In the case where public funding can leverage additional private spending in R&D, then public funding can indirectly impact GVA through the additional private R&D spending.

3.3.1 Grant-based Returns

To identify the first channel of impact, we explore the returns on the Innovate UK grant investment in recipient businesses. In doing this, we model output as a function of the knowledge stock generated by Innovate UK grants which is captured by the R&D capital stock formed by Innovate UK grant investment alone:

$$y_{it} = \lambda_t + \alpha L_{it} + \beta C_{it} + \gamma K_{it}^{int-net} + \varphi K_{it}^{int-pub} + \mu K_{it}^{ext} + \varepsilon_{it} \tag{4}$$

3.3.2 Additionality-based Returns

An intuitively simple way to measure the impact of Innovate UK grants on business private R&D spending would be to simply compare the private R&D investment of businesses having received grants with the private R&D investment of businesses that have not received grants. Although this approach is very appealing due to its simplicity and quick execution, it makes the strong assumption that the characteristics between grant recipient businesses and businesses that did not receive grants are essentially the same. However, both UK-based and international evidence has shown that recipient businesses are different to non-recipient businesses in a series of characteristics such as their size, their ownership status (i.e., foreign owned vis-à-vis domestic businesses), their exporting activity, and market share (Czarnitzki and Lopes-Bento, 2013; Vanino et al., 2019). Therefore, the results from such a simple approach would be biased due to the dissimilarity of grant recipient businesses and businesses that did not receive grants.

This heterogeneity in the characteristics between the two types of businesses is due to the selection to public R&D support programmes. For example, larger businesses may be more likely to apply and eventually receive public R&D support because they typically have a formal R&D department and more resources to allocate to both the application for funding and the execution of the R&D project after funding was received. On the other hand, certain R&D support programmes may be targeted towards businesses with specific characteristics which may be the result of either intended policy or any biases on behalf of the selection panel that decides which businesses would receive R&D support (Dimos and Pugh, 2016). In any case, and no matter where the source of selection lies, recipient and non-recipient businesses have different characteristics, and their private R&D investments are not directly comparable. In other words, businesses are not randomly allocated in the two groups defined by the receipt or non-receipt of public R&D support, and in order to estimate an unbiased effect of the Innovate UK grants a valid counterfactual needs to be constructed.

In identifying a causal effect of Innovate UK grants on business R&D investment, we employ the data pre-processing method of Entropy Balancing (EB) as this was introduced by Hainmueller (2012). Unlike matching methods where they only approximate a randomised experiment, entropy balancing can simulate a randomised experiment by eliminating any observable differences in the business characteristics variables between the treatment and control groups. These differences may not pertain only to the mean (i.e., first moment), as is the case with PSM, but also to higher moments (such as the variance and skewness). An additional advantage of the EB method lies in that, unlike PSM, there is no need to iterate on a matching model whereby after performing the match, the researcher checks the balance of the confounding factors (i.e., business characteristics) and, if unsatisfactory, amends the model to achieve an improved balance. On the contrary, EB ensures the best possible covariate balance between treated and untreated units at first place and then calculates appropriate weights that can be, in turn, used to infer causality.

More specifically, we use a series of key business characteristics that appear in the data and can influence selection in Innovate UK programmes and/or private R&D investment, such as business size in terms of employment (also modelling its squared value to capture any non-linear effects of size on the propensity to receive funding), type of ownership (i.e., foreign vs domestic ownership), gross operating surplus, capital intensity (defined as total capital divided by employment), and industry affiliation. Besides these business characteristics we additionally control for the region the headquarters of the business are located and the year of observation. We balance the business characteristics on two moments, i.e. the mean and variance. This is sufficient especially if we consider that for binary covariates adjusting for only the first moment is equivalent to adjusting for higher moments (Hainmueller and Xu, 2013).

Annex A. Matching Methods

A valid counterfactual would essentially shed light into understanding what would have happened to the R&D returns of recipient businesses in the absence of Innovate UK support. This could be done by constructing a control group containing non-recipient businesses (i.e., untreated businesses) that would resemble in all respects the treatment group containing recipient businesses (i.e., treated businesses) except for the treatment status – i.e., supported and non-supported businesses. Various methods have been proposed to construct a valid counterfactual with the most popular methods being the matching methods and, in particular, the Propensity Score Matching (PSM) variant.

Matching methods construct the counterfactual by matching untreated businesses to treated businesses based on a set of business characteristics. However, a significant weakness of matching methods when used on their own is that they only account for observable influences that may condition the selection in the R&D support programmes. This means that if other unobservable influences condition selection and/or R&D returns, then the effects estimated from matching methods would be biased. Indeed, in the public R&D support literature it has been shown that matching methods inflate the estimated subsidy effects vis-à-vis other methods that account for unobservable influences such as Difference-in-Differences (DiD) or Instrumental Variable (IV) estimation (Dimos and Pugh, 2016).

Another issue with matching methods is that in only taking into account businesses that are very similar to treated businesses they essentially discard an often large amount of untreated businesses. This is particularly true for the exact matching estimator where there is the requirement to match businesses in the two groups based on exact values of their characteristic variables. Although from one perspective this is desirable, from another perspective this constitutes a significant loss of information.

Finally, a third weakness of matching methods using propensity scores – i.e., scores capturing the propensity to receive public R&D support – lies in constructing an 'approximate' counterfactual (always based on observable characteristics) rather than the 'best possible' counterfactual. This is because in PSM the similarity of the business characteristics in the two groups is often regarded satisfactory when the differences in the characteristics variables in the two groups are not statistically different at the 10% level of significance (i.e., a p-value higher than 10%). Although this is understandable from a statistical perspective, still the success of matching for some variables may be 'marginal' (i.e., a p-value just above the 10% threshold) whereas for other variables close to randomised experiment conditions (i.e., a p-value above the 90% or 95% threshold) (Hainmueller, 2012).

After we extract the calculated weights from the EB method that achieve covariate balance, we use them as weights in estimating a Fixed Effects (FE) regression where the R&D expenditure net of Innovate UK funds is regressed on an indicator of whether a business has received Innovate UK grants. The EB weights render the recipient and non-recipient groups identical in terms of the business characteristics we control for, and therefore the coefficient $\beta 1$ on the indicator of grant receipt measures the Average Treatment Effect on the Treated (ATT):

$$RD_{it}^{net} = w_{it}^{EB}\left[\beta_0 + \beta_1 D_{it} + \beta_\kappa \sum_1^k X_{it}^k + \beta_m Ind_{it}^m + \beta_n Reg_{it}^n + \beta_l Year^l + \mu_i + \varepsilon_{it}\right] \quad (5)$$

where RD_{it}^{net} is the R&D expenditure of businesses net of Innovate UK funds, w_{it}^{EB} are the EB weights, D_{it} captures whether business i has received Innovate UK grants at time t , $\sum_1^k X_{it}^k$ is the sum of the k covariates X, Ind_{it}^m are the m industry indicator variables, Reg_{it}^n are the n region indicator variables, $Year^l$ are the l year indicator variables and μ_i is the vector of business-specific indicators (i.e., fixed effects). Although we controlled for the influence of covariates including industry, region and time-specific influences in the calculation of the EB weights, we additionally control for these influences to ensure that any potentially remaining covariate imbalance between the treatment and control groups is eliminated.

Besides controlling for observable influences, we additionally control for unobservable influences that are business-specific. Such influences may pertain to business characteristics such as ambition or access to banking finance among others. If selection into Innovate UK programmes and/ or investment in business R&D is conditioned by unobservable – besides observable – influences, then not controlling for the former would lead to biased estimates of Innovate UK grant effects. In other words, by controlling for unobservable influences we estimate an effect closer to the true but unknown underlying effect. Indeed, it has been shown that by controlling for observable influences alone inflates the estimated subsidy effects vis-à-vis methods that account for unobservable influences (Dimos and Pugh, 2016).

There are three possibilities regarding the ATT (i.e., the β_1 coefficient):

a. if the ATT is positive (and significant from a statistical perspective), it means that Innovate UK grants can leverage additional private R&D spending;

b. if the ATT is statistically insignificant, then the grants have no impact whatsoever on private R&D spending; and

c. if the ATT is negative (and statistically significant), then the grants crowd out private investment in R&D.

In the case where the Innovate UK grants have an impact on private R&D spending, i.e., the ATT is either positive or negative, then we further investigate the marginal effect of Innovate UK grants on private R&D spending – in other words, the additional spending in private R&D leveraged by receipt of£1 of Innovate UK grants. In doing so, we use the magnitude of the ATT and information on the size of Innovate UK grants and the R&D expenditure of non-recipient businesses.

4. DATA AND VARIABLE MEASUREMENT

4.1 Data Sources

Data from two sources are linked to create an appropriate dataset enabling estimation of the R&D returns:

a. The Annual Business Survey (ABS) which is the largest business survey conducted by the Office for National Statistics (ONS) in terms of the combined number of respondents and variables it covers. The ABS provides high-level indicators of economic activity such as the total value of turnover, the value of purchases and disposals of goods, materials and services, and employment. [see here]

b. The Business Enterprise Research and Development (BERD) survey which captures the R&D expenditure and R&D employment of UK businesses broken down by product sector. [see here]

Both surveys are of a longitudinal structure and are linked to enable estimation of business R&D returns by combining the production-related data of the ABS and the R&D-related data of the BERD.

In assessing the impact of Innovate UK grants, the two surveys are further linked to data published by Innovate UK which contain information on projects funded by Innovate UK since 2004. [see here] This dataset, which is in line with transparency practices in how public funds are spent, contains the start and end date of the funded project as well as the amount of grants received by businesses and other organisations broken down by the different products of Innovate UK (such as “Collaborative Research and Development” and “Feasibility Studies”).

To calculate the business-level net stocks of capital, additional data are used which are published by the ONS and The World Bank:

- The gross and net capital stocks for the UK economy broken down by industry. From this dataset, we extract the net capital stocks at the 2-digit Standard Industrial Classification (SIC) 2007 level.

- The ABS survey aggregated at the 2-digit SIC 2007 level. From this dataset, we use (i) the industry-level total employment costs, and (ii) the industry-level total purchases of goods, materials and services. This information enables us to allocate the industry-level net capital stocks to individual businesses based on their shares in total employment and purchases of goods, materials and services.

- GDP deflator for the UK economy published by The World Bank. It is used to produce constant price figures of capital stocks.

- To calculate the business-level and industry-level net stocks of R&D capital, the following additional data are used which are published by the ONS and the Organisation for Economic Co-operation and Development (OECD):

- Expenditure on R&D performed in UK businesses at the 2-digit SIC 2007 level (ONS and OECD). The industry-level data are drawn from two sources to complement missing values across years appearing in the one source but not in the other.

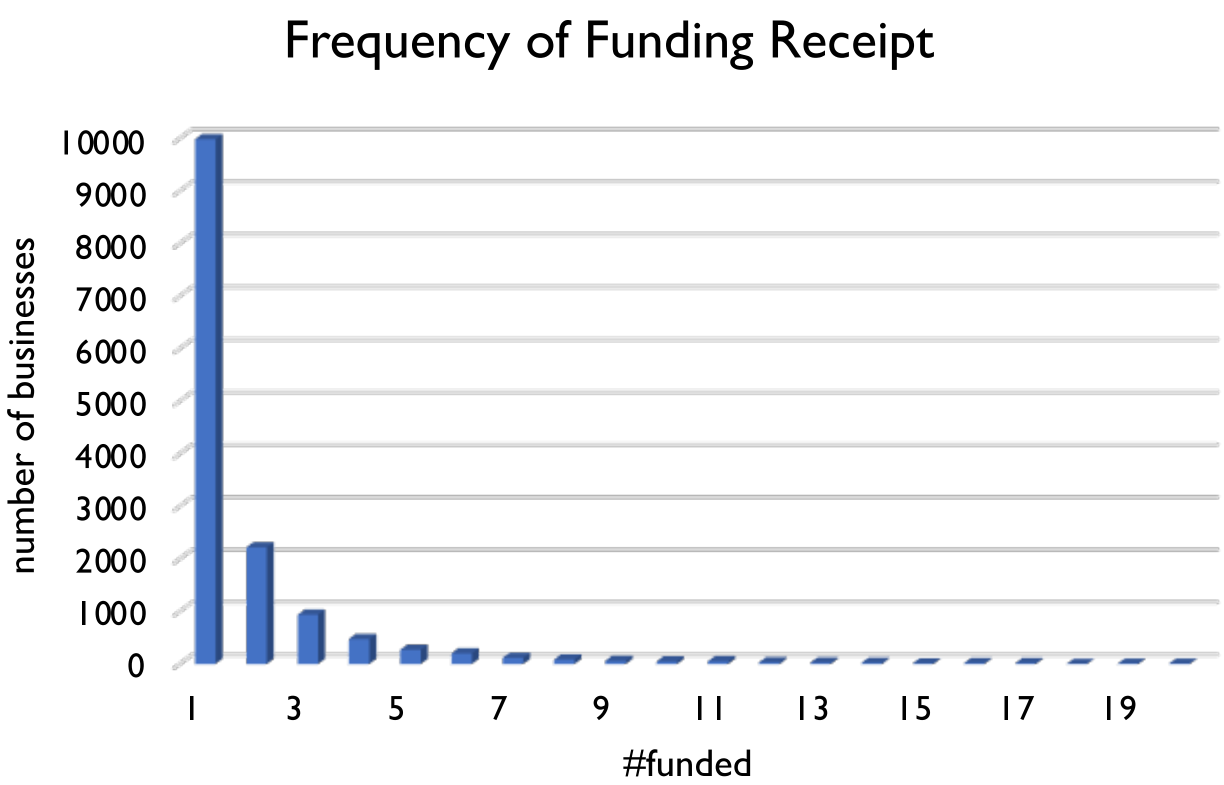
- Intangible assets deflators broken down by asset for the UK economy. The R&D deflator is used to produce constant price figures of investment in R&D.

4.2 Linking Data

We use the ABS and BERD survey waves covering the period 2008-2019. After linking the two surveys we construct a longitudinal dataset of 38,031 businesses and 187,421 business-year observations.

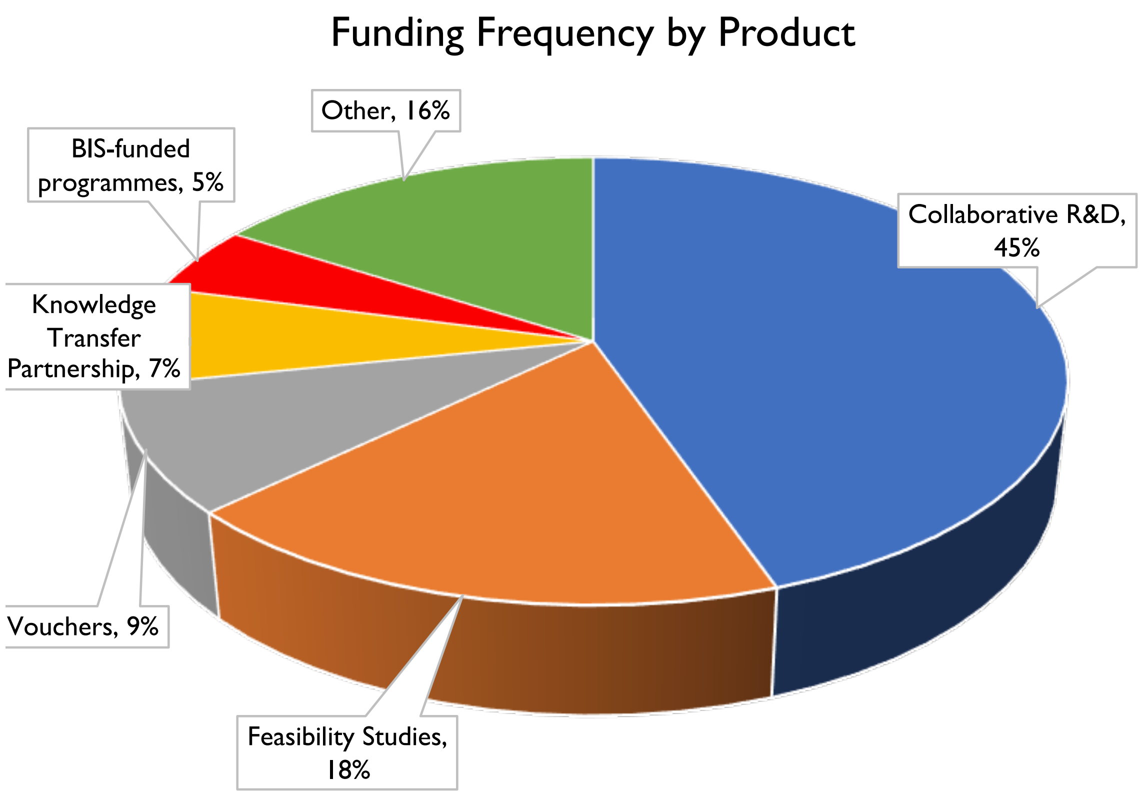
This combined dataset is further linked to the Innovate UK 'transparency data'. The latter dataset is cleaned from entries that pertain to: (a) missing CRN code as such entries cannot be identified and linked to the combined ABS/BERD dataset; (b) universities and charities, as these organisations are not private businesses; (c) withdrawn successful applicants, as these organisations did not receive funds from Innovate UK; (d) funding from the Department for Business, Energy and Industrial Strategy, Knowledge Transfer Network, centres, and launchpad, as these sources of funding are different to the core funding of Innovate UK; and (e) funding received in the 2020/21 financial year or later, as this funding lies outside the 2008-2019 period of study. The cleaned Innovate UK dataset consists of 30,010 entries that correspond to 14,681 businesses. This is due to some businesses having received funding more than once. Figure 2 illustrates the frequency of funding receipt for beneficiary businesses. While the majority of businesses have received funding only once (9,983 businesses), approximately one third of businesses have received funding more than once with the maximum being 215 times.

Figure 2. Frequency of funding receipt for businesses (2004-2019). Source: Authors.



With respect to the frequency of funding across the different Innovate UK products, in approximately half of the instances funding was awarded under the 'Collaborative R&D' product, with approximately one in five instances corresponding to the 'Feasibility Studies' product. Figure 3 illustrates the most frequently used Innovate UK products since 2004.

Figure 3. Funding Frequency by Innovate UK product (2004-2019). Source: Authors.



In linking the combined ABS/BERD dataset to the Innovate UK 'transparency data', the matching rate was approximately 11%. This means that approximately one tenth of the businesses appearing in the combined ABS/BERD dataset were funded at some point by Innovate UK (i.e., 4,450/41,171). These businesses constitute approximately one third of the businesses appearing in the Innovate UK dataset (4,450/15,000).[1]

4.3 Variable Measurement

4.3.1 Output / Inputs

Output is measured by the Gross Value Added (GVA) of individual businesses, defined as the gross output minus all purchased intermediate inputs, which is the most used measure in the estimation of R&D returns (Hall et al., 2010). This implies that the returns of R&D are also expressed in terms of GVA.

To eliminate the influence of inflation on the monetary series used, including GVA, we use appropriate deflators to deflate the corresponding series. All monetary variables used are expressed in constant 2019 prices, i.e., the last year of observation in our sample. For the GVA variable, we use an annual GDP deflator published by The World Bank. This deflator is used for all monetary series except for the R&D investments where R&D-specific deflators are used to calculate the real investments in R&D (see below).

1 Our viable sample size for analysis pertains to fewer than the 4,450 businesses due to missing values for some key variables.

The most complete series in the dataset is employment, and this variable is used as the basis for the imputation of missing values for other variables. In line with Gilhooly (2009), for business-year observations where there is a value for employment, any missing values of GVA are imputed by either interpolation/extrapolation or using the mean of the real series where interpolation/extrapolation is not possible.[2]

Labour inputs are measured by the number of employees of the business. An employment variable that is net of the number of R&D employees is used to avoid double-counting of R&D and avoid inducing bias to the estimates of R&D returns (see above).

The intermediate inputs are captured by the intermediate consumption of materials and fuels used in the production process.

The net capital stocks of businesses were calculated by two different approaches. In the first approach, we used the net capital expenditure of businesses broken down into three categories, namely 'dwellings, 'machinery and equipment' and 'vehicles'. For each category, we employed the Perpetual Inventory Method (PIM) where the sum of the written-down values (i.e. after depreciation) of capital investments for a given year is the net capital stock for that year. The PIM can be expresses as:

$$C_{it} = (1-\delta)C_{i,t-1} + CI_{it} \qquad (6)$$

where C_{it} is the tangible capital in the current period, δ is the depreciation rate of tangible capital, $C_{i,t-1}$ is the tangible capital in the previous period and CI_{it} is the real investment in tangible capital in the current period captured by the business net capital expenditure. Depending on the three types of capital expenditure, we use three different depreciation rates. We follow the ONS and for 'dwellings' we assume a service life of 50 years and use a depreciation rate of 0.02, for 'machinery and equipment' a depreciation rate of 0.06 and for 'vehicles' a depreciation rate of 0.20 (ONS, 2007).

Given that our investigation covers the 2008-2019 period, we are unaware of the level of businesses' net capital expenditure before 2008 that contribute to the accumulation of capital in 2008 and later. To address this issue, we follow Gilhooly (2009) and use industry-level data at the 2-digit on net capital stocks to estimate the initial capital stock of businesses for the first period observed in the sample. To do this, we use the total purchases of goods, materials and fuel, and total employment costs variables which are: (a) correlated with the capital stock, and (b) available at both the business and industry levels. We calculate the weighted average – the weights being 0.5 – of the following two shares: (i) the share of each business in the industry's total purchases, and (ii) the share of each business in the industry's total employment costs. This enables the allocation of industry's net capital stocks across individual businesses by using this overall share.

After the estimation of the initial net capital stock, we can initiate the PIM by using for each future year the depreciated capital from the previous period plus the net capital expenditure in the current year. However, the resulting net capital stocks series may result in some values being negative due to the estimation of a lower than actual initial stock of capital and/or the presence of negative values for net capital expenditure. Negative net stock values are by no means possible as tangible capital cannot be negative but only positive. To correct for these few values in relation to the sample size, we additionally inject capital in updating the initial capital stock by increments of 10% until all

[2] In the resulting dataset, approximately 30% of the GVA values are imputed. In imputing missing values for capital investment and by using longitudinal data based on the Annual Business Inquiry (ABI) (i.e., the previous name of the ABS survey), Gilhooly (2009) – essentially an ONS publication – recommend the use of a ratio of imputed to real values not greater than a 1:1 ratio. Based on this guideline, our imputation ratio is satisfactory. This also contributed that we did not impute any missing values on employment as in Gilhooly (2009), but instead used only the actual employment values.

capital stock values across all years are positive. Having calculated net capital stocks for each type of capital, we sum all net capital stocks to construct an overall measure of tangible capital. Finally, to address the double-counting of R&D we remove the R&D component that is already capitalised (this is available in the BERD dataset) from the estimated net capital stocks.

We also employ a second approach in calculating the net capital stocks of businesses which is simpler, yet it yields superior calculations of capital stock.[3] Contrary to the first approach, where only the initial capital stock, i.e., for the first year of observation of the business in the data, was calculated by using industry-level capital stock data and the overall share discussed above, in the second approach all values of businesses' net capital stocks are calculated directly from industry data without the use of the PIM and businesses' capital expenditure. This approach has the advantage that no negative values of capital stock are calculated as no (negative) net capital expenditures participate in the calculation of capital stocks.

4.3.2 Business R&D Capital Stock

Intangible assets constitute an increasingly growing share of the largest companies' value today and there is an increasing interest in their valuation (Corrado et al., 2017; HM Treasury, 2018a). From a capitalisation perspective, 'there is no basis … for treating investments in intangible capital differently from investments in plant and equipment, or tangible capital' (Corrado et al., 2005:13). For the capitalisation of tangible assets, the PIM is widely used which is a method that is now common practice for the capitalisation of intangible assets too (SPINTAN, 2016). The PIM, which is the methodological approach also used by the ONS, is the 'only practical device to arrive at meaningful estimates for net stocks for intangible assets' (Görzig and Gornig, 2016:110).

In employing the PIM, the sum of the written-down values (i.e. after depreciation) of intangible investments for a given year is the net capital stock for that year. In the case of R&D this means that the capital stock of R&D for a given year will be the sum of R&D investment in that year and all past depreciated R&D investments (Dey-Chowdhury, 2018). Therefore, we use data on the R&D expenditure of the business and employ the Perpetual Inventory Method (PIM) (Dey-Chowdhury, 2008) which is expressed as follows:

$$K_{it} = (1 - \delta^{'})K_{i,t-1} + R_{it} \qquad (7)$$

where K_{it} is the R&D capital in the current period, δ' is the depreciation rate of R&D capital, $K_{i,t-1}$ is the R&D capital in the previous period and R_{it} is the real investment in R&D capital in the current period captured by the business R&D expenditure.[4]

[3] As estimation of the production function has shown.
[4] Interestingly, by using R&D capital and tangible capital data to estimate the extended production function, private R&D returns are found to be double the size of returns to investment in tangible capital (Doraszelski and Jaumandreu, 2013).

To calculate the initial R&D capital stock we assume a service life of R&D of 7 years – in line with the ONS practice – and impute missing R&D expenditure data for the six years preceding 2008 (i.e., the 2002-2007 period) (Griliches and Mairesse, 1984). In doing so, we use the annual R&D expenditure growth figure of 3.5% which is calculated from 2-digit industry-level R&D expenditure data. By starting the PIM from year 2002 – and with a 7-year life service of R&D – we ensure that all investments in R&D before 2008 relevant for the calculation of R&D capital stocks in 2008 or afterwards are accounted for. Unlike capital stock where figures are published at the industry level and they can be allocated to businesses as outlined above, there is no industry-level information on the R&D stock and, therefore, the PIM must initiate before your sample start date.

Contrary to tangible assets, where depreciation relates to wear and tear, depreciation of intangible assets occurs due to obsolescence. In an R&D context, this means that new knowledge can render past knowledge obsolete and nullify part of its value (Hall, 2007). In theory, the depreciation rate is difficult to approximate, it is not easily observed and is unique to the business. Empirical evidence suggests that the depreciation rate of R&D varies between 0% and 40% depending on the method used (i.e., the production function or market value methods) and the period examined (Hall, 2007). The literature also suggests that depreciation rates are also economy-specific where higher depreciation rates apply for more dynamic and technologically advanced economies. For example, Corrado et al. (2016) recommend using a 7.5% rate for EU economies and a 11.5% rate for the US economy.

Although there is no consensus on a definitive depreciation rate in the literature, the most commonly used depreciation rate for R&D investment is 15%. This is also the rate at which the Office for National Statistics (ONS) depreciates R&D in its own net stock calculations while assuming an R&D service life of 7 years. We, therefore, also use an R&D depreciation rate of 15%. In any case, estimation of the rate of R&D return is not sensitive to the choice of the R&D capital depreciation rate (Hall and Mairesse, 1995; Harhoff, 1998).

In deflating the R&D investment series, we use R&D-specific deflators published by the ONS. These use of such deflators, which are published alongside other deflators for intangible assets, acknowledge the specific market for R&D where prices may not follow the same trend with the general level of prices in the economy.

4.3.3 Measurement of R&D spillovers

The public good characteristics of R&D, namely non-excludability and non-rivalry, along with imperfect intellectual property mechanisms give rise to knowledge (R&D) spillovers. These typically occur through imitation from competitors within the same industry the business operates into (Corderi and Lin, 2011; Corderi and Lin-Lawell, 2016; Inglesi-Lotz, 2017). To measure R&D spillovers, it is essential to construct a metric of proximity or similarity of businesses. The more technologically proximate or similar the businesses are, the more likely to mutually benefit from their R&D (Griliches, 1979). In practice, this may be a challenging exercise since the criteria on which such metrics are constructed are subject to the choice of the researcher.

Various metrics have been suggested in the literature. Patent information can be used to identify in which technological areas a certain business is active and accordingly codify this information and construct an appropriate indicator

(Jaffe, 1986; Jaffe, 1988). Crépon and Duguet (1993) use a proxy that is based on a variable where each business takes the value of total R&D spent in the industry net of the business's individual R&D. With this approach the authors attempt to identify the part of information that is relevant to competitors within the same industry. In measuring spillovers, Harhoff (2000) suggests allocating the R&D performing businesses of the sample into industries and product areas. Whereas the taxonomy across industries is straightforward, the taxonomy across product areas is determined by the share of R&D expenditure businesses allocate to each product area. Each spillover measure captures different types of spillovers. For example, a patent-based measure will mostly be reflecting "knowledge-based" spillovers whereas a product-area-based measure will mostly be reflecting "market-based" spillovers (Harhoff, 2000).

We follow Crépon and Duguet (1993) and construct a variable that captures the total R&D stock at the 2-digit Standard Industrial Classification (SIC) 2007 level net of the R&D stock of each business.[5] Our choice of measuring spillovers is conditioned by the data at hand. As R&D expenditure data by industry were only available at the 2-digit Standard Industrial Classification (SIC) 2007 level and not at a more 'granulated' level, a more detailed identification of competitors' R&D stocks is precluded. We are mindful that this spillover variable may also capture R&D that is not directly relevant and usable to each business and therefore with limited accruing benefits.

Inspired by Harhoff (2000) and exploiting available data in the ABS/BERD surveys, we additionally construct an alternative spillover variable, which allocates the businesses of the sample into regions and product areas. As the product areas appearing in the BERD survey are based on the industry classification, we cannot exactly imitate the method of spillover variable construction followed in Harhoff (2000). Instead of industries, we use the region the business operates in to capture spillovers taking place due to geographical proximity. By summing the R&D stocks of businesses operating in the same product area and region, this spillover variable may better capture R&D that is relevant to competitors. In any case, as the focus is on measuring private R&D returns, the use of a spillover variable mainly serves the purpose to control for external R&D capital.

4.3.4 Measurement of Public R&D Capital

Public R&D capital refers to the R&D capital stock created solely by the Innovate UK grants. The Innovate UK dataset does not record the exact timing of grant payment to businesses. However, as the duration of the project is recorded, we uniformly allocate the size of the actual grant received across the months of the project duration. This enables us to approximately determine the amount of grant received in each calendar year thus allowing for a direct linkage to information from the ONS datasets. As each business may have received multiple Innovate UK grants throughout the 2008-2019 period, we sum all grants received by a business in a given year.

The measurement of public R&D capital follows the same principle to the measurement of businesses' total R&D capital. We capitalise the real series of Innovate UK grants from 2008 until 2019 by employing the PIM and, similar to business R&D, we assume the service life of the R&D funded by Innovate UK grants to be 7 years therefore implying a depreciation rate of 15%.

[5] This variable was derived after capitalising the industry-level R&D expenditures in the same manner as for individual businesses' R&D capital stocks.

5. RESULTS

5.1 Impact of Total R&D

Before estimating the returns of Innovate UK grants, we estimate Eq.(1) to understand the returns on the total R&D investment of businesses, i.e., without differentiating between the sources of R&D funds (Innovate UK vs other funds). Table 1 presents the estimation results.

Table 1. Production Function estimation. Bootstrapped standard errors in parentheses. * denotes statistical significance at the 1% level. Source: authors.**

Production Function estimation	(1)	(2)	(3)
	Value Added (y_{it})	Value Added (y_{it})	Value Added (y_{it})
Labour (L_{it})	.5982*** (.0092)	.5277*** (.0089)	.5164*** (.0085)
Capital (C_{it})	.2524*** (.0167)	.2538*** (.0208)	.2562*** (.0169)
Internal R&D (K_{it}^{int})	-	.1088*** (.0050)	.1105*** (.0043)
External R&D (K_{it}^{ext}) (Industry R&D)	-	.0230*** (.0025)	-
External R&D (K_{it}) (Product group / Region R&D)	-	-	.0324*** (.0016)
Constant returns to scale (Wald test)	chi2=71.90 (p=0.000)	chi2=27.43 (p=0.000)	chi2=21.97 (p=0.000)
Observations			
# Business-year	187,421	186,876	187,421
# Businesses	38,031	37,929	38,031

The value-added elasticities with respect to labour and capital, α and β, are both positive while their magnitude is very consistent with international evidence on output elasticities (Column 1). This endorses our capital stock construction and imputation strategy. The sum of the two elasticities is close to but smaller than unity and the Wald test suggests that there are decreasing returns to scale (p=0.000). The value-added elasticity with respect to internal R&D capital, γ, is positive and statistically significant at the 1% level which provides evidence that knowledge stemming from internally conducted R&D creates value for the business. The estimated value-added elasticity γ are 0.109 (p=.000) and 0.023 (p=.000) respectively (Column 2). This means that a 1% increase in the R&D capital stock of the business would lead to a 0.109% increase in its value added. In other words, a doubling of its R&D capital stock (i.e., a 100% increase) would lead to a 10.9% increase in its value added. As businesses and policy makers are more interested in the ROI rather than elasticities, we calculate the ROI by using the median values of businesses' value added and own R&D capital stocks.[6]

[6] Unlike the mean, the use of the median is not sensitive to extreme values of R&D investment or value added that may exert an undue influence on results.

This results in the calculation of a rate of R&D return of 68%. This means that for each £1 invested in R&D, businesses benefit from an increase in value added of 68p. This effect is economically significant and in line with international evidence on R&D returns as taxonomized in Hall et al. (2010).

The value-added elasticity with respect to external R&D capital, μ, is positive and statistically significant at the 1% level meaning that knowledge stemming from externally conducted R&D also creates value for the business. The estimated value-added elasticity $\hat{\mu}$ is 0.023 (p=.000) (Column 2) which means that a doubling of the industry R&D capital stock ($K_{it}^{ext,1}$) would only lead to a 2.3% increase in the value added of the business. This increase is about five times smaller compared to the increase in value added caused by the R&D conducted in the business (10.9%). If we use the alternative external R&D variable ($K_{it}^{ext,2}$) that captures both technological and regional knowledge spillovers, the estimated elasticity for external knowledge somewhat increases to 0.032 (p=0.000) (Column 3) – however, it remains substantially smaller than the corresponding elasticity for internal knowledge of 0.111 (p=0.000) (Column 3). The elasticities for both measures of external knowledge confirm that industrial, product and regional knowledge spillovers constitute a significant input in businesses' effort to create more value added. However, it is clearly documented that external knowledge does not exert such a significant influence as the internal knowledge of businesses. As the focus of the study is on the return estimation of R&D conducted within the business and not externally, we only use external knowledge as a control variable in our model which allows for a more accurate estimation of internal R&D returns. Given that results are largely insensitive to the choice of the two variables, we only use the external R&D stock constructed by 2-digit industrial level R&D expenditure data (i.e., Column 2 in Table 1) in the rest of the analysis.

The private R&D return of 68% is not uniform across all businesses but it rather corresponds to the typical business in the UK. Besides this overall return, we additionally estimate the R&D returns across different types of businesses – Table 2 summarises these R&D returns and corresponding elasticities. With respect to business size, we find that large businesses can benefit double as much from their R&D investments in increasing their value added vis-à-vis micro businesses and SMEs. This may be due to their ability to better leverage the outcomes of their R&D as they tend to be less financially constrained than smaller businesses. Domestic and foreign-owned businesses appear to benefit from R&D returns of a similar magnitude which lie above 70%. Finally, the ROI for manufacturing businesses is smaller than the ROI for services businesses.

Table 2. Heterogeneity of R&D Returns.

***** denotes statistical significance at the 1% level. Source: Authors.**

Type of Business	Observations (#Business-year / #Businesses)[7]	Elasticity	Internal R&D Returns
	(1)	(2)	(3)
All businesses			
	186,876 / 37,929	.109*** (p=.000)	68%
Business size			
Micro and SMEs	168,389 / 34,959	.109*** (p=.000)	64%
Large	18,487 / 4,447	.124*** (p=.000)	141%
Ownership			
Domestic	65,517 / 13,792	.096*** (p=.000)	73%
Foreign	66,643 / 15,693	.110*** (p=.000)	75%
Sector			
Manufacturing	74,993 / 13,480	. 084*** (p=.000)	50%
Services	110,744 / 24,694	.123*** (p=.000)	74%

Businesses are not isolated from their geographical surroundings. The region in which businesses are located may condition their access to talent pools, crucial infrastructure and business networks among other factors that determine business operations and performance. Table 3 presents the R&D returns of businesses across the different regions and countries of the UK (except for Northern Ireland). For the businesses in most regions, R&D returns vary between 61% and 66%. However, businesses in West Midlands experience the lowest R&D returns (48%) whereas businesses based in Scotland the second highest returns (71%). The R&D of businesses based in London yields the highest returns where each £1 invested in R&D results in an equal increase in GVA.

[7] The sum of businesses within some business groups may exceed the total number of businesses as some businesses may appear in more than one category across the sampling period (e.g., for some years the business may be classified as an SME while for others as large).

Table 3. Heterogeneity of R&D Returns by Region.

***** denotes statistical significance at the 1% level. Source: Authors.**

Region	Observations (#Business-year / #Businesses)[8]	Elasticity	Internal R&D Returns
	(1)	(2)	(3)
London	23,055 / 5,429	.157*** (p=.000)	100%
Scotland	19,348 / 3,974	.126*** (p=.000)	71%
South East	28,896 / 5,856	.116*** (p=.000)	66%
Wales	7,422 / 1,423	.101*** (p=.000)	65%
Yorkshire and The Humber	15,578 / 3,184	.124*** (p=.000)	64%
North West	18,433 / 3,818	.095*** (p=.000)	63%
South West	16,040 / 3,218	.108*** (p=.000)	62%
East of England	18,549 / 3,761	.097*** (p=.000)	61%
North East	6,166 / 1,249	.101 (p=.161)	61%
East Midlands	14,616 / 2,952	.089*** (p=.000)	56%
West Midlands	17,634 / 3,613	.081*** (p=.000)	48%

5.2 Impact of Innovate UK Grants

5.2.1 Grant-Based Impact

Table 4 reports the results from estimating Eq.(4). We find positive and highly significant elasticity coefficients on both the internal R&D stock net of Innovate UK grants and the internal R&D stock created by Innovate UK grants. This means that both types of R&D have a positive effect on business GVA with their estimated elasticities γ and φ being similar in magnitude (0.052 and 0.063 respectively). For Innovate UK grants this means that a 1% increase in the R&D stock generated by Innovate UK grants (i.e., essentially 1% increase in Innovate UK investment through grants) leads to a 0.063% increase in business GVA. By using the median GVA and median Innovate UK R&D capital stock we calculate a marginal effect of 73%. This means that for each £1 of grants invested by Innovate UK in businesses, an increase of 73p in GVA takes place. The corresponding return for R&D net of the Innovate UK grants is 40%. This is somewhat lower than the return for total R&D for all businesses (beneficiary and non-beneficiary) calculated above (68%). This indicates that beneficiary businesses are not as effective as non-beneficiary

[8] The sum of business observations within some business groups may exceed the total number of businesses as some businesses may appear in more than one category across the sampling period (e.g., for some years the business may be classified as an SME while for others as large).

businesses in transforming their own R&D investments into GVA. The value-added elasticity with respect to external R&D ($\hat{\mu}$) is positive (0.005) but not statistically significant at the 10% level of significance. This implies that external knowledge may have a limited role for beneficiary businesses in creating value compared to the businesses' internal (funded or unfunded) R&D efforts. In any case, the external R&D stock serves as a control for external (positive) influences of industry R&D on business GVA.

Table 4. Production Function estimation. Standard errors in parentheses.

*****denotes statistical significance at the 1% level. Source: Authors.**

Production Function estimation	(1)
	Value Added (y_{it})
Labour (L_{it})	.5429*** (.0306)
Capital (C_{it})	.4195*** (.0263)
Internal R&D (net of Innovate UK funds) ($K_{it}^{int}{-net}$)	.0515*** (.0110)
Internal R&D (Innovate UK funds) ($K_{it}^{int}{-pub}$)	.0632*** (.0182)
External R&D (K_{it}^{ext}) **(Industry R&D)**	.0051 (.0096)
Region dummies	Included
Year dummies	Included
Hansen test of overidentification	chi2=90.28 (p=0.126)
Observations	
# Business-year	13,902
# Businesses	2,820

Overall the impact of Innovate UK funding was found to be tatistically significant and positive (73%). We find variation in the estimated return on Innovate UK funding across different types of businesses. The returns for micro and SMEs are statistically significant and positive (52%), the returns for large businesses was not found to be statistically significant. This highlights the importance or micro businesses and SMEs in generating returns (as per our earlier findings in Section 5.1). Although the returns on Innovate UK investments in large business was found to not be statistically significant, this is not to underplay the role of large businesses and the associated Innovate UK investment in terms of the broader innovation ecosystem. The Innovation & Research Caucus are scoping new research to better understand the impact of larger businesses supported by Innovate UK.

Table 5. Heterogeneity of Innovate UK R&D Returns. Standard errors in parentheses.

***** denotes statistical significance at the 1% level. Source: Authors.**

There is no statistical significance in the returns to domestic and foreign owned businesses Finally, the returns to businesses in the manufacturing sector from Innovate UK funds were found to be statistically significant, whereas the returns to services businesses where not found to be statistically significant. The analysis is important in identifying where the return was found to be statistically significant or not, and in so doing highlights areas for further research. This work has the potential to increase the impact and significance of returns from Innovate UK funding.

Type of Business	Observations (#Business-year / #Businesses)[9]	Innovate UK Stock Elasticity	Innovate UK R&D Returns
	(1)	(2)	(3)
All businesses			
	13,902 / 2,820	.063*** (.018)	73%
Business size			
Micro and SMEs	9,703 / 2,121	.081*** (.020)	52%
Large	4,199 / 871	-.016 (.031)	-175%[10]
Ownership			
Domestic	6,534 / 1,417	.033 (.023)	42%
Foreign	6,085 / 1,356	.041 (.031)	56%
Sector			
Manufacturing	7,902 / 1,497	.060*** (.021)	86%
Services	6,000 / 1,365	.009 (.027)	7%

[9] The sum of business observations within some business groups may exceed the total number of businesses as some businesses may appear in more than one category across the sampling period (e.g., for some years the business may be classified as an SME while for others as large).

[10] This figure is not statistically significant

With respect to the products Innovate UK used to provide grants to businesses, funding from the 'Collaborative R&D' product yields higher returns than funding from the 'Feasibility Studies' product with 'Other' products collectively yielding a return about half of the return of 'Collaborative R&D' (33%). However, only for the 'Other' products is the value-added elasticity statistically significant at the 10% level.

Table 6. Heterogeneity of Innovate UK R&D Returns by product. Source: Authors.

Product Type	Observations (#Business-year / #Businesses)	Elasticity	Public R&D Returns
Feasibility Studies	1,931 / 377	.054 (.041)	27%
Collaborative R&D	7,172 / 1,436	.035 (.025)	76%
Other	4,799 / 1,007	.045* (.025)	33%

5.2.2 Additionality-Based Impact

To estimate whether receipt of Innovate UK funding can leverage additional private R&D spending of businesses we estimate the counterfactual through the use of entropy balancing. We balance the business characteristics on two moments, i.e. the mean and variance. This is sufficient especially if we consider that for binary covariates adjusting for only the first moment is equivalent to adjusting for higher moments
(Hainmueller and Xu, 2013). These balancing results are reported in Appendix A. We identify the optimal weights for which the balancing for all covariates used (business size in terms of employment, the squared value of employment, type of ownership, gross operating surplus, capital intensity, industry affiliation, region the headquarters of the business are located, year of observation) is perfect on both the mean and variance. Even the skewness is pretty close between the treated and control groups (after weighting). Therefore, the EB weights render the two groups identical in terms of their observable business characteristics. By additionally accounting for any unobservable influences with the use of fixed effects for each business we ensure that we identify causal effects of Innovate UK grants on businesses' R&D expenditure.

Table 7 reports the estimated effects of the receipt of Innovate UK grants on businesses' R&D expenditure. By using the EB weights to weigh Eq.(5), we estimate a positive and highly statistically significant (at the 1% level of significance) ATT. Its value is 0.073 meaning that funded businesses spent on average 7.5% [exp(.073)=1.075, which corresponds to 7.5%] more in R&D compared to businesses that were not funded by Innovate UK, i.e., Innovate UK grants achieve input additionality. Selection in Innovate UK grant programmes is significant as businesses with more employees, more capital intensity and higher gross operating surplus are more likely to receive Innovate UK grants. In addition, industry affiliation is a determinant of grant receipt with regions the business is located in not playing an important role (see Appendix A). Indeed, not controlling for the characteristics that may influence selection of businesses in Innovate UK funding programmes (observable or unobservable), would (falsely) yield a much larger estimate as businesses that were funded by Innovate UK spent – on average – considerably more in R&D anyway vis-à-vis businesses that were not funded.[11]

51 Hiwgvtxzi erep}www jvsq e x1xiwx wls{w e hmjjivirgi sj 52<65... mr xli pskevmxlqmg rix V*H i|tirhmxyvi fix{iir xli x{s kvsytw sj fywmriwwiw {lmgl xverwpexiw mrxs et tvs|mqexip} 9 xmqiw qsvi rix V*H wtirhmrk jsv jyrhih fywmriwwiw zw1¬1zw yrjyrhih fywmriwwiw2

Table 7. Innovate UK grants effects ATT estimation. Source: Authors.

Additionality	Estimated Effect	Observations (#Business-year / #Businesses)
ATT (weighted)	.073*** (.024)	.054 (.041)

The additional business spending on R&D can also generate value-added that would have not been generated in the absence of Innovate UK grants. However, the ATT is not informative of the additional private R&D expenditure leveraged by a £1 of Innovate UK grants. In calculating this marginal effect, we multiply the average R&D expenditure of non-recipient businesses (£686,909) with the percentage change due to the grant (.075) to find the additional investment leveraged for the typical grant-recipient business (£51,518). We subsequently divide the latter by the average value of grant received by businesses (£150,757) and arrive at a marginal effect of 0.342. This effect means that for each £1 invested in businesses through Innovate UK grants, there is an 34.2p additional investment on behalf of the businesses that would have not taken place in the absence of the grants. Even though for many programmes and products Innovate UK requires recipient businesses to invest an equal amount of R&D – match funding – in practice businesses do not additionally invest £1 for each £1 of Innovate UK grant they receive but they instead may discontinue other R&D projects to "free-up" resources for the funded projects. In any case, the fact that Innovate UK grants by no means crowd-out private R&D investment (or leave private R&D investment unchanged) but instead trigger additional spending on behalf of businesses that would have not otherwise taken place is reassuring that Innovate UK grants are successful in mitigating the pervasive market failure of underinvestment in R&D by the private sector (Arrow, 1962).

To estimate the additionality-based impact of £1 Innovate UK grants on GVA, we multiply the additional investment of 34.2p leveraged by £1 of grants by the returns on R&D net of Innovate UK funds of beneficiary businesses (40%). This means that £1 of Innovate UK grants can approximately leverage 14p of GVA through increasing beneficiary businesses' R&D (i.e., the additionality-based impact).

5.3 Aggregate Returns of Innovate UK Grants

In estimating the cumulative over time returns of Innovate UK grants we consider three aspects. First, the service life of R&D which spans over 7 years (as per the ONS). The grant-based and additionality-based returns estimated above are short-run impacts of Innovate UK funding – however, R&D is 'useful' for 7 years albeit at a depreciated value to reflect knowledge obsolescence. Therefore, we calculate the effect over 7 years and use a depreciation rate for R&D of 15% (Hall et al., 2010).

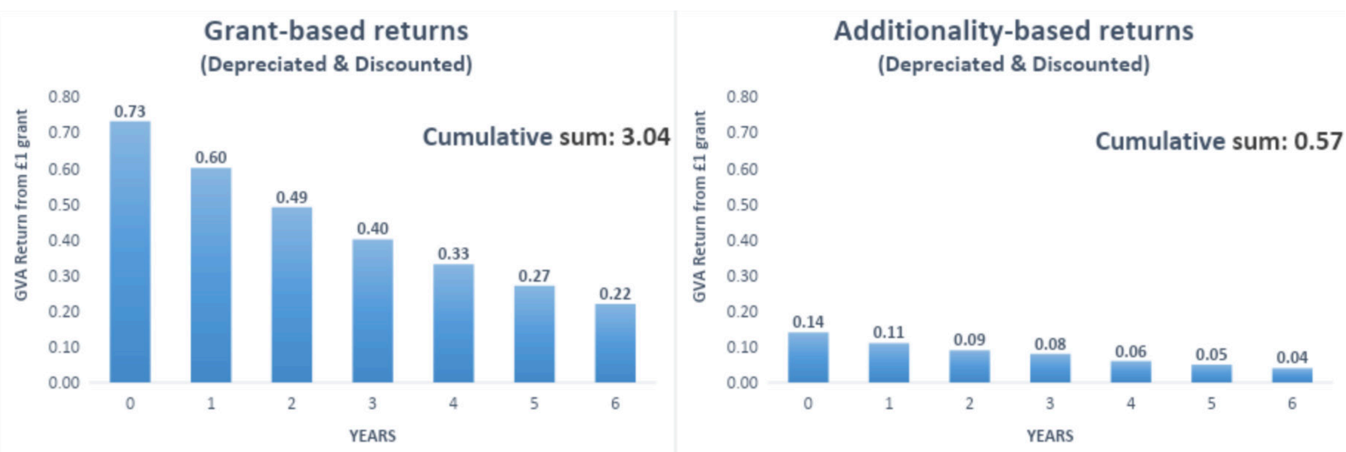
Second, the time preferences of the society which determine the value society places in current and future rewards. Time preferences go beyond the influence of inflation which we have accounted for by using appropriate deflators (GDP and R&D-specific deflators). For example, a business may prefer to appropriate Z returns today than, let's say, ($1.02 \times Z$) returns in a year, where Z is adjusted for inflation. If the business is indifferent between appropriating Z returns today or

($1.03 \times Z$) returns in a year (with Z being inflation-adjusted), the discount rate would be 3%. In other words, the discount rate captures by how much the future is discounted compared to the present. Therefore, we discount future returns of Innovate UK grants according to the time preferences of the society. The Green book published by the HM Treasury in 2018 and where best practice in policy appraisal and evaluation is set out, recommends the use of a discount rate of 3.5% (HM Treasury, 2018b: 28). This rate is somewhat larger than the average Social Rate of Time Preference (SRTP) of 2.22% calculated for the UK for the 1961-2013 period (Corrado et al., 2016). In the absence of discount rate calculations based on more recent data while being conservative in estimation, we use the 3.5% figure.

Third, we consider the wider positive impacts on business-to-business activity along the supply chain (indirect effects) and the wider positive impacts on household income (leveraged effects) stemming from Innovate UK funding. In order to capture these effects, Type I and Type II GVA multipliers are used. The ONS has published information only for the Type I GVA multiplier and only for year 2018. Instead, the Scottish Government has published detailed information on both Type I and Type II GVA multipliers uninterruptedly since year 1998. However, the latter only correspond to the Scottish economy whose structural dynamics are different to the whole nation's economy. Indicatively, the industry average Type 1 GVA multiplier for the UK economy in 2018 (ONS) is 1.89 whereas the corresponding multiplier for the Scottish economy is 1.44. However, insufficient published information on Type I GVA multipliers for the UK economy (as it is only available for a single year with our examined period spanning over 12 years) and the absence of any published information on Type II GVA multipliers for the UK economy leads us to use the consistently measured Type I and Type II GVA multipliers published by the Scottish Government. We use these multipliers unchanged, i.e., without adjusting them to reflect the wider UK economy structural dynamics which is in line with our conservative approach to inference.[12]

Figure 4 illustrates the depreciation and discounting patterns for both the grant-based and the additionality-based returns stemming from an £1 Innovate UK grant investment. For the grant-based returns, after depreciating the £0.73 return across 7 years and applying a discount rate of 3.5% we calculate an aggregate present value of future depreciated R&D returns of £3.04. The corresponding additionality-based returns are smaller and amount to £0.57 for an aggregate direct impact of £3.61.

Figure 4. Grant-based and Additionality-based returns (after depreciation and discounting). Source: Authors.



[12] For example, we do not use the 1.89/1.44 = 1.31 ratio to adjust the Type I multiplier to the whole UK economy as there is only one piece of relevant evidence (i.e., Type I multiplier for year 2018 – published by the ONS).

In considering the wider effects of Innovate UK grants to the economy, we take the average of Type I and Type II GVA multipliers across all industries for the 2008-2019 period.[13] This results into a figure of 1.44 for the Type I multiplier and a figure of 1.72 for the Type II multiplier. By multiplying the direct returns by the Type I multiplier, we calculate the sum of direct and indirect returns to be £5.20 [£3.61*1.44=£5.20; the sum of the direct returns – £3.61 – and indirect returns – £1.59 – in Column 3 of Table 8]. By multiplying the direct returns by the Type II multiplier we calculate the sum of direct, indirect and leveraged returns to be £6.21 [£3.61*1.72=£6.21; with the leveraged returns being £1.01]. Table 8 presents the direct, indirect and leveraged impact of Innovate UK grants for both the grant-based and additionality-based impact. (The terms 'impact' and 'returns' are used interchangeably.)

Table 8. Aggregate Innovate UK R&D Returns. Source: Authors.

Innovate UK Impact	Grant-based Impact	Additionality-based Impact	Grant-based & Additionality-based Impact
	(1)	(2)	(3)
Direct Impact	3.04	0.57	3.61
Wider Impact			
Indirect	1.34	0.25	1.59
Leveraged	0.85	0.16	1.01
Aggregate Impact	5.23	0.98	6.21

In sum, a £1 investment on behalf of Innovate UK in the form of R&D grants can cause an aggregate increase in GVA of £6.21 over the course of 7 years. This takes place through two channels: (a) the grant-based channel where the invested grant itself creates value for the recipient business and (b) the additionality-based channel where recipient businesses benefit from value created by an increase in their private R&D investment as a result of the grant receipt. It is also important to note that the social rate of return of Innovate UK grants is not identified in the report.

[13] We do so as we assume a sectorally homogeneous effect of the inc eased activity of recipient businesses on other businesses of the economy. Given the relatively small variation in multipliers across sectors, this assumption should not preclude the identification of the true underlying effect.

6. REFLECTIONS & NEXT STEPS

This study sets out the return on investments associated with projects funded by Innovate UK since 2004. As set out in the introduction, the report provides a comprehensive assessment of the returns that Innovate UK grants generate – providing new insights on the importance of public R&D support for businesses. As well as addressing the overarching aim, the study provides detailed insights on the returns of R&D in general (i.e., without differentiating between R&D funded by Innovate UK and other sources) and how returns based on (a) R&D in general and (b) R&D funded by Innovate UK vary between different types of businesses in terms of size, origin of ownership, knowledge stock, industry, and region.

The report also highlighted the difference between types of Innovate UK products, the most common being the Collaborative R&D and Feasibility Studies. While this study does not explicitly look beyond these products, or at a competition level there is potential to extend this work to include further analysis which could shed light on other key issues of interest. In particular there is scope to look at programmes delivered by Innovate UK but not funded by Innovate UK (i.e., funded by BEIS)

By investigating the impact of Innovate UK grants not only on recipient businesses but also on the wider economy, the study contributes towards understanding the impact of Innovate UK grants and their ability to ‘boost’ the UK economy. The implications of the findings need to be considered alongside other research insights, for example of the diversity of applicants and beneficiaries, which could inform the strategy of Innovate UK to develop specific programmes and interventions.

Other research to advance understanding as to the return on investment could also include understanding the social rate of return on Innovate UK investments, as well as the wider ‘public good’ benefits of publicly funded support for innovation. This could be achieved by undertaking case studies in relation to domains where there are particular public benefits (i.e., health, security). While Innovate UK has experience of supporting projects funding both individual firms and consortia of firms, this is another potential area of further research that would merit further research – including the interaction and collaboration of partners on different innovation projects.

There could also be merit in exploring areas that appear outside the primary scope of Innovate UK that are concerned with frontier innovation in R&D intensive industries. For example, understanding the performance of public-funding programmes promoting and supporting innovation in less R&D intensive sectors – what lessons and insights are there for Innovate UK? Furthermore, and while Innovate UK has primarily focused on frontier innovation, what opportunities are there that could increase return on investment by promoting the diffusion and adoption of innovation?

Finally, and while it is important to recognise the variation in returns, the timing of returns, and the profile of the returns, it is important to highlight the variety and heterogeneity of innovation projects supported by Innovate UK. Investing is one of three ‘I’s set out in Innovate UK’s ‘Plan for Action 2021–2025’, and their role in inspiring and involving current and prospective innovators are arguably as critical to increasing the return on investment over the medium and longer term.

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Innovation Caucus

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IMPACT ON BUSINESS AND ECONOMY

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