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RATE OF RETURN TO INVESTMENT IN R&D

A report for the Department for Science, Innovation and Technology

MARCH 2023

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EXECUTIVE SUMMARY

This report synthesises the literature on the returns to investment in research and development (R&D). It provides a meta-analysis of evidence relating to the private returns to R&D and summarises a range of wider evidence relating to drivers of the variation in returns.

DRIVERS OF THIS RESEARCH

There are theoretically good reasons why public funds should be used to support R&D. In particular, the social returns to R&D investment are commonly believed to be greater than the private returns, firms wanting to invest may be credit constrained, or firms may have imperfect information or be excessively risk averse.

Appraisals of public policies to support R&D require understanding of the value of R&D. It is important that such appraisals are based on the best, most recent and most relevant evidence so that they can withstand scrutiny and challenge.

Frontier Economics was commissioned by the Department for Science, Innovation and Technology (DSIT) to conduct an updated review of the rates of return to investments in R&D, building on a previous review conducted by Frontier in 2014. There was specific interest in updating understanding of the following:

- What is the rate of return to privately funded R&D and publicly funded R&D?
- How does the rate of return differ by the characteristics of the R&D project?
- What drives the differences in the rates of return to R&D?

A particular objective of this work was a meta-analysis of existing estimates of returns to R&D. The meta-analysis approach is valuable as it provides a structured way to synthesise the existing literature. Rather than relying on an estimate from any one paper, meta-analysis provides an average of the estimates from across the literature with the aim of ultimately providing a more accurate and robust estimate than any one paper can do alone. The approach is to collect comparable estimates of the returns to R&D. These are then regressed on a set of explanatory variables, which include differences in the data, specification, measurement etc. of the primary studies, and the precision with which the primary study is able to estimate the returns to R&D. Through this approach the meta-analysis methodology aims to produce an estimate of returns to R&D controlling for publication bias and to provide some quantitative insights on the variation in returns by observable features of the investment or the empirical strategy used to estimate returns.

SCOPE AND APPROACH

We searched for the most up-to-date academic literature (including published peer-reviewed papers and working papers) to collate evidence on rates of return to R&D in Organisation for Economic Co-operation and Development (OECD) countries. Our primary focus was on papers that estimate returns to R&D using the production function approach. This is so that the estimated returns are derived from a sufficiently similar methodology to support a meta-analysis.

Our review included studies estimating either an elasticity of output with respect to R&D or a rate of return to R&D investment. The *rate of return* is the £ increase in output that would be obtained from a £1 increase in R&D, while the *elasticity* of output is the % increase in output that would be obtained from a 1%

increase in R&D. As these approaches involve different assumptions and are not directly comparable, we conduct separate meta-analyses of papers that estimate elasticities and papers that estimate rates of return.

The returns estimated in the literature are typically the immediate impact on output in the year in which the R&D is conducted. The return to a particular R&D investment will be enjoyed for multiple years but will decline over time as the knowledge created by the R&D depreciates in market value. To the extent that the effect on output takes longer than a year to materialise, many estimates of returns to R&D in the literature may underestimate the true return.

PRIVATE RETURNS TO R&D: META-ANALYSIS RESULTS

Our best estimate is that the average private rate of return to R&D is at least 14% and is likely to be higher. This is consistent with previous estimates for OECD countries (Møen and Thorsen, 2017; Ugur et al 2016).

Examining studies that estimate a private rate of return to R&D, our meta-analysis suggests that after controlling for selection bias, the average private rate of return is 14%. While our meta-analysis corrects for selection bias in the evidence base, it cannot correct for other methodological limitations (largely due to data availability) in the primary studies that are likely to result in them underestimating rates of return, hence our view that this likely represents a lower bound.

Examining studies that estimate an elasticity of output with respect to R&D investment, our meta-analysis suggests that, after controlling for selection bias, the average elasticity is 0.07. Assuming that the estimated average elasticity of 0.07 is appropriate for UK manufacturing, which has an R&D intensity of around 5.2%, this would imply a rate of return of 19%.

Given our view that estimates from the meta-analysis may be underestimated, **a conservative assessment based on these findings is that an average private rate of return of around 20% is defensible**.

SOCIAL RETURNS TO R&D

When appraising the benefits of public support for R&D, it is the social rate of return – which incorporates not just the private return to the firm undertaking the R&D but also wider spillover effects – that is key.

A key limitation of the literature examined in this review is that the rates of return examined are based on firms' output or productivity. The social returns to R&D measured include spillover effects on the output of firms which were not involved in the R&D yet still benefit from the knowledge created by the R&D. However, the output or productivity metrics do not include other wider impacts, such as health, wellbeing or environmental impacts. This means that the estimates produced here will almost certainly underestimate the full social returns to R&D.

Our meta-analysis of studies that estimate returns to R&D at the industry level suggests that estimates of returns that incorporate within-industry spillovers are similar to estimates of private returns. This is likely due to positive spillovers (such as firms being able to benefit from the knowledge created by another firm's R&D) being offset by negative spillovers (such as firms losing market share to the firm that has conducted R&D). There are good theoretical reasons to expect positive between-industry spillovers. These are not captured in industry-level estimates of social returns, and including these would then suggest a social return greater than the private rate of return.

The literature that seeks to estimate spillovers directly contains many estimates of positive knowledge spillovers and social returns considerably in excess of private returns. However, a lack of good data, uncertainties over methodology and some evidence of publication bias mean that all these estimates should be treated with caution.

In our view **a relatively conservative approach to modelling the benefits to R&D could be to assume that the social returns to R&D are twice those of the private returns**.

VARIATION IN RETURNS TO R&D

There is substantial variation in the estimates of private and industry-level social rates of return that we examine: for example, estimates of the private rate of return in OECD countries range from -55% to +231%. While some of this variation is driven by different methodological approaches, our meta-analysis and wider review also highlight some variation that is likely to reflect systematic differences in returns to R&D in different contexts. The results on this should be treated with some caution as there is relatively limited literature on some aspects of variation in returns to R&D, which makes firm quantitative conclusions difficult to reach. With that caveat in mind:

- US firms are found to have higher rates of return on average than firms in the EU (including the UK). In part this is due to the higher R&D intensity of the USA and different industrial composition, but this does not appear to fully account for the difference. There is no strong evidence on whether returns in the UK are different to those in other non-US countries.
- Publicly funded R&D conducted by the private sector is found to have lower private rates of return than privately funded R&D. This is likely because public funding is targeted at investment with lower private returns but greater spillover or wider social benefits, and/or because public funding disproportionately supports basic R&D (as compared with private R&D spending), for which the returns may take longer to be realised.
- Returns to R&D are often found to be non-linear, with positive effects on output only after firms reach a certain threshold level of R&D spending, and with diminishing elasticities as the ratio of R&D spending to output increases.
- Returns to basic R&D take longer to realise than returns to applied R&D.
- Social returns to R&D performed by the public sector may be around 20%, although this is based on a single study specific to the UK context, with limited wider evidence to validate this.
- Average returns to R&D do not appear to have changed over the past four decades.

This research suggests that, on the basis of the relatively limited existing literature, **it is not possible to quantify an average return to R&D in different contexts**, such as for different industries, types of firms or types of R&D. When appraising the case for public support of any particular R&D project, in the absence of other information, it is therefore still reasonable to rely on the average return to R&D described above. However, where there is strong, context-specific evidence to suggest an alternative return (perhaps from previous evaluations or bespoke modelling), it would be appropriate to use that in developing appraisals of new interventions.

ACKNOWLEDGEMENTS

We are grateful to the DSIT project team for invaluable day-to-day steers on the project. We also thank members of a wider Steering Group for their feedback and suggestions on earlier drafts. We offer particular thanks to Professor Mehmet Ugur (University of Greenwich) and his co-authors, Eshref Trushin (De Montfort University), Edna Solomon (University of Greenwich) and Francesco Guidi (University of Greenwich), for making data from an earlier meta-analysis available to us. We also wish to thank our expert partner Gavin Wallis (Bank of England) for his steers and comments and our econometric expert adviser Professor Ron Smith (Birkbeck, University of London) for guidance and review of the meta-analysis. We are grateful to Lesley Ellen for copy-editing this report.

1 INTRODUCTION

1.1 CONTEXT FOR THE STUDY

Economic theory stresses that innovation is a key driver of technological progress, sustained economic growth and improvements in living standards. Investment in innovation, including in research and development (R&D), is a key input in determining the rate of technological progress, helping to generate new products, processes and knowledge.

There are good theoretical reasons why public investment in R&D, and public financial support for R&D conducted by the private sector, is justified (Department for Business, Innovation and Skills 2014). The most often-cited reason is that there are spillover benefits from R&D that are not taken into account by private firms when they choose whether or not to invest in R&D. In particular, the creation of knowledge or new products or processes that can be used by other firms is not valued by the firm undertaking the R&D, even though this benefits the economy and society as whole. In other words, the social returns to R&D investment are commonly believed to be greater than the private returns. Public support for R&D encourages more R&D to be undertaken; in the absence of this R&D, investment would be too low. Other reasons for public support of R&D, besides these spillover benefits, include helping firms that face credit constraints, and that would not otherwise be able to undertake valuable R&D, and encouraging R&D in the context of imperfect information or risk aversion on the part of private firms.

Appraisal of government policies to support or invest in R&D requires understanding of and high quality evidence on the returns to R&D. It is important that such appraisals can be demonstrably shown to be based on the best, most recent and most relevant evidence so that they can withstand scrutiny and challenge. To that end, Frontier Economics was commissioned by the Department for Science, Innovation and Technology (DSIT) to conduct an updated review of the rates of return to investments in R&D. There was specific interest in understanding the following:

1. What is the rate of return to privately funded R&D and publicly funded R&D?
2. How does the rate of return differ by the characteristics of the R&D project?
3. What drives the differences in the rates of return to R&D?

To address these questions we conducted a review and a synthesis of the existing literature, with a particular focus on new literature that has emerged since a previous review was conducted by Frontier Economics in 2014.[1] Adding to the rigour of our approach, we used meta-analysis to estimate the private rate of return to R&D, controlling for publication bias, and to provide some insights on the variation in returns by observable features of the investment or the empirical strategy used to estimate returns.

The report is organised as follows. In this introductory section we first set out a framework to guide the analysis. This explains the concept of private and social returns to R&D. We then describe how returns to R&D are quantified empirically and the parameters that are commonly estimated. In section 2 we describe our methodology, including the scope of our review, the literature search strategy and the meta-analysis approach. In sections 3 and 4 we review the evidence on overall private and social returns respectively. In section 5 we conduct multivariate meta-analysis and draw from the wider literature to review the evidence

[1] Frontier Economics (2014).

on drivers of variation in returns to R&D. We conclude in section 6, with particular emphasis on how policy makers should interpret these findings and the important caveats to bear in mind.

Our report is accompanied by an analytical matrix which sets out details of the papers underlying this study and the data underlying the meta-analysis.

1.2 PRIVATE AND SOCIAL RETURNS TO R&D

Investments in R&D are typically believed to help generate new products, processes or ideas which can then be used to create new or improved goods and services or to produce existing goods or services more efficiently. Private returns referenced in this report are defined as the increase in the output of companies that undertake the R&D.[2]

Investment in R&D may not just impact the output of the firm undertaking the R&D but may also impact the output of other firms or have wider consequences such as on health or environmental quality. The social return to R&D take account of these spillover effects over and above the private return to R&D enjoyed by the firm which undertook the investment. R&D can also be undertaken outside the private sector, for example by government departments or higher education institutions. There is no private return to such investment as these institutions do not have market output that can be impacted, but there will be these wider spillovers and therefore a social return.

Spillovers resulting from investment in R&D can take different forms:

- **Knowledge (or technology) spillovers**. These occur when R&D creates knowledge or technology that is not fully appropriated by the firm or organisation that invested in the R&D – for example, because the investor willingly chooses to share its innovations (as is often the case with public R&D) or because the innovation can be observed or reverse engineered from the created output and is not protected by intellectual property arrangements, or because the firm or organisation cannot appropriately value the knowledge created and sells the innovation to other firms for a price below the true value.
- **Market rivalry**. This occurs when R&D creates knowledge that gives the investing firm a competitive advantage and allows it to take market share from competing firms.
- **Obsolescence**. This occurs when R&D creates new products or processes that render old ones obsolete or less valuable. In other words, it increases the depreciation on some existing knowledge that may be held by other firms.
- **Wider impacts**. There may also be wider impacts from R&D investments and the consequent innovations, including impacts on health and environmental quality.

Our review focuses on increases in companies' output as the main measure of return. Impacts on other business outcomes such as profit are not explicitly considered. The measures of social returns examined include the first three types of spillovers listed above but do not include wider impacts (such as on health or the environment). We return to this discussion in section 4.

[2] Output is typically measured using 'turnover' (the market value of all goods and services which the company sells in a certain period) or 'value added' (turnover less the cost of raw materials, energy and other intermediate inputs). Studies sometimes examine the impact on productivity rather than output, making some assumptions about the impact of labour and capital inputs on output. The empirical methodologies used are discussed in more detail in Sections 1.2, 1.3 and Appendix A.

Knowledge spillovers increase overall economic activity, while market rivalry displaces existing economic activity and obsolescence displaces existing economic activity in the short run but may increase economic activity in the long run if there are productivity improvements. It is challenging to measure these spillovers separately as estimates of social returns often include all three simultaneously. This is discussed further in section 4.

1.3 METHODS FOR ESTIMATING RATES OF RETURN

Much of the literature that seeks to estimate returns to R&D relies on a production function framework.[3] In this set up, the output of a firm, industry or country is related to its inputs, with knowledge capital being included as an input alongside labour and physical capital.[4] Investments in R&D are assumed to increase knowledge capital, which then increases output.

Several major approaches have been followed within the production function framework. The most common is the 'primal approach'. This estimates a production function that is typically expressed as:

$$\ln Y_{it} = A + \alpha \ln C_{it} + \beta \ln L_{it} + \gamma \ln K_{it} \qquad [1]$$

where Y_{it} is the output of unit i at time t, A is a constant reflecting productivity, C is physical capital stock, L is labour and K is the stock of knowledge.

The returns to R&D can be thought of as the increase in annual output that results from the increase in the knowledge stock that arises from R&D spending. This requires the knowledge stock to be modelled. The majority of studies assume that the knowledge stock evolves over time according to the depreciation of existing knowledge and the generation of new knowledge by R&D:

$$K_{it} = (1 - \delta)K_{it-1} + R_{it} \qquad [2]$$

where K_{it-1} is the stock of knowledge last year, δ is the rate at which knowledge depreciates and R_{it} is new knowledge generated by R&D.

There are two issues of timing worth highlighting here. First, the production function relates output in one year to inputs in that year, and **R&D is typically modelled as having an immediate impact on the knowledge stock.** It may, however, take longer for R&D to have an impact on output – e.g. ideas may take time to be commercialised.[5] This means that estimates of returns may underestimate the benefits of R&D. The impact on output of the R&D stock in the previous year is sometimes examined, but the use of longer

[3] Early contributions to the production function literature include Solow (1957) and Jorgenson and Griliches (1967).

[4] Sometimes 'external knowledge capital' of other external firms, industries or countries is also included in the production function to capture spillover effects.

[5] The lag time for any particular R&D investment can vary dramatically. Various studies attempt to examine average lag times. Ravenscraft and Scherer (1982) find that 45% of companies reported a typical lag time of 1 to 2 years between beginning a development and the first introduction of a new project, while 40% reported a lag of between 2 and 5 years and 5% reported a lag of more than 5 years. Pakes and Schankerman (1984) derive a gestation lag that varies across industries and ranges from 1.2 to 2.5 years, similar to the findings of Rapoport (1971) and Wagner (1968). Ravenscraft and Scherer (1982) find a mean lag of 4 to 6 years. The lag time is also likely to vary according to the type of R&D. Basic research, which seeks to expand the base of scientific knowledge, would be expected to take longer to impact firms' output than applied research, which is designed to solve a specific practical problem or answer a specific question. Sun et al (2016), for example, find that basic research only affects productivity with 2 to 3 year lags, while applied research has more immediate impacts.

lags is relatively rare. In large part this is because long-running datasets are less commonly available, but it is also harder to control fully for other changes over time that might affect output.

The second issue is how long the returns to R&D are enjoyed for (i.e. for how many years the additional output will be produced). This will depend on how quickly knowledge depreciates. If there was no depreciation, then a one-off R&D investment would result in additional knowledge and therefore output forevermore. If there was 100% depreciation, then the additional knowledge, and thus output, would only be enjoyed for one year. Determining the rate of depreciation is extremely difficult (see Hall et al (2009) for a discussion of related literature) so **the majority of studies assume a 15% depreciation rate for returns to private knowledge**, following Griliches (1998).

In addition to the 'primal approach', there are other approaches for estimating the impacts of R&D that are based on a production function framework.

- The '**dual approach**' makes assumptions about both the production function and the behaviour of firms (e.g. that they are cost minimising or profit maximising). This is described in more detail in Hall et al (2009). This approach imposes many more assumptions and structure but has an advantage in that it does not assume that returns to R&D are necessarily constant.
- An approach often referred to as the '**CDM model**' after Crepon et al (1998) treats the relationship between R&D and knowledge slightly differently. There are several stages in this approach. The first stage estimates whether or not a firm engages in R&D and, if so, how much. The second stage estimates the impact of R&D investments on innovation (or knowledge). The final stage is the production function, where innovation (knowledge) is included as an input alongside labour and capital inputs. This approach does not generate a rate of return to R&D directly but is commonly used by studies that examine the impact of innovation on productivity.
- An approach introduced by Doraszelski and Jaumandreu (2013) estimates a **structural model** in which firms invest optimally in knowledge (through R&D) and physical capital in the face of uncertain returns (in the form of productivity gains) but with some expectation of what the future returns will be. This captures the idea that the outcome of R&D is likely to be highly uncertain.

1.4 INTERPRETING ESTIMATES FROM THE 'PRIMAL' PRODUCTION FUNCTION APPROACH

The meta-analysis conducted in this report brings together literature that uses the primal production function approach. The restriction to this particular subset of the literature is necessary because other approaches vary much more widely in their specifications and assumptions, making them unsuitable to include in a meta-analysis which relies on a degree of commonality in the underlying methodology.

There are many ways of implementing a primal production function approach, and the econometric and measurement issues that arise are discussed in Appendix A. However, two key aspects are worth drawing out here, as they fundamentally affect the interpretation of the estimated returns.

1.4.1 USING R&D STOCK OR FLOW IN THE PRODUCTION FUNCTION

The production function can be estimated using either a measure of the R&D capital stock or a measure of R&D intensity (the ratio of annual R&D spend to output) on the right-hand side of the production function (equation [1] above). The former will yield an estimate of the *elasticity*, and the latter will yield an estimate of the *rate of return* :

- The **elasticity** of output with respect to R&D is the % increase in output that would be obtained from a 1% increase in the R&D stock.
- The **rate of return** is the £ increase in output that would be obtained from a £1 increase in the R&D stock.

These two metrics are related: multiplying an elasticity by the ratio of output to R&D capital yields a rate of return.[6] However, the two approaches are not equivalent because they make different assumptions. Studies that estimate an elasticity assume that this is constant across firms (or industries) – for example, a £50 million R&D investment that increases the R&D stock from £50 million to £100 million would be expected to achieve the same % increase in output as a £100 million investment in R&D that increases the R&D stock from £100 million to £200 million (as these are both 100% increases in R&D). A constant elasticity implies that the rate of return to R&D declines as the ratio of firms' (or industries') R&D capital-to-output ratio increases. In contrast, studies that estimate a rate of return assume that this is constant across firms (or industries when using industry-level data) – for example, a £50 million increase in R&D would be expected to increase output by the same £ amount regardless of whether the initial R&D stock was £50 million or £100 million. A constant rate of return implies that the elasticity increases as the ratio of firms' (or industries') R&D capital-to-output increases.

1.4.2 UNIT OF ANALYSIS

When the production function is estimated using data on individual companies, the effect of own R&D investments on output can be interpreted as the private return to the firms undertaking the R&D. When the production function is estimated using aggregated industry-level data, the rate of return can be interpreted as the private rate of return to the industry, or as an estimate of the social return to R&D within the industry that incorporates both the private return and *within-industry* spillover effects. These will include knowledge spillovers, market rivalry and obsolescence effects. When data on individual countries is used, the elasticity or rate of return can be interpreted as an estimate of the *social return to R&D within the country*, incorporating both the private returns to R&D plus any domestic spillovers (including knowledge spillovers, market rivalry and obsolescence effects between firms in the same *or different* industries). This is set out in Table 1. We emphasise that any interpretation as a social return is only partial, as it will exclude wider benefits to R&D that do not flow through firm performance (e.g. environmental benefits).

[6] To see this, suppose a firm undertook a £1 R&D investment. To express this as a % change in R&D, divide by the original R&D stock (K) and multiply by 100. The elasticity (γ) tells us that that a $\frac{1}{K}$ % increase in R&D would result in a $\gamma * \frac{1}{K}$ % increase in output. To convert that into extra £ of output, we multiply by the original output (Y): $\gamma * \frac{1}{K} * Y$. The rate of return (ρ) is therefore equal to the elasticity multiplied by the ratio of output to R&D capital: $\rho = \gamma * \frac{Y}{K}$.

Table 1 Unit of analysis and interpretation of return to own R&D investments

UNIT OF ANALYSIS	INTERPRETATION AS A PRIVATE RETURN	INTERPRETATION AS A (PARTIAL) SOCIAL RETURN
Firm-level data	Private return to firm making the investment	
Industry-level data	Private return to industry making the investment	Private return to firms making the investments + spillovers on firms in the same industry
Country-level data	Private return to country making the investment	Private return to firms making the investments + spillovers on firms in the same industry + spillovers on firms in other industries

2 METHODOLOGY

Our approach builds on two previous reviews of the returns to R&D: Frontier Economics (2014) and Ugur et al (2016). These both synthesised the literature on this topic that had been published up to 2013, and therefore our focus for this current report was on identifying papers that estimate returns to R&D – particularly those estimated using a primal production function – published from 2014 onwards and on producing an updated review and meta-analysis of the collated body of evidence.

2.1 LITERATURE SEARCH STRATEGY

The active search for new literature published from 2014 onwards involved four components:

- First, we conducted a search of the peer-reviewed academic literature published from 2014 onwards that mentioned R&D and productivity or returns. This was conducted using Scopus, the largest database of peer-reviewed literature. For tractability of sifting the search results, papers had to be published in business or economics journals, be in English and include a term relating (broadly) to R&D or productivity in their keywords.[7] This search yielded 827 papers.
- Second, we conducted an initial sift of these papers on the basis of title and abstract to identify those deemed likely to estimate a return to R&D using a primal production function approach, and we then read the shortlisted papers in more detail to establish whether the study did indeed provide relevant estimates.
- Third, we conducted Google Scholar searches of papers that cited either Ugur et al (2016) or Hall et al (2009) (an earlier academic study that had underpinned much of the analysis in Frontier Economics, 2014), again using title and abstract to identify 'grey literature' studies and working papers published since 2014 that estimated returns using a primal production function approach.
- Finally, to capture working papers, we searched the National Bureau of Economic Research (NBER) working paper series for papers that related to R&D.

We also took soundings on recent studies to include from our expert adviser Dr Gavin Wallis (Bank of England) and the project Steering Board.

In total we identified 50 new papers, which we reviewed in detail. Of these, 8 were review papers, 17 used a production function approach and included only own R&D in inputs, 9 used a production function approach incorporating spillovers and 6 did not use a production function approach. These studies were then combined with the previously identified pre-2014 literature and data provided by Professor Mehmet Ugur to cover up to 1,474 estimates of rates of return for meta-analysis. This is available in a spreadsheet to accompany this report.

2.2 META-ANALYSIS

A challenge for policy makers is how to interpret the sizeable evidence base and many estimates of returns to R&D – particularly when studies differ in their approaches, the context they examine, and the quality of their data and estimation strategy. One approach is a narrative review, as conducted by Frontier Economics (2014) and Hall et al (2009). Narrative reviews can examine the distribution of estimates, identify papers that are of greater or lesser quality, account for differences in context and approach, and form a narrative conclusion on an appropriate rate of return based on these factors. However, narrative reviews may be

[7] A full description of the search string, including the key words selected, is included in Appendix C.

vulnerable to subjective interpretations and do not use statistical methods to identify or correct for biases in the evidence base. Publication bias is a particular concern: i.e. that published estimates of returns may not be representative of all estimates that have been produced. This could arise because journals favour publishing statistically significant results, peer reviewers use their prior expectations as an informal test of the validity of the results, or researchers' own expectations affect their choices of specifications and interpretation of their results. In the current context, publication bias could be suspected to bias upwards estimates of the return to R&D.

Meta-analysis offers a solution to some of the limitations of narrative reviews.[8] It is a statistical technique for systematically combining the findings of individual studies in order to estimate an overall 'effect' that is free from subjective interpretation. Meta-analysis is able to control for publication bias, which is an advantage over just taking the average estimate from a comprehensive review of the literature. Furthermore, with a sufficient evidence base, meta-analysis may be able to determine the extent to which differences in estimates are driven by the empirical approach of different papers or the sample studied. The main disadvantages of meta-analysis are that it can only be applied to estimates produced from comparable methodologies, and it does not necessarily yield the 'true' rate of return if the underlying evidence base is small or the approach taken cannot control for other relevant biases. We discuss this in section 2.2.3.

In this review we conduct a meta-analysis but combine this with a narrative review of some of the wider literature in order to benefit from the advantages of both approaches. The scope of our meta-analysis, the methodology we use, and the advantages and disadvantages of our approach are described in sections 2.2.1, 2.2.2 and 2.2.3 respectively.

2.2.1 SCOPE OF THE META-ANALYSIS

We follow the approach of Ugur et al (2016) in implementing meta-analysis of the literature on private rates of return to R&D.[9] Ugur et al (2016) study the literature published between 1980 and 2013. We extend their sample and conduct a meta-analysis of the literature published between 1980 and 2021.[10]

As in their study, there are three main restrictions on the scope of the literature included in the analysis:

- We restrict attention to studies that use the primal production function approach to estimate private rates of return, as meta-analysis requires estimates produced from comparable methodologies.
- We only include studies of countries in the OECD, among whom there is greater standardisation of definitions of R&D.
- We exclude studies that estimate (social) returns at the sector, region or country level. There are not many studies at these levels of analysis and their rate of return estimates have different interpretations (see Table 1).

[8] A brief non-technical introduction to meta-analysis can be found in Doucouliagos (2016).

[9] Wieser (2005), Møen and Thorsen (2017) and Ugur et al (2020) also conduct meta-analysis of aspects of the literature relating to returns to R&D.

[10] We are grateful to the authors of that study for making available replication data that facilitated our analysis without the need for replicating primary data collection from the studies published before 2014.

We include all elasticity and rate of return estimates contained in the surveyed papers. This is important both to extract all possible information (sensitivity analysis, for example, is indicative of the effect of different empirical specifications on estimated effects) and to avoid unconsciously introducing bias into the collated evidence on effect sizes.

We conduct separate meta-analyses of four samples: elasticity estimates from studies that use firm-level data, rate of return estimates from studies that use firm-level data, elasticity estimates from studies that use industry-level data, and rate of return estimates from studies that use industry-level data. The first two are meta-analyses of private returns to R&D, while the latter two are meta-analyses of within-industry social returns to R&D.[11] The number of estimates included in our meta-analyses are summarised in Table 2.

Table 2 Sample sizes for meta-analysis

	NUMBER OF ESTIMATES	NUMBER OF STUDIES
Firm-level elasticity	897	25
Industry-level elasticity	141	10
Firm-level rate of return	244	23
Industry-level rate of return	192	35

Note: The sample of estimates included in our meta-analyses is slightly smaller than the full sample of estimates for which descriptive statistics are produced in sections 3.2 and 4.3. This is because we exclude from the meta-analyses 9 firm-level estimates and 7 industry-level estimates that have undue influence on the results according to dfbeta tests.

Source: Frontier Economics

2.2.2 META-ANALYSIS METHODOLOGY

Our meta-analysis methodology follows Ugur et al (2016), which built on the methodology of Stanley (2005, 2008) and Doucouliagos and Stanley (2013).[12] The tests for publication bias are based on the idea that researchers with small sample sizes might try different empirical approaches, samples or data to find effect sizes that are sufficiently large as to be statistically different from zero. This would result in a correlation between effect sizes (e_i) and their standard errors (SE_i), which could be modelled as:

$$e_i = \beta + \alpha SE_i + u_i \qquad [3]$$

If there is no publication bias, then one should find $\alpha = 0$. In practice, this should be estimated using weighted least squares with precision ($\frac{1}{SE_i}$) as a weight, which is equivalent to estimating:

$$t_i = \beta(\frac{1}{SE_i}) + \alpha + v_i \qquad [4]$$

where t_i is the t-value associated with an estimate (i.e. the estimate divided by its standard error). Testing whether $\alpha = 0$ is the widely used funnel asymmetry test (FAT) for publication bias.

Stanley (2008) shows that if there is a genuine effect then β should be positive – this test is known as the precision effect test (PET). But if there is publication bias, then the estimate β of the genuine effect will be

[11] We do not meta-analyse studies that estimate (social) returns to R&D using country-level data. The number of studies producing estimates using a comparable approach is smaller than for firm- and industry- level studies, and definitions of R&D are less consistent. However, we discuss this literature in section 4.4.

[12] An introduction to meta-analysis can be found in Stanley and Doucouliagos (2012).

biased downwards. A specification corrected for this can be obtained by weighting [4] by precision-squared rather than precision, yielding:

$$t_i = \beta(\frac{1}{SE_i}) + \alpha SE_i + w_i \qquad [5]$$

This is known as precision effect estimation corrected for standard errors (PEESE), and the estimate β can then be interpreted as the estimated true effect size after controlling for publication bias.

Most studies estimate these equations using ordinary least squares (OLS) regression. However, as each study in our review can yield multiple estimates of the effect size, this can bias OLS estimates. To address this concern we follow Ugur et al (2016) in implementing hierarchical modelling. This allows for the estimates in our sample to be nested within each primary study, with study-specific intercepts or study-specific intercepts and slopes. For example, the hierarchical modelling variations of [5] are (with j denoting a study):

$$t_{ij} = \beta_0(1/SE_{ij}) + \beta_2 SE_{ij} + v_{ij} + \alpha_j \qquad [6]$$

$$t_{ij} = \beta_0\left(\frac{1}{SE_{ij}}\right) + \beta_2 SE_{ij} + v_{ij} + \alpha_{0j} + \alpha_{1j}(\frac{1}{SE_j}) \qquad [7]$$

Model [6] allows for only study-specific intercepts, while model [7] allows for study-specific intercepts and slopes. We use maximum likelihood tests to choose between these alternative modelling approaches.

Finally, to examine sources of variation in estimates of returns to R&D, we implement multivariate meta-regression. This adds a set of moderating factors to the models above which include characteristics of the estimation methodology as well as features of the R&D being examined. These moderating factors are introduced in the form of dummy variables:

$$t_{ij} = \beta_0\left(\frac{1}{SE_{ij}}\right) + \beta_1 + \sum_k \theta_k Z_k(1/SE_{ij}) + v_{ij} + \alpha_j \qquad [8]$$

$$t_{ij} = \beta_0\left(\frac{1}{SE_{ij}}\right) + \beta_1 + \sum_k \theta_k Z_k(1/SE_{ij}) + v_{ij} + \alpha_{0j} + \alpha_{1j}(\frac{1}{SE_j}) \qquad [9]$$

If $\theta_k > 0$ then this indicates that elasticity or rate of return estimates with the particular characteristic denoted by $Z_k = 1$ are larger than estimates with the reference characteristics, all else equal. Conversely if $\theta_k < 0$ then this indicates that estimates with the particular characteristic denoted by $Z_k = 1$ are smaller than estimates with the reference characteristics, all else equal.

One caution with the multivariate meta-analysis approach is that there is a high degree of correlation in some of the moderating factors of interest. To test the sensitivity of our results, we implement a general-to-specific routine, whereby the explanatory factor with the least statistical significance is iteratively dropped until only statistically significant moderating factors remain. The estimates for both the general and specific models are provide in full in Appendix B. We summarise the results from the general model in the text but highlight with caution where these differ from the results of the specific model.

2.2.3 ADVANTAGES AND DISADVANTAGES OF META-ANALYSIS

The meta-analysis approach synthesises the literature to produce a single estimate of the average private rate of return on R&D. The main advantages of the meta-analysis approach are:

- **Summarising the evidence base:** The meta-analysis approach pools evidence from the literature to produce a single estimate of the average return to R&D. This estimate takes account of how precisely underlying studies are able to estimate returns (giving more weight to more precise estimates), which is an advantage over a simple average of collated estimates or an estimate from any one study alone.
- **Correcting for publication bias:** The meta-analysis identifies and corrects for publication bias. This is valuable if publication bias means that low estimates of returns to R&D are not published and averages of collated estimates from the literature overstate the true value of R&D.
- **Revealing associations:** The meta-analysis can identify associations between features of the primary study (e.g. characteristics of the estimation process or the context of the R&D examined) and the resulting estimate. The ability to examine the effect of particular factors on estimates of returns depends on the availability of evidence in the primary studies on that factor.

There are, however, some limitations that need to be kept in mind when the results are interpreted. More specifically, some of these limitations are *likely to place downward bias* on the meta-analysis estimate of the rates of return:

- **Similarity requirements:** The meta-analysis approach is only able to compare estimates produced using similar empirical approaches – in this context, papers that estimate a primal production function. Studies with different estimation methods are not able to be included (e.g. qualitative evidence or quantitative estimates that are obtained from non-comparable approaches). The similarity requirements mean meta-analysis does not capture the totality of evidence because it focuses on studies that use similar methodology.
- **Methodological biases remain:** Our meta-analysis, in common with most applications, makes use of precision as an indicator of the 'quality' of an estimate. This means that the most precisely estimated effects are assumed to be closest to the true effect, However, while estimates with the greatest precision may be the most certain in a statistical sense, they may not necessarily be closest to the true value if there are other sources of error or bias in the estimation methodology.
- **Status-quo bias:** Our meta-analysis relies on papers that have been published in the literature that estimate a production function. Differences in data availability across countries and industries may bias the meta-analysis to sectors and countries which have better reporting data on R&D. If these countries or industries have systematically different returns to R&D then the average return estimate derived through the meta-analysis will not be representative of the average return across all UK R&D investments.
- **Asymmetric distribution:** Meta-analysis identifies publication bias on the basis of asymmetry of estimated effects. In other words, compared to the estimates with the highest precision (which are assumed to be closest to the true effect), are there more larger estimates than there are smaller estimates? If so, then this is interpreted as publication bias. However, the returns to R&D may not be symmetrically distributed – the potential downside of an R&D project is limited from a revenue perspective, while successful projects will have very high returns. As Møen and Thorsen (2017) discuss, this may mean that meta-analysis 'over-corrects' for publication bias and produces too low an estimate of the true effect size.

These limitations do not mean that the meta-analysis is not valuable for producing a summary estimate of the return to R&D in the UK. They just need to be kept in mind when that estimate is interpreted and used.

3 PRIVATE RETURNS TO R&D

3.1 KEY SUMMARY OF FINDINGS

Taking all of the studies, we identify which directly produced an estimate of the private rate of return to firms' own R&D investment – **a simple mean average of the return is 24%** (shown in Table 3). Our meta-analysis finds evidence of publication bias and yields a **publication-bias adjusted estimate of the private rate of return to R&D of 14%** (shown in Table 4).

However, we believe that **this meta-analysis estimate likely understates the private rate of return to R&D**, based on two potential methodological biases:

- First, estimates of the rate of return commonly use data on the ratio of observed R&D to output (i.e. R&D intensity) in estimating the production function. If some of this R&D is used to replace R&D investments that have depreciated, this will overstate the addition to the R&D capital stock. As discussed in Appendix A, this biases down estimates of the impact of R&D capital. Hall et al (2009) illustrate that, with median growth in R&D of 3-10% per year and depreciation of 15%, the true rate of return to R&D may be 2.5 to 5 times the values reported.
- Second (as described in section 1.3) the returns to R&D are typically measured based on impacts on output in the year in which the R&D takes place, or sometimes with a one-year lag. However, it may take longer than a year for R&D to fully impact output. These lags before returns are realised will cause returns to be underestimated.

The **mean private elasticity estimate in the production function literature that we review is 0.095** (shown in Table 3). We find that publication bias is less severe in the case of elasticity estimates and adjusting for this generates a **publication-bias adjusted estimate of the mean elasticity of 0.07** (shown in Table 4). This elasticity suggests an implied rate of return of up to 74% for the UK, assuming a depreciation rate of 15% for R&D and given the mean R&D intensity of the UK weighted by sector.[13] However, we do not think this is a credible implied rate of return. It is subject to two key assumptions: first, that the rate of depreciation of R&D is constant across firms/sectors; and second, that the elasticity is constant across firms/sectors – specifically, across those with different R&D capital-to-output ratios. These assumptions are unlikely to be true in practice. Focusing on the manufacturing sector only (as many studies estimate returns to R&D for firms in the manufacturing sector where data availability is greater and R&D intensities are higher) and using the mean R&D intensity of the UK manufacturing sector yields an **implied rate of return of 19%**, which is slightly greater than the publication-bias adjusted average direct estimate of the private rate of return.[14]

Overall our best estimate is that the **average private rate of return to R&D is at least 14%** but is likely to be higher. This is consistent with previous estimates on rates of returns and elasticities for OECD countries

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[13] The rate of return is equal to the elasticity multiplied by the ratio of R&D capital to output (as set out in section 1.4). The implied rate of return for each sector is calculated using data on the R&D spend-to-output ratio for UK sectors (taken from OECD (2019)) combined with an assumption that the depreciation rate is 15% and therefore the stock of R&D capital is around seven times the annual R&D spend. The rate of return for the UK as a whole is calculated as the weighted average of these rates of return, with sectors weighted according to their gross value added.

[14] OECD (2019) put the R&D flow-to-output ratio at around 5.2% for the UK's total manufacturing sector. Assuming a depreciation rate of 15%, and therefore a stock of R&D that is around seven times the annual flow of R&D (7 ≈ 100%/15%), this suggests an R&D capital stock for UK manufacturing of around 36% (≈ 7*5.2%). Multiplying the meta-analysis elasticity estimate of 0.07 by the inverse of 36% (i.e. the ratio of output to the R&D capital stock) yields an estimate of the rate of return of 19% (=0.07*(1/0.36)).

(Møen and Thorsen, 2017; Ugur et al, 2016). **A defensible approach is to assume that the average private rate of return to R&D is around 20%.** This is consistent with the elasticity-based estimate and R&D intensity in the UK manufacturing sector while taking a conservative stance on possible downward biases in the meta-analysis, the scale of which is very difficult to assess.

3.2 ESTIMATES FROM THE PRODUCTION FUNCTION LITERATURE

Table 3 summarises the evidence on private returns to R&D investment. These studies all draw on the primal production function approach and estimate either the elasticity of output with respect to R&D or the rate of return to R&D. They all use firm-level data and, as such, estimate the return of own R&D activities to the individual firm in question (i.e. not including any spillover benefits).

In total, our sample includes 63 studies that provide 1,150 estimates of returns to R&D: 902 estimates of an elasticity and 248 estimates of a rate of return. The range of estimated returns is very large: from -55% to +231% for rates of return, and from -0.4 to +2.15 for elasticities. The mean rate of return is around 24%, and the median is slightly lower at 16%. The mean elasticity is around 0.1 – which implies that a 1% increase in R&D spending increases output by around 0.1% – while the median elasticity is around 0.08.

Seven studies examine UK firms specifically, and there are several other studies which include UK firms in cross-country samples of firms. Taking only UK-specific estimates, the mean rate of return is around 20%, lower than the mean across all study estimates, while the median is higher at 21%. The mean and median estimated elasticities, at 0.05 and 0.04 respectively, are lower than those across all studies. However, given the small number of UK-specific studies and the wide range of estimates in the literature, it is not possible to draw strong conclusions about whether estimates of returns in the UK are different to the overall rate of return.

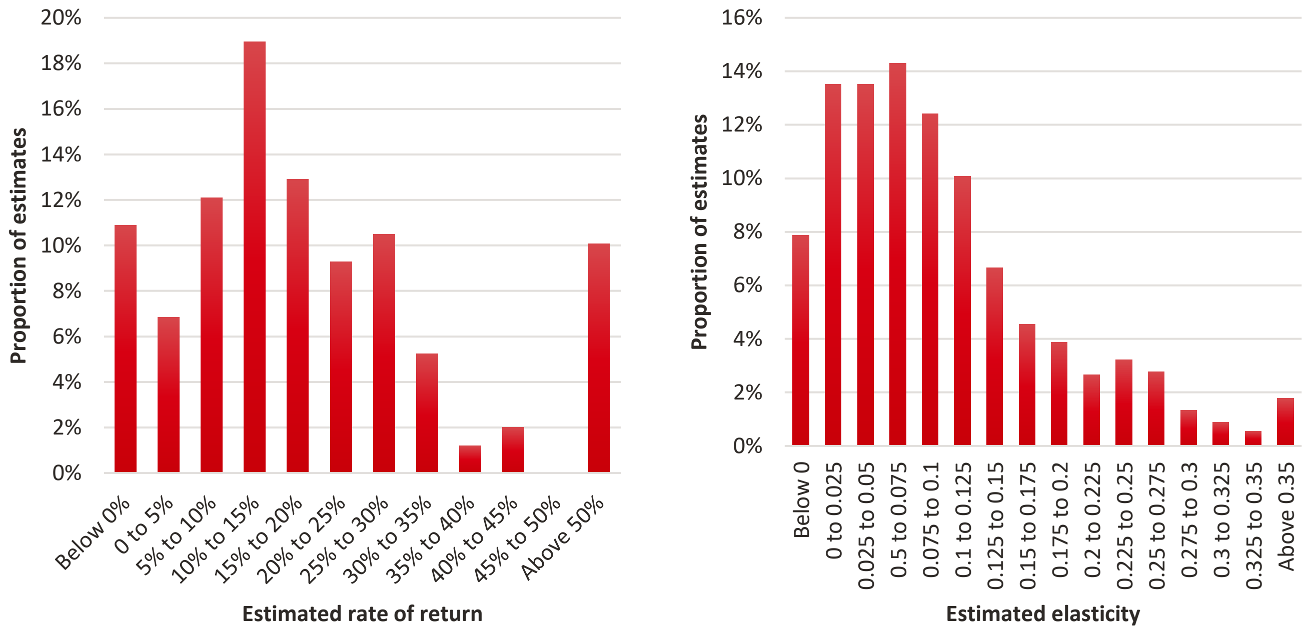
Table 3. Estimates of private returns to R&D investments from firm-level studies

	NO OF PAPERS	NO OF ESTIMATES	MIN VALUE	MAX VALUE	MEDIAN	MEAN
All studies	63	1,150				
Estimate rate of return	27	248	-55%	+231%	+16%	+24%
Estimate elasticity	45	902	-0.399	2.149	0.076	0.095
UK-specific	*7*	*87*				
Estimate rate of return	*2*	*32*	*-21%*	*+64%*	*+21%*	*+20%*
Estimate elasticity	*6*	*55*	*-0.328*	*0.238*	*0.037*	*0.053*

Note: Some studies estimate both rates of return and elasticities (and therefore the number of papers does not sum to the total). The rate of return is equal to the elasticity multiplied by the ratio of R&D capital to output (as set out in section 1.4). Estimates can therefore be compared using data on the R&D capital-to-output ratio. A common assumption is that R&D capital depreciates at a rate of 15% per year, and therefore the stock of R&D capital is around seven times the annual R&D spend. Therefore for a firm with annual R&D to output of 5%, the rate of return implied by an elasticity of 0.076 is 22% (=0.076(1/0.05*7)), while the elasticity implied by a rate of return of 16% is 0.056 (=0.16*(0.05*7)).*
Source: Frontier Economics

The full distribution of estimates is shown in Figure 1. The left-hand graph shows the distribution of rate of return estimates. The most common value of the private rate of return to R&D is 10-15%. The right-hand graph shows the distribution of elasticity estimates. For both the rate of return estimates and the elasticity estimates, the most common value is similar to the median shown in Table 3, but there are several higher estimates, which is why the mean estimate is greater than the median.

Figure 1. Distribution of estimated private rates of return to R&D investments



Source: Frontier Economics

3.3 META-ANALYSIS OF ESTIMATES AND PUBLICATION BIAS

While these studies suggest positive returns to R&D, Møen and Thorsen (2017) point out potential publication bias in this field. The prior beliefs of economists that R&D should generate positive returns, combined with the technical difficulties in estimating these returns, create a setting conducive to publication bias. As discussed in section 2.2, this bias could arise from three sources: scientific journals favouring the publication of statistically significant results, peer reviewers using their prior expectations as an informal test of the validity of the results, and researchers' own expectations affecting their choices of specifications and their interpretation of their results.

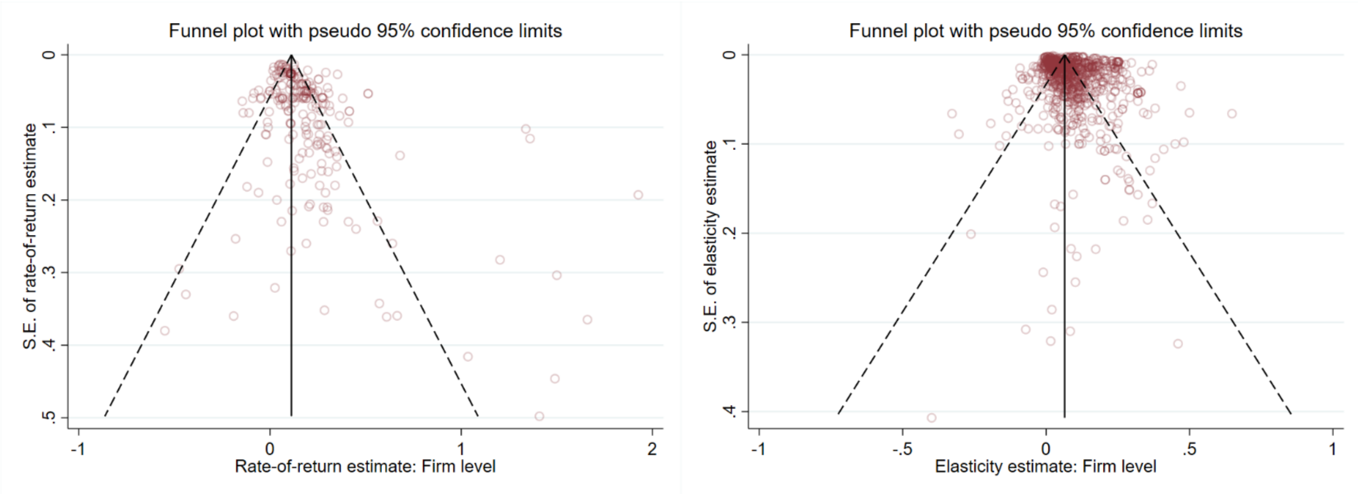
We examine the presence of publication bias using funnel plots and regression-based tests. Funnel plots are scatter graphs where each estimate is plotted according to the estimated effect size on one axis and its precision on the other. The estimates that have the greatest precision are assumed to be closest to the true value, and in the absence of publication bias one would then expect a symmetric funnel-shaped pattern around that true value (driven by statistical variation).

The funnel plots for the firm-level estimates are shown in Figure 2 for rate of return estimates and elasticity estimates separately. For ease of visualisation we restrict the graphs to estimates with a standard error of less than 0.5 (which excludes 1% of elasticity estimates and 5% of rate of return estimates).

The plot for rate of return estimates suggests some asymmetry, with a greater density of estimates to the right of the assumed true value and a number of outlying estimates with relatively high rates of return. This could be indicative of publication bias.

The plot for elasticity estimates is much more concentrated around the value of the estimates with the highest precision and there is less obvious asymmetry.

Figure 2. Funnel plots – firm-level estimates



Note: "S.E." means standard error.
Source: Frontier Economics

To formally test for the presence of publication bias, we employ funnel asymmetry tests (FATs), as described in section 2. In the absence of publication bias, estimates should be independent of their standard error, and so testing whether $\alpha = 0$ is the widely used FAT test for publication bias. Stanley (2008) also shows that if there is a genuine effect then β should be positive – this test is known as the precision effect test (PET).

Table 4. Funnel asymmetry tests and precision effect tests

	FAT/PET TESTS		PEESE TESTS	
	ELASTICITY	RATE OF RETURN	ELASTICITY	RATE OF RETURN
PET for genuine effect (β)	0.070***	0.088***	0.073***	0.135***
	(0.013)	(0.016)	(0.010)	(0.016)
FAT for publication bias (α)	0.316	1.226***	0.814	1.900***
	(0.488)	(0.284)	(1.673)	(0.658)
Observations	897	244	897	244

Note: Full results are available in Table 12 in Appendix B. The first two columns report the results of the FAT tests for publication bias. In the presence of publication bias, the true effect is known to be underestimated by the PET test (discussed in section 2.2.2). The final two columns (PEESE tests) correct for this, so estimates of the genuine effect controlling for publication bias are taken from the final two columns.
Source: Frontier Economics

The results of these tests are shown in the first two columns of Table 4 for the elasticity and rate of return estimates respectively. There is found to be substantial publication bias in the rate of return estimates, with the point estimate for α being 1.226 and statistically different from zero. For the elasticity estimates, publication bias appears less of an issue: the point estimate for α is positive but not statistically different from zero. The coefficient β is found to be positive and significant in both columns, indicating that, after controlling for publication bias, there is a still a positive elasticity/rate of return. However, this size of the true effect is known to be underestimated by these tests if there is publication bias. The final two columns of Table 4 therefore conduct what is known as a precision effect estimation corrected for standard errors (PEESE) test, which aims to correct this problem. Here the mean elasticity estimate (controlling for publication bias) is around 0.07, while the mean estimated rate of return (controlling for publication bias) is around 14%. This compares to the raw mean elasticity estimate of 0.095 and raw mean rate of return estimate of 24%.

Our findings on the presence of publication bias and the mean returns controlling for publication bias are very similar to those in Ugur et al (2016). They are also broadly in line with the findings of Møen and Thorsen (2017), who examine publication bias on a more limited subset of the literature.

4 SOCIAL RETURNS TO R&D

4.1 KEY SUMMARY OF FINDINGS

Estimating the social returns to R&D is inherently more challenging than estimating the private returns, but overall the evidence points to **social returns to R&D that are greater than private returns**.

Our meta-analysis suggests that estimates of within-industry social returns are similar to estimates of private returns. However, this may still imply greater *net* social returns if depreciation of R&D capital is lower at the industry level than the firm level (as might be expected), and if there are positive between-industry spillovers.

The literature that seeks to estimate spillovers directly finds sizeable knowledge spillovers that more than offset the market-stealing effects of R&D. Some of the most careful and robust studies which estimate spillovers suggest sizeable social returns, around four times the size of private returns to R&D. However, a lack of good data, uncertainties over methodology and some evidence of publication bias mean these estimates should be treated with caution. **A relatively conservative approach to modelling the benefits to R&D could be to assume that the social returns to R&D are twice those of the private returns**.

4.2 APPROACH

We consider the evidence on social returns to R&D from two empirical approaches, both within the production function framework.

The first estimates the return to 'own' R&D for a whole industry or country rather than for individual firms. This produces an estimate of the social return within an industry or within a country (respectively), incorporating the private return to firms within the industry of their own R&D plus the net effect of any within-industry or within-country spillovers (see Table 1 for the different interpretations of the different units of analysis). This literature is discussed in sections 4.3 and 4.4 respectively.

The second explicitly models spillovers by including one or more measures of external R&D stock in the production function alongside own R&D capital and other production inputs (labour and physical capital).[15] If external R&D has an impact on a firm's output over and above the firm's own R&D and other inputs, then this suggests that R&D has spillover effects. This approach yields estimates of both the private return to R&D and the return to specified spillovers, which can be combined to produce an estimate of the social return. This approach can also be estimated at the firm, industry or country level, which will affect the interpretation of the returns estimated. This literature is discussed in section 4.5.

As set out in section 1.2, both of these approaches relate to measuring social returns defined in terms of a total increase in output (as opposed to just an increase in output for the unit undertaking the R&D). They do not examine the broader returns of R&D investment, such as any impacts on wages, health, environment, public service delivery, etc. The social returns discussed here will therefore understate the true social return. Returns may also be underestimated due to lags in the benefits of R&D being felt (as was discussed in section 1.3 and section 3.1 with respect to private returns). This may be even more of an issue for social returns as knowledge spillovers, in particular, may take some time to influence other firms.

[15] This approach is discussed in more detail in section A.2 of Appendix A.

4.3 INDUSTRY-LEVEL ESTIMATES OF RETURNS

Estimates of the return to own R&D that are produced at the industry level are estimates of the social return to R&D incorporating the private return to firms within the industry of their own R&D, plus the net effect of any within-industry spillovers.

Table 5 summarises the evidence on returns to R&D investment estimated using the primal production function approach using industry-level data. In total our review includes 23 studies that provide 340 estimates of returns to R&D: 195 estimates of a rate of return and 145 estimates of an elasticity. As with the private returns estimated on firm-level data (shown in Table 3), the range of estimated returns is very large: from -74% to +90% for rates of return, and from -0.12 to +0.81 for elasticities. The mean rate of return is around 24%, and the median slightly lower at 22%. The mean elasticity is around 0.1 while the median elasticity is around 0.06. These are very similar to the average private returns in firm-level studies as shown in Table 3.

Table 5. Estimates of within-industry social returns to R&D investments

	NO OF PAPERS	NO OF ESTIMATES	MIN VALUE	MAX VALUE	MEDIAN	MEAN
Industry-level analysis	23	340				
Estimate rate of return	14	195	-74%	+90%	+22%	+24%
Estimate elasticity	10	145	-0.120	0.810	0.057	0.104

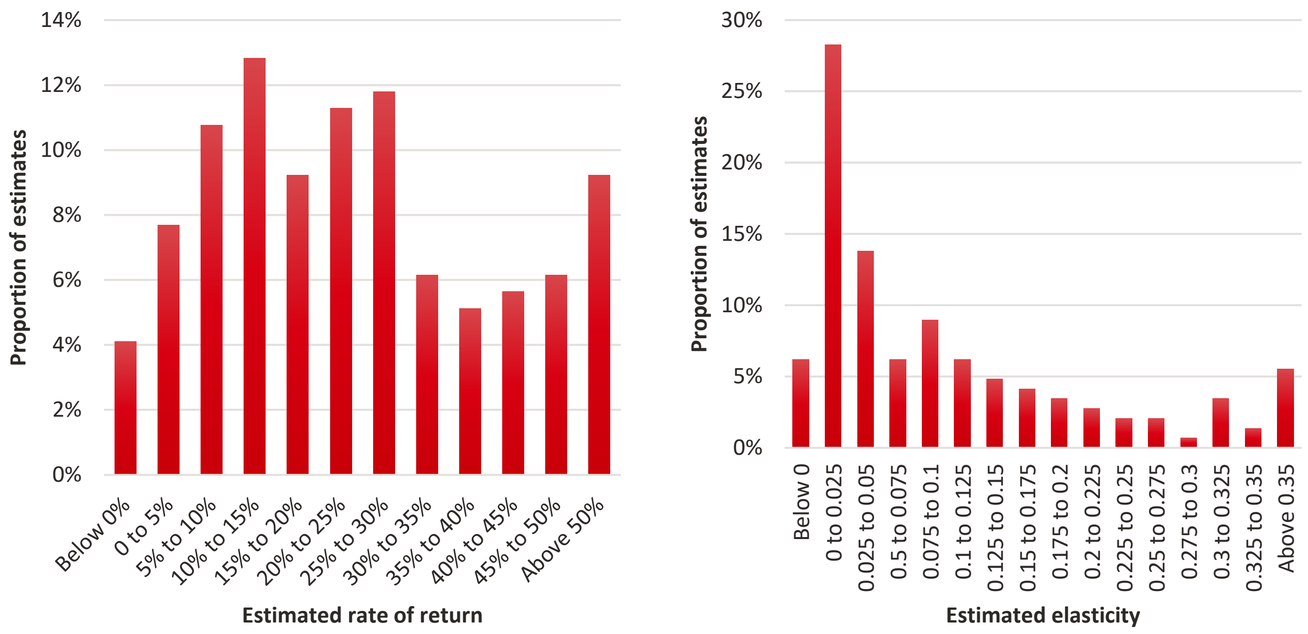
Note: One study estimates both rates of return and elasticities (and therefore the number of papers does not sum to the total). The rate of return is equal to the elasticity multiplied by the ratio of R&D capital to output (as set out in section 1.4). Estimates can therefore be compared using data on the R&D capital-to-output ratio. A common assumption is that R&D capital depreciates at a rate of 15% per year, and therefore the stock of R&D capital is around seven times the annual R&D spend. Therefore for an industry with annual R&D to output of 5%, the rate of return implied by an elasticity of 0.057 is 16% (=0.057(1/0.05*7)), while the elasticity implied by a rate of return of 22% is 0.077 (=0.22*(0.05*7)).*
Source: Frontier Economics

The full distribution of estimates is shown in Figure 3 below, again grouped by whether the paper estimates a rate of return directly or an output elasticity.

It is worth caveating that the peak in the distribution of elasticity estimates is driven by one particular study which contributes 55 estimates, of which 30 lie between 0 and 0.025. That aside, the distribution of elasticity estimates is similar to that produced by firm-level estimates of the private return to R&D. The distribution of industry-level rates of return lies somewhat more to the right than was the case for private rates of return, with more estimates above 35% and fewer estimates below 0%.

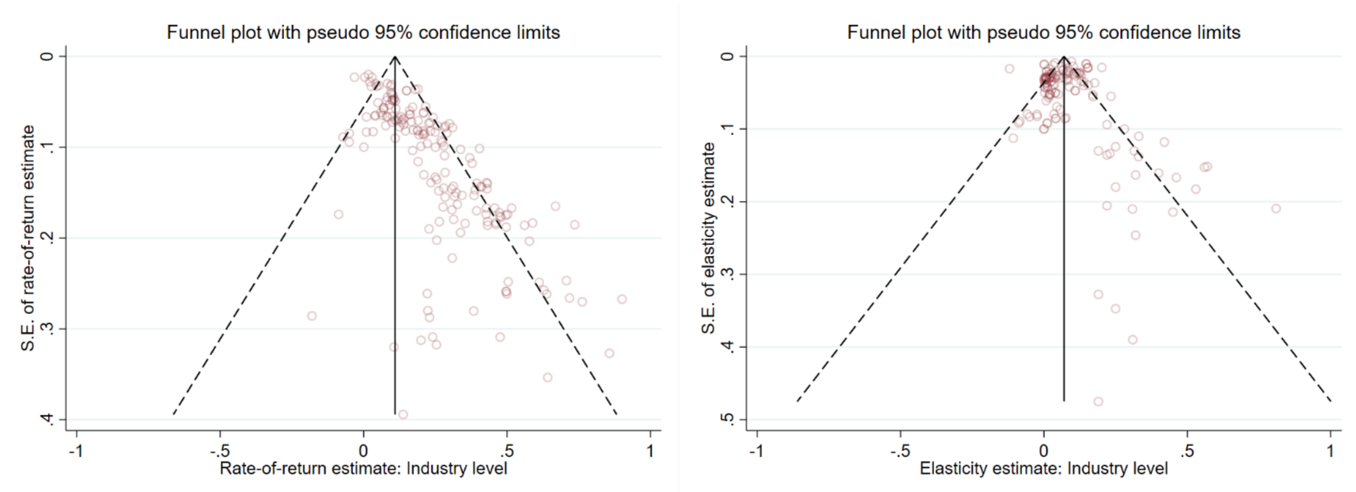
We conduct the same meta-analysis approach as was described in section 3.3 to test for the presence of publication bias. The funnel plots are presented in Figure 4 and show a clear asymmetry for rates of return estimates, with less precise estimates being much more likely to be large and positive than small or negative. The plot of elasticity estimates is less striking but is also suggestive of asymmetry.

Figure 3. Distribution of estimated private rates of return to R&D investments – industry-level estimates



Source: Frontier Economics

Figure 4. Funnel plots – industry-level estimates



Source: Frontier Economics

The formal FAT tests for publication bias are presented in the first two columns of Table 6. The results suggest substantial publication bias in the rate of return estimates and positive, albeit not statistically significant, bias in elasticity estimates.

The PET tests (top two rows) suggest that there is a positive return to R&D after publication bias is controlled for. The final two columns conduct the PEESE tests to produce a better estimate of the true effect after controlling for publication bias.

The results suggest a **mean industry-level rate of return estimate of 12% and a mean elasticity of around 0.07**. These are very similar to the average effects found for the private returns to R&D at the firm level in section 3.2 (Table 3).

Table 6. Funnel asymmetry tests and precision effect tests

	FAT/PET TESTS		PEESE TESTS	
	RATE OF RETURN	ELASTICITY	RATE OF RETURN	ELASTICITY
PET for genuine effect (β)	0.067*** (0.018)	0.087** (0.041)	0.075*** (0.018)	0.115*** (0.033)
FAT for publication bias(α)	0.576 (0.379)	1.107** (0.464)	-0.484 (0.788)	-0.178** (0.089)
Observations	141	192	141	192

Note: Full results are available in Table 13 in Appendix B. The first two columns report the results of the FAT tests for publication bias. In the presence of publication bias, the true effect is known to be underestimated by the PET test (discussed in section 2.2.2). The final two columns (PEESE tests) correct for this. The estimate of the genuine elasticity controlling for publication bias is therefore taken from the final column.
Source: Frontier Economics

While the industry-level estimate of returns to R&D, which incorporates within-industry spillovers, is the same as the private return to R&D, this does not necessarily imply that there are no spillover benefits from R&D. In addition to the possibility of wider spillovers on things other than firm-level output (such as health or environmental impacts), there are three other main reasons for this:

- First, there are theoretically both positive knowledge spillovers and negative displacement effects. The finding that the within-industry social return is similar to the within-firm private return could therefore indicate offsetting effects. For example, part of the private return to own R&D that investing firms enjoy may come at the cost of other firms' market share (market stealing). If this were the only spillover then the industry-wide return to R&D would be lower than the firm-level return (because some firms are losing output as a result). But this may be offset by knowledge spillovers, increasing the output of other firms and increasing the industry-wide return to R&D to the level of the private return.[16]
- Second, the rates of return estimated by the literature are technically 'gross' rates of return that contain a component of depreciation. Pakes and Schankerman (1984) and Griliches (1992) point out that the private rate of depreciation at the firm level is likely greater than that at the overall industry level – particularly if the latter involves some component of social return – and therefore the net social return to R&D could be higher than the net private return to R&D even if the gross rates of return were the same.
- Third, examining returns to own R&D at the industry level only captures the within-industry social return – the private return to firms in that industry and any spillovers between firms in that industry. There may be far wider spillovers, particularly knowledge benefits, that occur between industries and even between countries. This would increase the social return beyond the amounts estimated here.

[16] Lucking et al (2019), discussed in section 4.5, is one of the few papers that seeks to separately estimate these separate spillover effects. They find, in their context, that knowledge spillovers more than offset market-stealing effects.

Intra-industry spillovers are captured in estimates of social returns, estimates using country-level data (section 4.4) and often in estimates of spillover effects (section 4.5). We therefore turn now to an assessment of this evidence.

4.4 COUNTRY-LEVEL ESTIMATES OF RETURNS

One approach to account for inter-industry spillovers is to estimate returns to R&D at the country level. This implicitly includes both the private return to R&D and any knowledge spillovers or displacement effects that affect firms in the same country whether in the same industry or not.

There are some disadvantages to estimating returns at the country level. It may be difficult to control for other unobservable differences that correlate with both a country's R&D and its output or productivity – particularly when R&D spending and R&D intensity have, in many countries, trended strongly upwards over time. Studies may also be based on relatively small sample sizes compared with firm-level or industry-level studies or may draw on samples of countries that might be considered to be quite different. If returns differ substantially across countries (an issue we come back to in section 5) due to different institutional contexts, estimating an elasticity or rate of return that is assumed to be constant across countries or geographies may not be appropriate.

With these caveats in mind, Table 7 summarises estimates of elasticity and rates of return to R&D estimated at the country level. The mean average rate of return presented in the studies summarises ranges from -22% to +123%, with a median of 15% and a mean of 36%. The mean average estimated elasticity presented ranges from -0.03 to +0.56, with a median of 0.07 and a mean of 0.09.

These are similar to the average estimated elasticities and rates of return obtained from firm-level and industry-level studies (Table 3 and Table 5 respectively). While this might be interpreted as social returns being similar to private returns, even after inter-industry knowledge spillovers and displacement effects are accounted for, we would caution that methodological differences mean this may not be quite comparing like with like. Country-level analyses typically examine returns to total R&D spending conducted by four sectors (businesses, higher education institutions, government and the not-for-profit sector), while firm- and industry-level analyses focus on returns to R&D spending conducted by businesses. Furthermore, country-level analyses are based on very small sample sizes compared to industry- and firm-level analyses, and country-level analyses are subject to greater concerns about whether unobserved factors that correlate with both R&D and output are adequately controlled for.

Table 7. Estimates of returns to R&D investments at the country level

	NO OF PAPERS	NO OF ESTIMATES	MIN VALUE	MAX VALUE	MEDIAN	MEAN
All studies	47	397				
Estimate rate of return	10	32	-22%	123%	15%	36%
Estimate elasticity	37	365	-0.027	0.560	0.071	0.094

Note: The min, max, median and mean are calculated across the mean estimate from each study.

Source: Estimates collated from Hall et al (2009), and Ugur et al (2020), with the addition of Ziesemer (2021) and van Elk et al (2019) which were identified through our literature search.

4.5 SPILLOVERS APPROACH

An alternative approach to estimating social returns is to estimate a version of a production function that includes one or more terms that capture spillover effects from others' R&D investments explicitly. This approach is described in more detail in Appendix A.2. The social return to the R&D conducted by a particular firm is then the sum of the private benefit and the returns on spillovers for other firms that receive R&D spillovers.

This is challenging, as it requires construction of the external R&D stock for each firm, industry or country being analysed. The external R&D stock is defined as a weighted sum of the R&D done by other firms (or industries or countries), where the weights are proportional to the potential spillovers between firms, industries or countries. This requires not just good data on the output and R&D activities of each firm, industry or country but also on the links between them. Many different approaches to weights have been used in the literature, including (but not limited to): intermediate input transactions (e.g. Terleckyj, 1980), positions in patent classes (e.g. Jaffe, 1986), similarity of output (e.g. Bloom et al, 2013), network connections of researchers (e.g. Zacchia, 2020), geographical proximity (e.g. Audretsch and Belitski, 2020), and labour transitions (Goodridge et al, 2017). The choice of weighting is therefore very important and Van Meijl (1997) demonstrates that the estimated social return depends heavily on the weighting used.

Several early reviews of the literature on spillovers suggest that the returns to external R&D are positive, and greater than the returns to own R&D (Griliches, 1992; Mohnen, 1996; Cincera and Van Pottelsberghe de La Potterie, 2001). Hall et al (2009) summarise the results of 27 papers that estimate spillovers at the firm, country or industry level. They find that elasticities with respect to external R&D are generally around 0.05 to 0.09, which is of a similar magnitude to the estimated elasticities for own R&D.[17] Under certain simplifying assumptions, this would imply that the social returns are around twice the private returns to R&D.[18]

More recently, Ugur et al (2020) conducted a review of much of the literature on spillovers from R&D investment. Specifically, they conducted a meta-analysis of linear estimates of elasticities from primal production function studies. Their analysis includes 983 estimates of returns to spillovers and 501 estimates of returns to own R&D, drawn from 60 empirical studies. They find significant evidence of publication bias in estimates of returns to spillovers and estimates of returns to own R&D. Even after controlling for publication bias, however, they find a mean elasticity of productivity from own R&D of around 0.07 (equivalent to that found in sections 3.3 and 4.3 above) and a mean elasticity of productivity from spillovers of 0.04. The mean productivity elasticity of spillovers is found to be larger (at 0.07) when the sample is restricted to estimates that are most likely to represent knowledge spillovers.[19] Ugur et al (2020) find that the mean return to spillovers is positive for country-level studies but insignificant for firm- and industry-level studies due to publication bias. However, while not statistically significant, the estimate for returns to spillovers is similar in magnitude to the estimate for returns to own R&D for firm-level studies. Overall the authors interpret their results as indicating that the returns to R&D spillovers are lower than suggested in earlier narrative reviews (Griliches, 1992; Mohnen, 1996; Cincera and Van Pottelsberghe

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[17] For the papers that estimate rates of return directly, the rates of return summarised are highly variable and range from negligible (Wolff and Nadiri, 1993) to 80% (Goto and Suzuki, 1989) – and even higher in some cases when returns are estimated for separate industries.

[18] Specifically, under the assumptions that all firms have the same linkages with other firms (and therefore receive the same spillovers) and that all firms are the same in terms of the ratio between their R&D stock and their output.

[19] These are estimates of the return to external R&D where the weights used in calculating the external R&D stock do not relate to transactions.

de La Potterie, 2001), and not higher than the returns to own R&D. However, any degree of positive spillovers suggests a social return in excess of the private return. As stated above, under certain simplifying assumptions, if the elasticity on spillovers is the same as the elasticity with respect to own R&D, then the social return is twice that of the private return.

Meta-analysing the literature on spillovers is inherently challenging, not least because papers take very different approaches to defining and constructing measures of the external R&D stock. This has three important implications:

- First, it means that the estimated effect of spillovers on output would be expected to vary substantially, as different types of spillovers are captured across different approaches. For example, spillover estimates may include a large component of market-stealing effects if external R&D stock is calculated by weighting external firms (or industries or countries) using product similarity. However, the spillovers identified are more likely to represent knowledge spillovers if the external R&D stock is calculated by weighting external firms according to the technological similarity of their production process. Ugur et al (2020) show that the estimated productivity effects vary according to the spillover measured.
- Second, the social return to R&D depends not just on the estimated elasticities with respect to own R&D and the spillovers but also on how many firms benefit from those spillovers and their R&D-to-output ratios. This is described in more detail in section A.2 of Appendix A. This means that it is not possible to quantify accurately the social return implied by meta-analysis results.
- Finally, it means the results of adjustments for publication bias should be interpreted cautiously. As discussed in section 2.2.3, meta-analysis relies on precision of estimates to unpick the true underlying effect. In papers that estimate spillover effects, the quality of the estimates will depend heavily on the quality of the data and theoretical underpinnings for the chosen weighting matrix, and this is not necessarily reflected in the statistical precision of estimates.

Given these limitations of meta-analysis, it is worth highlighting the results of some studies that we judge to have produced robust estimates, having taken considerable methodological care in their data construction and estimation strategies. Two such papers (which are not included in the Ugur et al (2020) meta-analysis as they were published too recently) are Lucking et al (2019) and Goodridge et al (2017).

Lucking et al (2019) build on Bloom et al (2013) and estimate the effects of R&D spillovers on four firm outcomes: market value, R&D spending, productivity and patenting. They exploit rich, high quality panel data on US firms (largely manufacturing firms) over the period 1985 to 2015 and use patent class proximity between firms to identify knowledge spillovers and product similarity between firms to identify market rivalry effects. They identify large, positive technology spillovers and smaller negative product rivalry effects. Their estimates suggest that the social return to R&D is 57.7%, compared with a private return of 13.6%, taking account of the effect of spillovers. Put another way, they find a social return that is around four times that of the private return.

Goodridge et al (2017) mainly focus on estimating returns to, and spillovers from, intangible investments (such as software, design or training). Their estimates suggest an elasticity of productivity with respect to external R&D of 0.25 or 0.21 when the production function is only augmented with R&D (and not also other intangibles) and of internal R&D of 0.04 or 0.07, depending on whether the external R&D stock is calculated using intermediate consumption weights or labour transition weights (respectively). They find that social returns are at least four times the size of private returns using the estimates produced with labour transition weights,[20] and assuming for simplicity that industries have similar R&D-to-output ratios. This again suggests that social returns are around four times the size of private returns.

Taken together, we view the evidence from the spillovers literature as indicating that social returns to R&D are greater than private returns. While there is evidence of market-stealing effects of R&D, this is more than offset by knowledge spillover benefits. Some of the most careful and robust studies which estimate spillovers suggest sizeable social returns, around four times the private returns to R&D. However, a lack of good data, uncertainties over methodology and some evidence of publication bias mean these estimates should be treated with caution. A relatively conservative approach to modelling the benefits to R&D could be to assume that the social returns to R&D are twice those of the private returns. This would be broadly consistent with the literature reviewed in Hall et al (2009) and with the meta-analysis results of Ugur et al (2020).

[20] The ratio is higher than four when intermediate consumption weights are used.

5 VARIATION IN RETURNS TO R&D

5.1 SUMMARY OF KEY FINDINGS

Our meta-analysis and narrative review of the wider literature that could not be included in the meta-analysis highlight that rates of return to R&D likely differ in different contexts. However, on the basis of the relatively limited existing literature, **it is not possible to quantify an average return to R&D in different contexts**, such as for different industries, types of firms or types of R&D. When appraising the case for public support of any particular R&D project, in the absence of other information, it is therefore still reasonable to rely on the average return to R&D described above.

While these results should be treated with some caution, as there is relatively limited literature on some aspects of variation in returns to R&D, our review of the current evidence suggests that:

- Returns to small firms may be larger than returns to larger firms;
- Average returns to R&D do not appear to have changed over the past four decades;
- US firms have higher rates of return on average than firms in the EU (including the UK). In part this is due to the higher R&D intensity of the USA and different industrial composition, but this does not appear to fully account for the difference. There is no strong evidence on whether returns in the UK are different to those in other non-US countries;
- Publicly funded R&D conducted by the private sector has lower private rates of return than privately funded R&D. This is likely because public funding is targeted at investment with lower private returns but greater spillover or wider social benefits, and/or because public funding disproportionately supports basic R&D (as compared with private R&D spending), for which the returns may take longer to be realised;
- Returns to R&D may be non-linear, with positive effects on output only after firms reach a certain threshold level of R&D spending, and with diminishing elasticities as the ratio of R&D spending to output increases;
- Returns to R&D are positive in both manufacturing and service sectors, but there is less consistent evidence on which sectors or industries have relatively higher returns; and
- Returns to basic R&D take longer to be realised than returns to applied R&D.

5.2 APPROACH

It is important to understand whether differences in estimated rates of return are associated with observable factors. First, systematically different estimates arising from different empirical approaches may indicate methodological biases that the meta-analyses in sections 3.3 and 4.3 do not control for. Second, if estimates differ systematically across contexts, then this may indicate that the true rate of return to R&D differs across these contexts, which may affect how the estimate of the 'average' rate of return is used.

In general, the focus is on variation in firm-level private returns or industry-level returns (which contain elements of both private and social returns as outlined in section 1.4.2). The variation here does not explore social returns in the broader sense, e.g. including wider societal impacts.

To explore these drivers of differences in rate of return estimates, we conduct multivariate meta-regression analysis, as described in section 2.2.2. The full results for both the general model with all moderating variables and the specific model after the iterative exclusion of moderating factors that are not statistically significant are in Appendix B. In section 5.3 we discuss the first group of moderating factors considered: features of the empirical approach taken, such as the estimation approach or control variables used. These features may affect the estimated rate of return produced by the analysis but are unlikely to be indicative of genuine variation in the underlying rate of return in a way that has meaningful policy implications. In section 5.4 we discuss the second set of factors we consider: features of the R&D or firms/industry being examined. Differences in estimates of returns that are correlated with these dimensions are more likely to be indicative of genuine differences in underlying average returns to R&D in different contexts. In section 5.4 we also include, where relevant, a narrative review of studies that examine differences in returns to R&D but that are not included in our meta-analysis (because they do not use a production function approach or because they produce non-linear estimates of returns to R&D).

5.3 VARIATION IN ESTIMATES ASSOCIATED WITH EMPIRICAL APPROACH

Estimated returns to R&D do seem to vary systematically with some aspects of the empirical approach taken by different studies. In particular:

- Estimates published in journal articles are typically lower than estimates that are published in other forms (such as working papers or book chapters) – for example, 0.045 lower in the case of firm-level elasticity estimates and 7.4 percentage points lower in the case of firm-level rate of return estimates.[21]
- Industry-level studies that explicitly control for spillovers from external R&D have lower estimated elasticity and rate of return estimates with respect to own R&D than those that do not.
- Studies that include industry dummies have higher mean elasticity estimates, although there is no significant difference in rate of return estimates.
- Some aspects of data definition have an impact on estimates.[22] Controlling for double counting of R&D inputs in the production function is associated with higher elasticity estimates in the firm-level studies. This is in line with the theoretical prediction that R&D spending often includes some labour and capital costs (which are also counted separately as inputs in the production function – leading to double counting), which biases estimates of returns downwards. Studies that calculate the knowledge capital stock using the method described in section 1.3 (known as the perpetual inventory method) produce estimates of elasticities (in firm-level studies) that are on average higher than studies that assume that the addition to the knowledge stock from new R&D depends on the existing level of the knowledge stock.
- The estimation process used also has an effect on estimates. In particular, methods that difference observations over time (first differencing and within approaches) on average produce lower elasticity estimates. There is a known issue that time-differencing tends to bias estimated coefficients towards zero (Hall et al, 2009), and this finding reflects that. Furthermore, the use of instrumental variables approaches is, in some cases, correlated with lower mean estimates. This suggests that simple OLS approaches may be upward biased due to endogeneity – such as output and R&D both responding in the same direction in response to external shocks.

[21] Given the proportion of estimates in our data that are published in journals, this would imply (all else equal) an average elasticity in journals of 0.051 compared to 0.096 in other publications (yielding an average elasticity of 0.073) and an average rate of return estimate published in journals of 11% compared to an average estimate published elsewhere of 19% (yielding an average of 14%).

[22] These issues, and theoretical impact on estimates of returns, are discussed in more detail in Appendix A of Frontier Economics (2014) and Hall et al (2009).

As described, some of these associations may indicate the effect of methodological biases on the average estimated effect. However, the sample sizes for identifying some of these moderating influences are relatively small, and it is difficult to truly distinguish between the effects of different aspects of methodological approaches when they are highly correlated with each other. We therefore note these associations but do not feel confident in using these results to adjust the estimated effects produced by the meta-analysis (first reported in Table 3 and Table 5) for sources of bias other than publication bias.

5.4 VARIATION IN RETURNS TO R&D

We turn now to a discussion of drivers of variation in returns to R&D in terms of the characteristics of the R&D or the context considered. The relevant results from the multivariate regression analysis are summarised in Table 8 (full results are available in Appendix B). These show how the mean estimated effect varies according to the characteristics of the estimate relative to some reference characteristic. For example, the first cell indicates that, among the firm-level studies that estimate elasticities, all else equal the estimated elasticity is around 0.04 higher for studies that consider a time period ending before 1980 than studies that consider a time period ending between 1980 and 1994 (the 'reference' category). We discuss these possible drivers of variation that are examined in the meta-analysis in turn, drawing on wider literature where relevant.

Table 8 Selected results from multivariate meta-regression: general model results

	ELASTICITY ESTIMATES				RATE OF RETURN ESTIMATES			
	FIRM LEVEL		INDUSTRY LEVEL		FIRM LEVEL		INDUSTRY LEVEL	
	b	se	b	se	b	se	b	se
Data period ends before 1980	0.041*	(0.022)	-0.278***	(0.070)	-0.041	(0.028)	-0.012	(0.046)
Data period ends 1980-1994	Ref.		Ref.		Ref.		Ref.	
Data period ends 1995-2007	0.000	(0.022)	0.064*	(0.034)	0.031	(0.048)	-0.256	(0.206)
Data period ends after 2007	0.022	(0.028)	n.o		0.010	(0.050)	-0.308	(0.199)
Mixed or large firms	Ref.		Ref.		Ref.		Ref.	
Small firms	-0.017**	(0.008)	n.o		0.066*	(0.039)	n.o.	
French data	0.010	(0.010)	0.014	(0.020)	0.060	(0.114)	0.192**	(0.082)
German data	0.002	(0.039)	0.001	(0.020)	0.127*	(0.073)	0.004	(0.070)
UK data	-0.009	(0.027)	0.020	(0.020)	0.046	(0.062)	0.004	(0.071)
US data	0.044***	(0.009)	0.014	(0.020)	0.031*	(0.018)	-0.022	(0.066)
Other OECD data	Ref.		Ref.		Ref.		Ref.	
R&D intensive firm/industry	0.030***	(0.008)	0.076***	(0.015)	-0.065*	(0.039)	0.060	(0.096)
Mixed or non-intensive firm/industry	Ref.		Ref.		Ref.		Ref.	
Publicly funded R&D	-0.130***	(0.034)	n.o		-0.069**	(0.033)	-0.303***	(0.034)
Mixed or privately funded R&D	Ref.		Ref.		Ref.		Ref.	
Observations	897		141		244		192	

*Note: Full regression results are available in Table 14 in Appendix B. 'Ref.' indicates reference group within each category. 'n.o' indicates no observations. *,**,*** indicate statistical significance at the 10%, 5% and 1% level respectively.*
Source: Frontier Economics

5.4.1 FIRM SIZE

Theoretical arguments can be made in favour of either small or large firms having greater returns to R&D. For example, on the one hand, smaller firms may be nimble, efficient and able to observe and respond to market needs. On the other, larger firms may benefit from economies of scale and easier access to finance for R&D and may have more market power.

Our analysis suggests that there is mixed evidence on whether R&D investments by small firms have higher rates of return. The meta-analysis suggests that the elasticity estimated for small firms tends to be smaller than the elasticity estimated for large firms (or when firms are not differentiated by size), while the rate of return estimated tends to be larger for smaller firms than large or mixed firms.

In Table 9 we summarise the estimates produced for small and large firms (and, where applicable, medium-sized firms) for the nine studies included in our meta-analysis that directly examine differences by firm size, taking the mean where a paper has multiple relevant estimates. The results suggest a higher mean elasticity and rate of return for small rather than large firms. The difference between this finding and the meta-analysis is likely driven by the choice of 'preferred' specification in these studies.[23] We believe that the within-paper differences between the estimates for small and large firms set out in Table 9 are a more accurate indication of the relative returns to different sized firms than the results of the meta-analysis.

Table 9 Summary of estimates examining differences in returns by firm size

STUDY	MEAN ESTIMATE: SMALL FIRMS	MEAN ESTIMATE: MEDIUM FIRMS	MEAN ESTIMATE: LARGE FIRMS	ESTIMATE TYPE
Møen (2019)	0.125		0.100	Rate of return
Lehto (2007)	0.039		0.021	Elasticity
Andries and Thorwarth (2014)	0.102	0.084	0.053	Elasticity
Di ubaldo and Siedschlag (2021)	0.016	0.173	-0.399	Elasticity
Kafouros (2005)	0.035		0.044	Elasticity
Goya et al (2016)	0.014	0.039	0.005	Elasticity
Cincera (1998)	0.199	0.197	0.100	Elasticity
Klette (1991)	0.176	0.108	0.083	Rate of return
Kwon and Inui (2003)	0.039	0.036	0.088	Elasticity
Kwon and Inui (2003)	0.301	0.063	0.139	Rate of return
All	**0.079**		**0.032**	**Elasticity**
	0.165		**0.101**	**Rate of return**

Note: Averages for all studies in the final row are not produced for medium firms as not all studies estimate a separate figure for medium firms and therefore this would be derived from a different set of studies than the figure for small or large firms.
Source: Frontier Economics

Two other relevant studies that examine differences in return by firm size and are not included in our meta-analysis are also worth highlighting. Solomon (2021) estimates returns to R&D for UK firms using a production function approach but allowing for a quadratic relationship between R&D and output. Solomon (2021) finds that rates of return are positive for both small and large firms, but that returns are slightly

[23] This is particularly likely to arise if authors test many different specifications or conduct lots of sensitivity analysis. While some differences in specifications (such as the outcome variable and the estimation strategy) are controlled for in our meta-analysis, other differences (such as the set of control variables included) are not.

higher for small firms. Spescha (2019) examines how the impact of R&D spending on sales growth varies according to firm size, firm age and industrial concentration, allowing for interactions between these. Spescha (2019) also finds that smaller and more mature firms have a higher elasticity than larger or younger firms, and that firms in industries consisting of many small firms enjoy greater returns than firms in industries consisting of only a few large firms.

On balance we believe this **evidence is suggestive that returns to R&D are larger for small firms (all else equal) than for large firms**. However, it is not possible to reliably quantify this, given that the simple comparison in Table 9 does not control for other estimation differences or publication bias in the way that the meta-analysis does. We would therefore not recommend assuming that returns vary by firm size.

5.4.2 TIME

There is discussion about whether returns to investment in R&D have changed over time. We attempt to examine this in our meta-analysis by including an indicator of whether an estimate is obtained from data with a time period ending (i) before 1980, (ii) after 1980 but before 1995, (iii) after 1995 but before 2008 and (iv) from 2008 onwards. The separation in 1995 is due to the hypothesis that the introduction of the internet changed the nature of returns to R&D (Kafouros, 2005). The separation in 2008 aims to investigate the idea that returns differed before and after the financial crisis. This is, however, a relatively crude way of attempting to examine changes in returns over time.

The results from the meta-analysis are not particularly conclusive. There is some suggestion that firm-level studies on data prior to 1980 yield higher elasticity estimates than later studies, but the opposite is true of estimates from industry-level studies where estimated elasticities are particularly high for studies using data more recent than 1995. There is less evidence of any significant association between time and estimated rates of return.

A few papers explicitly examine whether returns to R&D vary over time by estimating returns for different time periods using consistent data and methodology. Kafouros (2005) examines the impact of R&D on the productivity of UK manufacturing and finds that the elasticity was around zero from 1989 to 1995 but then increased substantially (to around 0.9 by 2000). Lucking et al (2019) examine whether the returns to own R&D and spillovers (knowledge spillovers and product market rivalry effects) have changed over time. They find that estimated elasticities are relatively stable over the thirty-year period from 1985 to 2015, although in the period from 1995 to 2005 knowledge spillovers are greater and market rivalry spillovers are smaller – which the authors attribute to the dot.com boom. The full pattern of private and social rates of return over time are somewhat sensitive to the choice of which measure of R&D capital to output is used to calculate the implied rate of return, but comparing 2015 to 1985 rates of return are judged to be broadly similar.

Overall we interpret this evidence as suggesting that **returns have not changed substantially over the past four decades**. We therefore believe that it continues to be appropriate to calculate an average rate of return from all the studies in our review, rather than only focusing on the estimates produced by studies that focus on returns to R&D conducted in the last decade or two.

5.4.3 COUNTRY

In our meta-analysis we included four dummy variables to examine whether estimates based on data from the USA, the UK, France or Germany were systematically different to estimates based on data from other

OECD countries. **No significant differences were identified for estimates derived from UK data** as compared to other OECD countries (excluding the USA).

The main effect picked up was that both firm-level elasticity and rate of return estimates were, on average, higher for the USA than other OECD countries. This is somewhat different to previous meta-analysis (Weiser, 2005; Ugur et al, 2016) which found differences between the USA and other OECD countries for elasticity estimates but not for rate of return estimates.

Several recent studies have focused explicitly on trying to understand differences of returns to R&D between the USA and the EU. Cincera and Veugelers (2014) estimate rates of return for top R&D spenders in the USA and EU and find that returns are positive in the USA (particularly among young firms), while EU firms fail to realise significant returns (even among young firms). Castellani et al (2019) compare top R&D spenders in the USA and EU and find a higher elasticity in the USA. Their analysis suggests that the difference is consistent with three explanations put forward in the literature: the possibility of a 'threshold' effect in the effectiveness of R&D, given that R&D is higher in the USA; differing industry composition combined with different returns to R&D in different industries; and intrinsic differences in the ability of US as compared to EU firms to convert R&D investments into productivity improvements (which is often linked to differences in access to finance for growth).

5.4.4 PUBLIC FUNDING

PUBLIC SUPPORT OF R&D IN THE PRIVATE SECTOR

Government can encourage R&D investments in the private sector either by offering fiscal incentives (such as tax breaks or subsidies) to firms undertaking R&D or by allocating grants to private companies to conduct research. A particularly important question when appraising publicly supported R&D is what rate of return should be attached to publicly supported R&D.

There are only six studies that examine differences in returns to R&D according to funding source across the studies included in our meta-analysis.[24] We include an indicator of whether the estimated return to R&D relates specifically to publicly funded R&D in our analysis (in all cases this R&D is conducted by the private sector). **Although it was not possible to compare their full social returns, the results indicate that estimated private returns to R&D, whether estimated as an elasticity or a rate of return, are substantially lower when the R&D in question is publicly funded.** Specifically, for firm-level studies, the results indicate that the mean elasticity for publicly funded R&D is 0.130 lower than the mean elasticity for privately funded R&D (or total R&D where funding is unknown), while the mean rate of return for publicly funded R&D is 7 percentage points lower than the rate of return for privately (or unknown) funded R&D. Given the proportion of estimates in our data that relate to publicly funded R&D, this would roughly imply an average elasticity of 0.074 for privately funded R&D and -0.06 for publicly funded R&D (yielding an average elasticity of 0.073), and an average rate of return of 14% for privately funded R&D and 7% for publicly funded R&D (yielding an average rate of return of 14%).

There are many reasons why such a difference could occur:

[24] These are Mansfield (1980), Terleckyj (1980), Bartelsman (1990), Lichtenberg and Siegel (1991), Wolff and Nadiri (1993) and Møen (2019).

- Publicly funded R&D may be intentionally concentrated by policy makers in areas with lower private returns but greater social returns, as that is where private actors are most likely to underinvest in R&D from a social perspective.
- Publicly funded R&D may have a greater focus on basic research or capacity building than private R&D, and the returns to this may be more uncertain or take longer to emerge.
- Publicly funded R&D may not be aimed at increasing private sector output at all in the short run but may be targeting other outcomes such as improvements in public health, defence or environmental impacts (which may of course have benefits for firms in the long run).
- Firms may be less efficient in using public funds than they are their own funds.

While the last point would clearly be problematic, there is no evidence for this in the papers we reviewed. The other explanations indicate that a substantially lower private return to publicly funded R&D than privately funded R&D – indeed even a zero private return to publicly funded R&D – is still entirely **consistent with that public investment in R&D being an optimal policy decision.**

One recent study by Møen (2019) examines differences in the return to R&D investments according to whether publicly supported R&D was funded through direct (matching) grants or tax credits. The study finds that the form of public funding matters: R&D investments funded through direct grants are estimated to have private rates of return that are not significantly different from zero, while R&D funded through tax credits is estimated to have a mean rate of return that is only slightly lower than that arising from privately funded R&D. These findings may be specific to the Norwegian context examined, and it is not possible to distinguish whether the different form of the public support drives different returns or whether different public funding mechanisms support investments that (irrespective) have different expected rates of return. However, these findings highlight that even within publicly funded R&D, different forms of support may yield different returns. If tax credits subsidise private R&D and encourage firms to do more of it, one would expect the private returns to tax-supported R&D to be similar to those of fully privately funded R&D. If directly funded public R&D is different in nature (earlier stage, more uncertain, focused on social impacts), then one would expect the private returns observed to be lower.

R&D CONDUCTED IN THE PUBLIC SECTOR

In addition to financially encouraging R&D in the private sector, the government can also conduct R&D directly itself through public research centres, higher education institutions or within government departments (such as the Ministry of Defence). This will not yield private returns measured with turnover as there is no simple measure of 'output' for the public sector which would lend itself to a production function-style analysis. However, there may be social returns as a result of spillovers (in particular, knowledge spillovers) onto the private sector. The literature which attempts to do this is fairly limited and is summarised below. **Given the relatively small evidence base, firm conclusions about social returns to R&D conducted in the public sector are difficult to reach. The most relevant evidence remains the study by Haskel et al (2014) which estimates a social return to public R&D of around 20%.**

One recent paper that attempts to estimate this is van Elk et al (2019). They examine the return, at the country level, to publicly conducted R&D as compared to privately conducted R&D and conclude that publicly conducted R&D does not uniformly correlate with higher GDP and productivity growth. Estimated returns depend on the specification used and the country context. The estimated elasticity of output with respect to public R&D for the UK varies from -0.289 to +0.014 depending on specification when using translog production functions (which allow the return to public R&D to vary across countries).

In the UK context Haskel and Wallis (2013) examine the correlation between public R&D and total private sector productivity growth using aggregate data. Consistent with van Elk et al (2019), they find little evidence of market spillovers from defence or 'civil' or Higher Education Funding Council (HEFC) public sector R&D spending (of 'civil', 36%, 15% and 12% went to the Departments of Health, Foreign Development and Environment and Rural Affairs respectively; HEFC spend is the part of university budget labelled as research support). Haskel and Wallis (2013) do, however, find a robust correlation between research council spending (which is almost entirely performed at universities) and market sector productivity growth. The estimated social return to research council spending declines over time as the level of such spending has increased substantially (almost trebling over the course of the 2000s) from a rate of return of over 30% prior to 2004 to around 15% (and not statistically significantly different from zero) by 2009. Along similar lines, Haskel et al (2014) use industry-level data, measures of the extent to which industries engage with publicly funded science and aggregate measures of public R&D investments (made by research councils, higher education and government departments) to estimate the impact of public R&D spending on private productivity at the industry level. They find that total public R&D spending yields a social rate of return of around 20%.

Frontier Economics (2014) also conducted some analysis of the returns to research council investments. While interpretation of the findings is limited by sample sizes (and therefore many of the results are not statistically significant), they find a pattern in which research council investments are associated with positive and significant social returns, that public investments in basic research are not associated with significant social returns (which is interpreted as being likely due to the short timeframe over which returns are estimated) and that investments made by councils that are 'nearer to market' (e.g. those focused on scientific and medical research) are higher than other councils, although social returns are positive for all councils.

5.4.5 R&D INTENSITY

The final dimension of variation that we explore through our multivariate meta-analysis is the association of returns with the R&D intensity of the firm or industry conducting the R&D. Furman et al (2002) describe that the returns to R&D may be sensitive to the level of R&D intensity (past R&D investments) for two opposing reasons.[25] On the one hand, there is the 'standing on shoulders' effect that R&D will be more productive if it comes on top of an existing stock of knowledge accumulated from past R&D. On the other hand, the marginal productivity of R&D may decline with R&D intensity if easier ideas have been found first and remaining ideas are harder to find (the 'fishing out' effect). These effects, and their interaction, could result in a non-linear relationship between the returns to R&D and the level of R&D intensity.

In our meta-analysis we include an indicator of whether an estimate relates to a firm or industry that is defined as 'R&D intensive' by the study author. The results indicate that mean elasticity estimates are higher for more R&D intensive firms and industries – suggesting that the standing on shoulders effect dominates and that those firms/industries are better able to leverage productivity improvements from R&D investments. The relationship between R&D intensity and rate of return estimates, however, is less stable, being different between the firm-level and industry-level estimates and between the general and specific specifications of our multivariate meta-analysis.

[25] These are reasons why the level of R&D intensity may matter, all else equal. For a given firm, for a given type of R&D, would the return to a marginal investment in R&D be larger or smaller if marginal R&D came on top of a high R&D stock compared to a low R&D stock? Empirically, R&D intensity also varies dramatically across industries, which could reflect differences in perceived rates of return. Differences in returns between industries are discussed in section 5.5.1.

In recent years there have been a number of papers that have taken different approaches to examining more directly whether there are non-linearities in the returns to R&D. Bond and Guceri (2017) examine the effect on productivity of whether *any* R&D is conducted. They find that productivity is on average about 14% higher among particular plants (of firms) that conduct R&D themselves as compared to those that do not. Conditional on conducting R&D, there is no significant evidence that the productivity advantage increases with the level of R&D spending. Solomon (2021) examines rates of return to R&D where R&D intensity has a quadratic relationship with output and finds evidence of diminishing returns to R&D spending in manufacturing, while in services the returns to R&D are more linear. Pleticha (2021) examines differences in non-linearities for publicly and privately funded R&D and finds that privately funded R&D offers significant returns only after reaching a critical mass, while returns to public R&D do not demonstrate the same non-linearities. Kancs and Siliverstovs (2016) do not employ a production function approach and are able to examine flexible non-linearities by using the structural production function estimator of Doraszelski and Jaumandreu (2013). They find that R&D investment increases firm productivity with a mean elasticity of 0.15, but the impact of R&D investment on firm productivity varies with the level of R&D intensity and is highly non-linear. The estimated elasticity ranges from -0.02 for very low levels of R&D intensity to 0.33 for high levels of R&D intensity, and R&D investments therefore only increase productivity after a critical mass of knowledge is accumulated.

Overall we interpret this evidence as indicating that the return to additional R&D may depend on the level of R&D already being conducted. However, given the limited and quite diverse literature on this, which suggests that the relationship may vary across industries and sources of R&D funding, it is not possible on the strength of current evidence to reliably quantify how, on average, the returns to R&D vary with R&D intensity.

5.5 OTHER LITERATURE ON VARIATION IN RETURNS TO R&D

The meta-analysis approach only lends itself to exploration of particular forms of variation in the returns to R&D. In this section we consider evidence relating to other aspects of variation, drawing on insights from particular studies outside the meta-analysis: variation in returns to R&D across industries, variation in returns to different types of R&D (basic, applied and experimental R&D) and variation in returns to R&D that is done in house (intramural) versus that externally commissioned (extramural).

In each case we note that there are only a handful of relevant papers identified, and therefore it is not possible to draw strong quantitative conclusions about how returns to R&D differ along these dimensions. Instead we summarise the findings of these papers narratively.

5.5.1 INDUSTRY

The literature focuses on variation between returns to R&D in manufacturing compared with other (non-manufacturing) sectors. Table 10 summarises differences in estimates of returns from relevant studies. **Most of these papers find positive productivity effects in both sectors but paint a mixed picture in terms of whether returns in manufacturing exceed those in other sectors**.[26] Comparisons of elasticity estimates are also complicated by very different R&D intensities in manufacturing and non-manufacturing sectors, meaning that even the same elasticity would imply very different rates of return.

[26] The estimates for returns in the manufacturing and service sectors are typically derived from separate regressions on different subsamples of firms, and differences in mean estimates are therefore not tested for statistical significance.

Table 10 Summary of variation in estimates for manufacturing versus non-manufacturing

STUDY	(MEAN) ESTIMATE: MANUFACTURING	(MEAN) ESTIMATE: NON-MANUFACTURING	ESTIMATE TYPE	FURTHER DETAIL EXAMINED
Di Ubaldo and Siedschlag (2021)	0.286	-0.164	Elasticity	
Solomon (2021)	0.079[+]	0.196[+]	Rate of return	By Pavitt class
Ortega-Argilés et al (2015)	0.1315	0.1405	Elasticity	High-tech vs other
O'Mahoney and Vecchi (2009)	0.170	0.251	Elasticity	
Rogers (2010)	0.115	0.175	Elasticity	By Pavitt class
Rogers (2010)	0.173	0.164	Rate of return	

Note: [+] Solomon (2021) estimates returns to R&D using a quadratic functional form. The coefficient estimates for manufacturing firms are 0.079 for R&D intensity and -0.0004 for R&D intensity squared. The coefficient estimates for non-manufacturing firms are 0.196 for R&D intensity and 0.0028 for R&D intensity squared. These have been converted into an average rate of return assuming R&D intensity of 5.2% for manufacturing and 0.9% for manufacturing based on data for the UK in OECD (2019).
Source: Frontier Economics

Several recent papers examine differences in rates of return across different manufacturing industries. Ortega-Argilés et al (2015), Añón Higón et al (2017), Kafouros (2005) and Kancs and Siliverstovs (2016) examine differences in returns between high-tech and other manufacturing, and they find that returns are greater for firms in high-tech sectors. Goya et al (2016) examine how inter- and intra-industry spillovers from R&D differ across industries. They find little evidence of R&D having a direct impact on firms' productivity but support for positive spillovers between industries that benefit low-tech firms.

Rogers (2010) and Solomon (2021) examine differences in returns by Pavitt class in the UK.[27] Both papers find evidence of variation, and their results suggest lower rates of return for 'science-based' industries than for 'scale-intensive' industries. Doraszelski and Jaumandreu (2013) examine differences in returns across nine manufacturing sectors in Spain and find that net rates of return vary substantially from around 10% in 'food, drink and tobacco' to around 66% in 'metals and metal products'.

Ortega-Argilés et al (2015) suggest that there are three reasons why high-tech sectors and R&D-based services have higher returns to R&D. First, 'technological opportunities' are more frequent and more radical. Second, these sectors have rising demand, which is a crucial incentive for effective R&D investment.[28] Finally, there are more likely to be complementarities between R&D, higher skills and organisational change, which may have a more substantial joint impact on productivity.

[27] The Pavitt classification aims to categorise firms according to technological trajectories: sources and appropriability of technology and the flow of knowledge between firms. The main Pavitt sectors are: 'supplier dominated' (traditional manufacturing, generally small firms with weak in-house R&D); 'scale intensive' (large firms, producing standard materials or durable goods); 'specialised suppliers' (tend to be smaller firms which are technologically specialised producing technology – e.g. machinery or instruments – to be sold to other firms, with a high level of appropriability); and 'science-based' (high-tech firms which produce technology from in-house R&D that is often based on basic R&D from elsewhere). These are sometimes augmented with 'information-intensive' and 'software-related firms' when non-manufacturing is included.

[28] Although increasing demand may also increase the risk of biasing estimates if it drives both R&D and output and this is not adequately controlled for.

Taken together, the existing literature suggests that there may be differences in average returns between industries and sectors. However, there is not currently sufficient evidence to robustly quantify these differences.

5.5.2 BASIC, APPLIED OR EXPERIMENTAL R&D

Only a couple of the studies in our review examine differences in returns to R&D according to the stage of development of the R&D. Solomon (2021) examines the private returns to basic R&D conducted in the UK private sector compared with the private returns to applied/experimental R&D. The results suggest that there are positive private returns to applied/experimental R&D, albeit with evidence of diseconomies of scale but negative private returns to basic R&D. However, the author suggests that this is most likely because basic R&D takes longer to result in productivity improvements (Solomon's production function approach correlates R&D intensity with growth in value added the following year), while applied research has more immediate benefits. Solomon (2021) also identifies complementarities between basic R&D and applied/experimental R&D, suggesting that basic R&D may increase the ability of firms to incorporate the innovations from other R&D or otherwise increase the quality or quantity of innovations arising from other R&D investments.

Sun et al (2016) also examine the influences of different R&D types on productivity using cross-country analysis for OECD countries. They implement a data envelope analysis (DEA) approach, where R&D can impact both the technological frontier and how far countries operate from that frontier.[29] They find that applied and experimental R&D have important and immediate effects on productivity. Specifically, these forms of R&D increase the efficient use of technology and allow catch-up to the technological frontier. Basic research, on the other hand, affects productivity through shifting the technological frontier, and it only does so with lags of two to three years. The impact of basic research is largest overall, followed by applied research.

These papers both suggest that all three types of R&D are important and improve productivity but act in different ways. Applied and experimental R&D has more immediate impacts, but the effects are limited and not sustainable as they are mainly associated with movements towards the technological frontier. Basic research has longer lag times but ultimately greater impacts on productivity.

5.5.3 INTRAMURAL AND EXTRAMURAL R&D

R&D may be conducted in house by the firm funding the R&D (intramural R&D), or it may be funded by a firm but commissioned from an external provider (extramural R&D). A few papers examine whether this is associated with any systematic difference in the productivity impact of the R&D. Lokshin et al (2008) and Solomon (2021) both find positive returns to intramural R&D (albeit with diminishing returns) and complementarities between intramural and extramural R&D – in other words, the productivity effect of each type of R&D is increased in the presence of the other type of R&D. Solomon (2021) finds that extramural R&D in isolation does not improve productivity. Lokshin et al (2008) find that extramural R&D only has a positive impact when there is a sufficient amount of intramural R&D as well. They argue this is

[29] DEA provides a means of comparing productivity levels across (in this context) countries, where the productivity of each country is calculated relative to the highest productivity of the set of countries. R&D can then be modelled as potentially impacting both the highest level of productivity (the 'technological frontier') and the relative productivity of countries that are not the most productive (how far countries are from the technological frontier).

likely due to intramural R&D having an important role in increasing the absorptive capacity of firms – i.e. firms' ability to understand, adapt and implement external innovation to increase productivity.

The complementary effects of intramural and extramural R&D, combined with diseconomies of scale in each, suggest that both types of R&D are important. Indeed, Lokshin et al (2008) suggest that overall productivity would be improved if the proportion of external R&D within total R&D was increased.

The returns to intramural as compared with extramural R&D also likely varies with context. One exploration of this is Andries and Thorwarth (2014) who examine differences in the contribution of internal basic R&D and external basic R&D to productivity, and how that varies by firm size. They find that, in general, in-house and outsourced R&D activities are equally productive. However, for basic research specifically, their results suggest that small firms benefit from outsourcing their basic research activities, while medium/large firms have a greater productivity increase from in-house basic research than outsourced basic research. The authors argue that taking firm size into account is therefore important when seeking to understand the benefits/costs of outsourcing research.

6 SUMMARY AND POLICY IMPLICATIONS

This report presented our updated review and synthesis of the literature on returns to R&D investment. This included meta-analysis to generate a summary estimate of the private rate of return to R&D, controlling for publication bias, and to provide some insights on drivers of variation in returns.

Our best estimate is that the mean private rate of return to R&D is at least 14% and is likely to be higher. Examining studies that estimate a private rate of return to R&D, our meta-analysis suggests that, after controlling for selection bias, the average private rate of return is 14%. However, while our meta-analysis corrects for selection bias in the evidence base, it cannot correct for other measurement errors or specification biases in the primary studies. These issues are likely to result in returns to R&D being underestimated in primary studies. Therefore, in our view, the average rate of return is likely to be greater than the meta-analysis estimate of 14%. Examining studies that estimate an elasticity of output with respect to R&D investment, our meta-analysis suggests that, after controlling for selection bias, the average elasticity is 0.07. Assuming that this estimate is appropriate for UK manufacturing, which has an R&D intensity of around 5.2%, this would imply a rate of return of 19%. **A defensible approach is to assume that the average private rate of return to R&D is around 20%.**

Estimating the social return to R&D is inherently more challenging than estimating the private return. **A relatively conservative approach to modelling the benefits to R&D could be to assume that the social returns to R&D are twice those of the private returns.**

Our meta-analysis of studies that estimate returns at the industry level suggests that estimates of within-industry social returns are similar to estimates of private returns. This does not suggest that there are no spillover effects from R&D; it is more likely that knowledge spillover benefits are offsetting other displacement effects (which form part of the private return). Furthermore, this may still imply *net* social returns that are greater than private ones if depreciation of R&D capital is lower at the industry level than the firm level (as might be expected). There are also good theoretical reasons to expect positive between-industry spillovers which are not captured in industry-level estimates of social returns.

The literature that seeks to estimate spillovers directly contains many estimates of positive knowledge spillovers and social returns that are considerably in excess of private returns in the literature. While recent meta-analysis of these results (Ugur et al 2020) suggests that these should be treated with some caution, due to low precision and publication bias in the literature, under some simplifying assumptions the meta-analysis results are still consistent with social returns being around twice the size of private returns. Some of what are, in our view, the most careful and robust recent studies (Goodridge et al, 2017; Lucking et al, 2019) suggest sizeable social returns, around four times the size of private returns to R&D. However, a lack of good data, uncertainties over methodology and some evidence of publication bias mean that all these estimates should be treated with caution.

A key limitation to be kept in mind is that the rates of return examined in this review are based on firms' output (measured by turnover or value added) and do not include other potentially wider impacts of R&D investments, such as on wages, health, wellbeing or the environment. This means that the estimates produced here will almost certainly underestimate the full social return to R&D.

There is substantial variation in the estimates of private and industry-level social rates of return that we examine. While some of this variation is driven by different methodological approaches, our meta-analysis and wider review also highlight some variation that is likely to reflect systematic differences in returns to R&D in different contexts. This indicates that there is not in reality a 'one-size-fits-all' return. The type of

R&D conducted, and by what kind of firm in what industry, has implications for the expected return and the timeframe over which that may be realised. However, on the basis of the relatively limited existing literature, **it is not possible to quantify a mean return to R&D for different contexts** (such as different industries or types of firms or types of R&D). When appraising the case for public support of any particular R&D project in the absence of other information, it is therefore still reasonable to rely on the average return to R&D described above. However, where there is strong, context-specific evidence to suggest an alternative return (perhaps from previous evaluations or bespoke modelling), it would be appropriate to use that in developing appraisals of new interventions.

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APPENDIX A. THE PRODUCTION FUNCTION APPROACH

This appendix provides additional information on the production function-based methodologies that are commonly used to estimate rates of return to R&D. The primal approach, which is the approach taken by the literature included in the meta-analysis, is discussed in section A.1. The augmented version of this, which is used to estimate spillover effects from R&D (discussed in section 4.5), is described in section A.2.

A.1. THE PRIMAL APPROACH

Studies that estimate returns to R&D using a production function approach usually start from a Cobb-Douglas production function that includes labour, physical capital and R&D as inputs. The typical specification is:

$$Y_{it} = AC_{it}^{\alpha}L_{it}^{\beta}K_{it}^{\gamma} \qquad [1]$$

where Y_{it} is the output of unit i at time t, A is a constant, C is physical capital stock, L is labour and K is the stock of R&D. The model can be applied to data at the firm, industry or country level.

By taking logs of the production function, equation [1] can be represented in a linear form:

$$\ln Y_{it} = A + \alpha \ln C_{it} + \beta \ln L_{it} + \gamma \ln K_{it} \qquad [2]$$

There are two broad approaches to estimating this relationship in practice – one yields an *elasticity* of output with respect to R&D while the other yields a *rate of return* to R&D.

- **Estimating an elasticity:**

  Given suitable data, equation [2] can be estimated directly or after taking first differences:

  $$\Delta \ln y_{it} = \alpha \Delta \ln C_{it} + \beta \Delta \ln L_{it} + \gamma \Delta \ln K_{it} + \Delta \mathrm{u}_{\mathrm{it}} \qquad [3]$$

  First differencing has the advantage that it controls for time-invariant unobserved firm-, industry- or country-level effects that may be correlated with R&D and output.

  Estimating this relationship using data on the level or growth rate of output and the level or growth rate of inputs would yield an estimate of the parameter γ, the *elasticity* of output with respect to R&D. This is the percentage change in output that arises from a percentage change in R&D stock: $\gamma = \frac{(\delta Y/Y)}{(\delta K/K)}$.

  Given an estimate of γ and an empirical value of the ratio of the stock of R&D to output, a rate of return can be derived. This is because $\gamma * \frac{K}{Y} = \frac{(\delta Y/Y)}{(\delta K/K)} * \frac{K}{Y} = \frac{\delta Y}{\delta K}$ and $\frac{\delta Y}{\delta K}$ is the rate of return – i.e. how much output changes for a marginal change in K.

- **Estimating a rate of return:**

  An alternative to estimating the production function with a measure of the R&D stock on the right-hand side is to estimate equation [3] with R&D *intensity* – the ratio of R&D flow to output – on the right-hand side. This specification yields a parameter estimate that can be interpreted directly as the rate of return.

To see that this is the case, note that $\Delta \ln K \approx \frac{\Delta K}{K}$. Then using the definitions of elasticity $\gamma = \frac{(\delta Y/Y)}{(\delta K/K)}$ and rate of return $\rho = \frac{\delta Y}{\delta K}$ we can reformulate equation [3] as follows:

$$\Delta \ln y_{it} = \alpha \Delta \ln C_{it} + \beta \Delta \ln L_{it} + \gamma \Delta \ln K_{it} + \Delta \mathrm{u_{it}}$$

$$\Delta \ln y_{it} = \alpha \Delta \ln C_{it} + \beta \Delta \ln L_{it} + \gamma \frac{\Delta K_{it}}{K_{it}} + \Delta \mathrm{u_{it}}$$

$$\Delta \ln y_{it} = \alpha \Delta \ln C_{it} + \beta \Delta \ln L_{it} + \frac{(\delta Y/Y)}{(\delta K/K)} \frac{\Delta K_{it}}{K_{it}} + \Delta \mathrm{u_{it}}$$

$$\Delta \ln y_{it} = \alpha \Delta \ln C_{it} + \beta \Delta \ln L_{it} + \frac{\delta Y_{it}}{\delta K_{it}} \frac{\Delta K_{it}}{Y_{it}} + \Delta \mathrm{u_{it}}$$

The change in the capital stock ΔK_{it} is given by $\Delta K_{it} = R_{it} - \delta K_{it}$. That is, the R&D stock increases each period by the amount of new investment in R&D R_{it} less an amount by which the existing knowledge stock depreciates each period (determined by the depreciation rate δ). Therefore:

$$\Delta \ln y_{it} = \alpha \Delta \ln C_{it} + \beta \Delta \ln L_{it} + \rho \frac{(\mathrm{R_{it}} - \delta K_{it})}{Y_{it}} + \Delta \mathrm{u_{it}}$$

The coefficient ρ can then correctly be interpreted as the gross (of depreciation) rate of return to R&D. The return net of depreciation would be $\rho^N = \rho - \delta$.

Using a simple measure of observed R&D intensity on the right-hand side, as is common practice in the literature, implicitly assumes that the depreciation is zero. Hall et al (2009) argue that this is clearly problematic at the firm level, where much of R&D investments may represent 'replacement' investments. They illustrate that the estimated gross rate of return in the above formulation underestimates the true rate of return by the ratio of R&D growth to the sum of R&D growth plus depreciation.

The elasticity and the rate of return are related: multiplying an elasticity by the ratio of R&D capital to output yields a rate of return. However, the two approaches are not equivalent because they make different assumptions. Studies that estimate an elasticity assume that this is constant across units, and a constant elasticity implies that the rate of return to R&D declines as the ratio of R&D capital to output increases. In contrast, studies that estimate a rate of return assume that this is constant across units, and a constant rate of return implies that the elasticity increases as the ratio of R&D capital to output increases.

Hall et al (2009) note that it is intuitively more appealing to assume that the rate of return is constant across units rather than the elasticity. All else equal, this suggests using the second approach in preference to the first. However, parameter estimates for the second approach are found to be less stable. In practice, the decision of whether to estimate a production function with an estimate of the R&D stock or a measure of R&D intensity on the right-hand side is normally driven by data availability.

A.1.2. METHODOLOGICAL CHALLENGES

There are many other methodological challenges and choices in estimating returns to R&D using a primal production function approach. Here we simply list some of the main ones. These are discussed in more detail in Appendix A of Frontier Economics (2014) and in Hall et al (2009) and include the following:

- Issues in the choice of approach:

    - Whether the production function is estimated using a measure of the stock of R&D or the flow of R&D investments
    - Whether the outcome of interest is output or productivity
- Definitional issues:
    - How output is defined (e.g. gross output, sales, value added)
    - Whether labour/capital inputs are adjusted to remove labour and capital costs that are a component of R&D spending ('double counting')
    - How the stock of R&D capital is estimated (which typically requires assumptions about the depreciation of the R&D stock and the growth rate of R&D)
    - How R&D (and other variables) should be deflated to real terms
    - Whether R&D is separable in the production function
    - How to adjust for quality improvements
- Econometric issues:
    - Measurement error
    - Omitted variable bias (for example, cyclical fluctuations which could affect both output and R&D)
    - Endogeneity from simultaneous determination of outputs and inputs
    - Multicollinearity
    - Sample selection

A.2. ESTIMATING R&D SPILLOVERS

One method for estimating R&D spillovers is to augment a Cobb-Douglas production function with a measure of external R&D in addition to other inputs. It is not feasible to include an additional variable for the R&D of every other unit, so the common approach is to aggregate the R&D of other firms into a single measure of external R&D. Equation [2] therefore becomes:

$$\ln y_{it} = A + \alpha \ln C_{it} + \beta \ln L_{it} + \gamma \ln K_{it} + \vartheta lnS_{it} + v_{it} \qquad [4]$$

where y_{it} is the output of unit i at time t, A is a constant, C is physical capital stock, L is labour, K is own R&D stock and S is the external R&D stock. The external R&D stock (S_{it}) available to unit i is the weighted sum of the R&D stock of other units where the weights w_{ji} are designed to capture the proportional spillover flows between unit j (who conducts the R&D) and unit i (who receives the spillover):

$$S_{it} = \sum_{j \neq i} w_{ji} K_{jt} \qquad [5]$$

These weights capture the idea that spillovers will be more likely, or more impactful, between some firms than others. Many different approaches to weights are used in the literature, including (but not limited to): intermediate input transactions, technological proximity (patent class similarity), lines of business (product similarity), network connections, geographical proximity, and interactions between these. The different weights are likely to capture different types of spillovers. For example, weights based on product similarity might be more likely to capture market rivalry effects, while weights based on technological proximity might be more likely to capture knowledge spillovers.

Equation [4] can be estimated in the same ways discussed above in section A.1, yielding either estimates of the *elasticity* of output with respect to own R&D ($\gamma = \frac{(\delta Y/Y)}{(\delta K/K)}$) and with respect to the relevant external R&D stock ($\vartheta = \frac{(\delta Y/Y)}{(\delta S/S)}$), or estimates of the gross *rate of return* with respect to own R&D ($\rho_K = \frac{\delta Y}{\delta K}$) and the relevant external R&D stock ($\rho_S = \frac{\delta Y}{\delta S}$).

The social rate of return to R&D conducted by a particular unit i (K_i) is the sum of the private return (the increase in output for the firm that performs the R&D) and the sum of the returns for all recipients of spillovers from that firm:

$$
\begin{aligned}
MSR_i &= \frac{\delta Y_i}{\delta K_i} + \sum_{j \neq i} \frac{\delta Y_j}{\delta K_i} \\
&= \rho_K + \sum_{j \neq i} \frac{\delta Y_j}{\delta S_j} \frac{\delta S_j}{\delta K_i} \\
&= \rho_K + \sum_{j \neq i} \rho_S w_{ij}
\end{aligned}
$$

The social return to R&D therefore depends not just on the estimated coefficient ϑ or ρ_S (which is sometimes referred to as the effect of the 'spillover') but also on the weights w_{ij} used to construct the external R&D stock. Under the simplifying assumption that all firms are the same in terms of their links between firms (i.e. $w_{ji} = w$), this becomes $MSR_i = \rho_K + \rho_S$. The ratio between the social and private rate of return is: $\frac{MSR_i}{MPR_i} = \frac{\rho_K + \rho_S}{\rho_K}$.

Given elasticity estimates, the marginal private rate of return to R&D conducted by firm i is given by $MPR_i = \gamma \frac{Y_i}{K_i}$, while the marginal social rate of return to R&D conducted by firm i is given by $MSR_i = \gamma \frac{Y_i}{K_i} + \vartheta \sum_{j \neq i} w_{ji} \frac{Y_j}{K_i}$. Under simplifying assumptions that all firms are the same in their links between firms (i.e. $w_{ji} = w$) and all firms have the same level of output and R&D stocks, then the marginal social return simplifies to $MSR_i = (\gamma + \vartheta) \frac{Y_i}{K_i}$ and the ratio of the social to private rate of return is given by: $\frac{MSR_i}{MPR_i} = \left(\frac{\gamma + \vartheta}{\gamma}\right)$

APPENDIX B. META-ANALYSIS REGRESSION RESULTS

Table 11. Overview of primary studies included in the meta-analysis

	DATA START	DATA END	MEAN ESTIMATE	MEDIAN ESTIMATE	NUMBER OF ESTIMATES
Firm-level studies (rate of return)					
Aiello et al (2020)	2007	2009	1.724	1.870	3
Bartelsman et al (1996)	1985	1993	0.161	0.173	9
Cincera (1998)	1987	1994	0.380	0.380	1
Cincera and Veugelers (2014)	2004	2009	0.069	0.064	29
Clark and Griliches (1998)	1970	1980	0.190	0.190	6
Fan et al (2020)	2003	2013	0.655	0.655	2
Griliches and Mairesse (1991a)	1973	1980	0.332	0.284	6
Griliches and Mairesse (1991b)	1973	1978	0.078	0.120	13
Hall and Mairesse (1995)	1980	1987	0.184	0.212	20
Harhoff (1998)	1977	1989	0.235	0.221	6
Heshmati and Hyesung (2011)	1986	2002	0.128	0.128	2
Klette (1991)	1981	1985	0.113	0.108	20
Kwon and Inui (2003)	1995	1998	0.232	0.232	2
Lichtenberg and Siegel (1991)	1981	1985	0.358	0.189	33
Link (1981)	1973	1978	1.250	1.250	2
Link (1983)	1975	1979	0.055	0.055	2
Lokshin et al (2008)	1996	2001	0.262	0.301	4
Mansfield (1980)	1960	1976	0.455	0.105	25
Mate-Garcia and Rodriguez-Fernandez (2008)	1993	1999	0.266	0.266	1
Medda et al (2003)	1995	1998	0.327	0.327	2
Moretti et al (2021)	1980	2015	0.040	0.040	1
Møen (2019)	1993	2001	0.104	0.155	20
Odagiri (1983)	1966	1980	-0.109	-0.109	2
Odagiri and Iwata (1986)	1966	1973	0.163	0.170	4
Rogers (2010)	1990	2000	0.210	0.205	18
Spescha (2019)	1995	2012	0.003	0.003	1
Wakelin (2001)	1988	1992	0.189	0.265	14
Firm-level studies (elasticity)					
Aiello and Cardamone (2005)	1995	2000	0.070	0.068	4
Aldieri et al (2008)	1988	1997	0.250	0.255	16
Andries and Thorwarth (2014)	2002	2007	0.075	0.066	8
Añón Higón, D., Gómez, J. and Vargas, P.	1993	2005	0.006	0.058	6
Ballot et al (2006)	1987	1993	0.063	0.052	10
Bartelsman (1990)	1956	1988	0.064	0.055	12
Bartelsman et al (1996)	1985	1993	0.072	0.115	22
Blanchard et al (2005)	1994	1998	0.104	0.030	7
Boler et al (2012)	1997	2005	0.052	0.016	5
Bond and Guceri (2017)	1997	2008	0.021	0.053	4
Bond et al (2003)	1987	1996	0.020	0.187	12
Branstetter (1996)	1985	1989	0.187	0.156	2
Castellani et al (2019)	2009	2012	0.169	0.230	30
Cincera (1998)	1987	1994	0.226	0.099	58
Cincera and Veugelers (2014)	2004	2009	0.104	0.130	7
Cuneo and Mairesse (1984)	1972	1977	0.135	0.105	20
Di Ubaldo and Siedschlag (2021)	2006	2012	0.255	0.018	10
Doraszelski and Jaumandreu (2013)	1991	1999	0.024	0.012	18
Goya et al (2016)	2004	2009	0.012	0.024	8
Griffith et al (2006)	1990	2000	0.022	0.075	14
Griliches (1980)	1957	1965	0.081	0.117	59
Griliches (1998)	1967	1977	0.124	0.143	17

Griliches and Mairesse (1981)	1972	1977	0.129	0.025	32
Griliches and Mairesse (1991b)	1973	1978	0.025	0.030	2
Hall (1993)	1986	1990	0.043	0.093	85
Hall and Mairesse (1995)	1980	1987	0.128	0.116	56
Harhoff (1998)	1987	1989	0.116	0.068	59
Harhoff (2000)	1977	1989	0.068	0.005	5
Hsing and Lin (1998)	1994	1994	0.204	0.204	2
Kafouros (2005)	1995	2002	0.046	0.040	17
Kwon and Inui (2003)	1995	1998	0.059	0.052	82
Lehto (2007)	1987	1998	0.030	0.031	18
Li and Bosworth (2020)	2000	2008	0.010	0.010	2
Los and Verspagen (2000)	1977	1991	0.022	0.012	12
Mairesse and Hall (1996)	1985	1989	0.032	0.031	63
Ortega-Argilés et al (2010)	2000	2005	0.104	0.110	8
Ortega-Argilés et al (2015)	1990	2008	0.131	0.119	30
O'Mahoney and Vecchi (2000)	1993	1997	0.186	0.168	9
O'Mahoney and Vecchi (2009)	1988	1997	0.093	0.124	9
Rahko (2021)	2004	2011	0.068	0.068	2
Rogers (2010)	1990	2000	0.145	0.127	12
Schankerman (1981)	1963	1963	0.099	0.082	18
Smith et al (2004)	1997	1997	0.098	0.089	10
Spescha (2019)	1995	2012	0.012	0.003	5
Zacchia (2020)	1981	2001	0.064	0.056	15
Industry-level studies (rate of return)					
Cameron et al (2005)	1970	1992	0.636	0.638	9
Griffith et al (2004)	1974	1990	0.499	0.473	15
Griliches and Lichtenberg (1984)	1973	1978	0.296	0.233	20
Hanel (2000)	1974	1989	0.182	0.152	8
Lee (2020)	1995	2009	0.347	0.333	24
Moretti et al (2021)	1987	2015	0.046	0.038	16
Scherer (1982)	1972	1978	0.149	0.192	4
Scherer (1983)	1973	1978	0.351	0.363	4
Sterlacchini (1989)	1979	1984	0.128	0.125	6
Sveikauskas (1981)	1959	1969	0.207	0.194	20
Terleckyj (1980)	1948	1966	0.147	0.225	12
van Meijl (1997)	1978	1992	0.099	0.080	15
Verspagen (1995)	1973	1988	0.170	0.223	28
Wolff and Nadiri (1993)	1958	1977	0.217	0.180	14
Industry-level studies (elasticity)					
Añón Higón (2007)	1970	1997	0.309	0.313	4
Bonte (2003)	1980	1993	0.013	0.008	8
Eberhardt et al (2013)	1980	2005	0.061	0.044	18
Frantzen (2002)	1972	1994	0.164	0.152	7
Goto and Suzuki (1989)	1976	1984	0.34	0.250	21
Griliches (1980)	1969	1977	0.045	0.044	5
Ortega-Argilés et al (2010)	1987	2002	0.061	0.062	8
Sasso and Ritzen (2019)	2007	2007	0.128	0.123	7
Verspagen (1995)	1973	1988	0.031	0.019	55
Verspagen (1997)	1974	1992	0.086	0.081	12

Note: Includes estimates that were subsequently excluded from our meta-analysis due to being classed as outliers.

Source: Frontier Economics

Table 12 Full PAT/PET/PEESE regression results for firm-level estimates

	FAT/PET tests		PEESE tests	
Dependent variable: t-value	Elasticity	Rate of return	Elasticity	Rate of return
PET for genuine effect (β)	0.070***	0.088***	0.073***	0.135***
	(0.013)	(0.016)	(0.010)	(0.016)
FAT for publication bias (α)	0.316	1.226***	0.814	1.900***
	(0.488)	(0.284)	(1.673)	(0.658)
Std. dev. of random slopes	-2.815***	-3.512***	-2.811***	-3.130***
	(0.136)	(0.261)	(0.132)	(0.376)
Std. dev of random intercepts	0.409**	-0.680**	0.408**	-0.456
	(0.205)	(0.269)	(0.183)	(0.313)
Std. dev. of residuals	1.479***	0.707***	1.479***	0.713***
	(0.197)	(0.218)	(0.198)	(0.230)
Observations	897	244	897	244
Studies	45	23	45	23
LR test chi2	29.111	30.450	49.450	157.472
P>chi2	0.000	0.000	0.000	0.000

Note: Robust standard errors (in brackets) are clustered at the study level.
Source: Frontier Economics

Table 13 Full PAT/PET/PEESE regression results for industry-level estimates

	FAT/PET tests		PEESE tests	
Dependent variable: t-value	Elasticity	Rate of return	Elasticity	Rate of return
PET for genuine effect (β)	0.067***	0.087**	0.075***	0.115***
	(0.018)	(0.041)	(0.018)	(0.033)
FAT for publication bias (α)	0.576	1.107**	-0.484	-0.178**
	(0.379)	(0.464)	(0.788)	(0.089)
Std. dev. of random slopes	-3.071***	-2.698***	-3.107***	-2.427***
	(0.315)	(0.538)	(0.283)	(0.218)
Std. dev of random intercepts	-0.328	-0.113	0.009	0.407**
	(0.298)	(0.629)	(0.396)	(0.205)
Std. dev. of residuals	0.443	-0.107	0.439	-0.132
	(0.297)	(0.154)	(0.300)	(0.137)
Observations	141	192	141	192
Studies	10	15	10	15
LR test chi2	14.088	4.466	17.331	17.778
P>chi2	0.000	0.035	0.000	0.000

Note: Robust standard errors (in brackets) are clustered at the study level.
Source: Frontier Economics

Table 14 Multivariate meta-regression: general model results

	ELASTICITY				RATE OF RETURN			
	Firm level		Industry level		Firm level		Industry level	
	b	se	b	se	b	se	b	se
Precision	-0.019	(0.025)	0.350***	(0.081)	0.191**	(0.087)	0.369*	(0.190)
Journal article	-0.045**	(0.021)	p.mc.		-0.074*	(0.041)	-0.170***	(0.061)
Control for spillovers	0.016	(0.014)	-0.233***	(0.064)	-0.033	(0.025)	-0.051***	(0.013)
Control for capacity utilisation	-0.027	(0.056)	0.016	(0.035)	-0.030	(0.034)	-0.006	(0.016)
Include industry dummies	0.009***	(0.003)	0.050***	(0.009)	-0.011	(0.036)	-0.004	(0.046)
Include time dummies	0.045***	(0.008)	-0.040	(0.027)	-0.011	(0.042)	-0.018	(0.035)
Control for double counting	0.022***	(0.004)	0.000	(0.012)	-0.057	(0.058)	-0.006	(0.122)
R&D capitalised using perpetual inventory method	0.067***	(0.020)	-0.012	(0.047)	0.013	(0.087)	n.o.	
Output measured as value added	0.049***	(0.005)	-0.308***	(0.069)	0.018	(0.032)	-0.006	(0.015)
Data period ends before 1980	0.041*	(0.022)	-0.278***	(0.070)	-0.041	(0.028)	-0.012	(0.046)
Data period ends 1995-2007	0.000	(0.022)	0.064*	(0.034)	0.031	(0.048)	-0.256	(0.206)
Data period ends after 2007	0.022	(0.028)	n.o		0.010	(0.050)	-0.308	(0.199)
Small firms	-0.017**	(0.008)	n.o		0.066*	(0.039)	n.o.	
French data	0.010	(0.010)	0.014	(0.020)	0.060	(0.114)	0.192**	(0.082)
German data	0.002	(0.039)	0.001	(0.020)	0.127*	(0.073)	0.004	(0.070)
UK data	-0.009	(0.027)	0.020	(0.020)	0.046	(0.062)	0.004	(0.071)
US data	0.044***	(0.009)	0.014	(0.020)	0.031*	(0.018)	-0.022	(0.066)
R&D intensive firm/industry	0.030***	(0.008)	0.076***	(0.015)	-0.065*	(0.039)	0.060	(0.096)
Publicly funded R&D	-0.130***	(0.034)	n.o		-0.069**	(0.033)	-0.303***	(0.034)
Common factor frame estimation	n.o		0.226***	(0.069)	n.o		n.o	
First difference estimation	-0.054***	(0.005)	-0.038	(0.031)	0.003	(0.059)	-0.070	(0.146)
GMM estimation	-0.018	(0.012)	0.298	(0.297)	-0.046	(0.061)	n.o	
IV estimation	-0.013	(0.011)	-0.377***	(0.064)	0.649	(0.734)	-0.024**	(0.011)
Long differenced estimation	-0.008	(0.010)	0.022	(0.041)	-0.076	(0.075)	-0.119	(0.165)
Within estimation	-0.016***	(0.004)	-0.031***	(0.010)	0.114	(0.109)	0.454***	(0.140)
Constant	0.295	(0.346)	-0.204	(0.268)	0.894***	(0.260)	1.003***	(0.368)
Std. dev. of random slopes	-3.053***	(0.136)	-13.291	(1090.4)	-0.780	(0.530)	0.167	(0.266)
Std. dev. of random intercepts	0.190	(0.200)						
Std. dev. of residuals	1.298***	(0.024)	0.330***	(0.060)	0.634***	(0.048)	-0.374***	(0.055)
Observations	897		141		244		192	
Number of studies	45		23		10		15	
LR test Chi2	467.123		500.346		132.012		214.883	
P>Chi2	0.000		0.000		0.000		0.000	

*Note: 'n.o' indicates no observations. 'pmc' indicates dropped due to perfect multicollinearity. GMM stands for Generalised Method of Moments. IV stands for instrumental variables. *,**,*** indicates statistical significance at the 10%, 5% and 1% level respectively.*

Source: Frontier Economics

Table 15 Multivariate meta-regression: specific model results

	ELASTICITY				RATE OF RETURN			
	Firm level		Industry level		Firm level		Industry level	
	b	se	b	se	b	se	b	se
Precision	-0.021	(0.022)	0.298***	(0.061)	0.097***	(0.013)	0.148***	(0.041)
Journal article	-0.037**	(0.018)					-0.105**	(0.043)
Control for spillovers			-0.192***	(0.060)			-0.049***	(0.010)
Control for capacity utilisation								
Include industry dummies	0.009***	(0.003)	0.047***	(0.009)				
Include time dummies	0.047***	(0.008)	-0.061***	(0.014)				
Control for double counting	0.021***	(0.004)						
R&D capitalised using perpetual inventory method	0.071***	(0.017)						
Output measured as value added	0.050***	(0.005)	-0.250***	(0.059)				
Data period ends before 1980	0.043**	(0.021)	-0.216***	(0.061)				
Data period ends 1995-2007			0.067***	(0.020)				
Data period ends after 2007							-0.102**	(0.040)
Small firms	-0.017**	(0.008)						
French data							0.228***	(0.036)
German data					0.142**	(0.059)		
US data	0.039***	(0.007)			0.035***	(0.013)		
R&D intensive firm/industry	0.031***	(0.008)	0.073***	(0.014)	-0.057***	(0.015)	0.178***	(0.035)
Public funded R&D	-0.129***	(0.034)			-0.068**	(0.033)	-0.296***	(0.034)
Common factor frame estimation			0.171***	(0.063)				
First difference estimation	-0.053***	(0.005)						
IV estimation			-0.330***	(0.058)			-0.023**	(0.010)
Long differenced estimation					-0.092***	(0.016)		
Within estimation	-0.015***	(0.004)	-0.033***	(0.010)			0.393***	(0.127)
Constant	0.188	(0.339)	-0.120	(0.265)	1.226***	(0.233)	1.181***	(0.359)
Std. dev. of random slopes	-3.071***	(0.131)	-7.935	(306.5)	-0.946*	(0.525)	0.224	(0.249)
Std. dev. of random intercepts	0.203	(0.195)						
Std. dev. of residuals	1.302***	(0.024)	0.352***	(0.060)	0.676***	(0.047)	-0.362***	(0.055)
Observations	897		141		244		192	
LR test Chi2	460.919		472.825		108.606		204.702	
P>Chi2	0.000		0.000		0.000		0.000	

*Note: 'n.o' indicates no observations. 'pmc' indicates dropped due to perfect multicollinearity. IV stands for instrumental variables. *,**,*** indicates statistical significance at the 10%, 5% and 1% level respectively.*

Source: Frontier Economics

APPENDIX C. SEARCH STRING

We conducted an active search for new literature published from 2014 onwards using the following search strings in Scopus, a gold standard database of academic literature:

- TITLE-ABS-KEY (('R&D' OR 'research and development' OR 'research & development') AND (productivity OR return))

- AND (LIMIT-TO (SUBJAREA , 'BUSI') OR LIMIT-TO (SUBJAREA , 'ECON'))

- AND (LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017) OR LIMIT-TO (PUBYEAR , 2016) OR LIMIT-TO (PUBYEAR , 2015) OR LIMIT-TO (PUBYEAR , 2014))

- AND (LIMIT-TO (LANGUAGE , 'English'))

This provided an initial list which we refined through additional searches for at least one of the following keywords:

- AND (LIMIT-TO (EXACTKEYWORD , 'Research And Development') OR LIMIT-TO (EXACTKEYWORD , 'Productivity') OR LIMIT-TO (EXACTKEYWORD , 'Innovation') OR LIMIT-TO (EXACTKEYWORD , 'R&D') OR LIMIT-TO (EXACTKEYWORD , 'Total Factor Productivity') OR LIMIT-TO (EXACTKEYWORD , 'R&D Investment') OR LIMIT-TO (EXACTKEYWORD , 'Spillovers') OR LIMIT-TO (EXACTKEYWORD , 'TFP') OR LIMIT-TO (EXACTKEYWORD , 'Knowledge Spillovers') OR LIMIT-TO (EXACTKEYWORD , 'R&D Spillovers') OR LIMIT-TO (EXACTKEYWORD , 'Research And Development (R&D)') OR LIMIT-TO (EXACTKEYWORD , 'R&D Intensity') OR LIMIT-TO (EXACTKEYWORD , 'R&D Productivity') OR LIMIT-TO (EXACTKEYWORD , 'Total Factor Productivity (TFP)') OR LIMIT-TO (EXACTKEYWORD , 'Innovations') OR LIMIT-TO (EXACTKEYWORD , 'R&D Expenditure') OR LIMIT-TO (EXACTKEYWORD , 'Innovation Policy') OR LIMIT-TO (EXACTKEYWORD , 'Knowledge Production Function') OR LIMIT-TO (EXACTKEYWORD , 'Technology Spillovers') OR LIMIT-TO (EXACTKEYWORD , 'Labour Productivity'))