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A Microeconometric Analysis of the Rate of Returns to Australian Business R&D Across Fields of Research and Industry

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Report for the Strategic Examination of R&D (SERD)

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Executive Summary

1. This report presents a microeconometric analysis of R&D investment by Australian firms, commissioned by the Strategic Examination of R&D (SERD). Using an unprecedented dataset integrating the Business Longitudinal Analysis Data Environment (BLADE) and the Person Level Integrated Data Asset (PLIDA), this study provides new evidence on three critical areas: (1) the productivity benefits to business of R&D activity (i.e., private and social returns to R&D), (2) the role of worker mobility as a channel for transmitting R&D knowledge and any associated knowhow (we call this 'spillovers'),[1] and (3) quantifying how much additional R&D is induced by the R&D Tax Incentive (RDTI).

   We only estimate the impact of corporate (i.e., for-profit) R&D on other businesses within the corporate sector. We do not measure the impact of R&D on household well-being, the not-for profit sector or government. It is important to note that the term 'social returns' refers only to commercial returns. **Social returns are equal to commercial returns to the R&D investing firm (called private return) plus commercial returns to other firms in the ecosystem (called spillovers). We do not capture non monetised benefits such as householder well-being.**

2. Returns to R&D, which include the for-profit firm undertaking said R&D and other for-profit firms in the same ecosystem, are high and heterogeneous, primarily driven by supplier-side spillovers.

   a) Significant returns to businesses: Over the whole economy, $1 investment in R&D results in a lifetime net return of $4.60 to the firm undertaking the R&D. The total net return (i.e. to the own firm plus firms within the same ecosystem) is $7.14.[2] By 'net' we mean after holding constant the firm's level of employment, tangible capital stock and miscellaneous, unobservable time-invariant factors, such as managerial acumen. Effectively, these returns symbolise the increase in productivity due to the R&D.

   b) This confirms a substantial gap between private and social returns, providing a clear economic rationale for public R&D support. Note: we are only modelling the impact of R&D undertaken by for-profit sector. As such we do not model the effects of higher education sector and non-profit sector R&D.

   c) Spillovers are not uniform, depending on the characteristics of both the source and recipient of the spillovers. We find strong, positive spillovers from suppliers to customers (downstream). Spillovers from customers to suppliers (upstream) are also positive in the overall average, however the magnitude is smaller compared to downstream spillovers.

   d) In two recipient industries (Agriculture and Mining) the R&D spillovers are negative, suggesting that product market rivalry effects may dominate, but these effects may vary by distinction between downstream and upstream spillover.

   e) Firms in Manufacturing and Financial insurance services appear to receive the largest average benefit from other firms' R&D (i.e., spillovers)

   f) Field of research also matters: The highest social returns are produced by Information and Computing. Fields such as Biology/Biotech and Maths/Physics

[1] Our economic modelling will pick up any flows of knowhow, knowledge, information, work and business culture etc. that is correlated with R&D activity. As such the term spillovers is not limited to prescribed technical knowledge.

[2] Assuming a depreciation rate of 15% and an interest rate of 3%.

show much lower or negligible spillovers. It is plausible that the high use of patents by firms in the biology and biotech technologies limits the use of its knowledge by other firms. In the case of Maths/Physics, it is probable that the generated knowledge is too abstract to be easily monetised. In addition, as we exclude the impact of R&D on organisations such as hospitals, not-for-profit agencies and governments, we may be understating spillover effects of the knowledge generated in physical and biological sciences.

g) Absorptive capacity in the recipient firm is key: R&D-active firms are better at benefiting from external knowledge and knowhow, capturing on average two-thirds of the spillover return, compared to a third for non-R&D firms.

3. Labour mobility is a measurable and significant channel for knowledge transmission, particularly from the corporate sector.

   a) Hiring R&D talent boosts productivity: The movement of high-tech workers from R&D-active firms is a key spillover channel. Hiring R&D-experienced workers from other corporate firms has a significant positive impact; a 1 percentage point increase in these workers as a share of a firm's workforce is associated with a 0.267% increase in productivity.

   b) Public vs. private sector mobility: In contrast, hiring R&D-experienced workers from the public sector (including universities) has a negligible, non-significant impact on firm productivity.

   c) CRC and Research Service Provider experience: The exception to (b) above is hiring workers with prior experience in Cooperative Research Centres (CRCs) or in a Research Service Providers (RSPs) provides an additional productivity boost. This is probably because CRCs and RSPs operate in highly competitive and commercial environments.

   d) Firm size: The productivity benefit from hiring corporate R&D workers is strongest in large firms (over 200 employees). This is probably because they have the depth and sophistication to fully utilise inventive workers.

4. The R&D Tax Incentive (RDTI) is effective, but its additionality is highly concentrated among specific firms and activities.

   a) Positive Overall Additionality: Using a Regression Discontinuity Design (RDD) at the $20 million turnover threshold, we find the RDTI is effective. Our primary specification shows that for every $1 of tax revenue forgone, the incentive induces $1.57 in new R&D investment.

   b) Driven by "Core," Not "Supporting," R&D: The program's effectiveness is driven entirely by Core R&D activities (additionality of $1.58). We find no statistically significant effect for Supporting R&D expenditure.

   c) Industry and field effects: The RDTI is most effective in Manufacturing (additionality of 1.63) and Services (1.82). By research discipline, the strongest response is in Engineering (1.65).

5. Policy Implications: These findings suggest R&D policies should be targeted. The significant gap between own-firm returns and returns to the ecosystem validates the RDTI, but its "one-size-fits-all" horizontal nature may be inefficient. Policy levers could be refined to limit subsidies to Core R&D activities, and high-spillover technologies like Information & Computing. Consideration should be given to assessing whether alternative policies are better for low spillover technologies, or whether there are non-commercial benefits that this analysis has not captured. Furthermore, the demonstrated

productivity benefits of worker mobility highlight the value of programs that encourage collaboration and talent circulation between firms, such as the CRC program.

1. Introduction

This report presents empirical estimates on first, the effect of one firm's R&D on other firms within their ecosystem in Australia, secondly, whether this influence is (partly) transmitted through worker mobility, and lastly, the variation in the effectiveness of R&D tax incentives. Stimulating business investment in Research and Development (R&D) has been a cornerstone of industrial policy in many countries. This is justified by a core economic principle that the benefits of R&D may not be fully captured by the investing firm since the output of such investment has public good characteristics. R&D may generate new general and technical knowledge and knowhow, that spills over to competitors, suppliers, and customers, creating a "social return" that far exceeds the "private return." This gap, a classic market failure, could leads to systemic underinvestment in R&D by the private sector if left to market forces alone.

Although the market failure theory of R&D investment is well-established, quantifying the magnitude of the spillovers and identifying the specific channels through which they flow remains a significant empirical challenge. Furthermore, the effectiveness of policy instruments used to correct this market failure, such as the R&D Tax Incentive (RDTI), is a subject of continuous policy and academic debate. In Australia, understanding the additionality of the RDTI (the new R&D induced per dollar of tax forgone), and how its effectiveness varies across the economy, is critical for ensuring public funds are deployed efficiently to foster innovation and lift national productivity. This is particularly important given that, in the Australian case, the RDTI is currently a very major part of government assistance regarding research and development.

The SERD tasked the study team with estimating:

- The aggregate level of spillovers and its impact on productivity of business R&D?
- Whether export status of the R&D firm affects spillovers/external benefits in the economy?
- How the size of the firm undertaking R&D affects the level of R&D spillovers?
- Whether R&D spillovers generated by different types of technologies/industries varies and how this contributes to productivity growth?
- Whether collaborative R&D in particular business-Higher Research institutions generate a higher level of spillover and external benefits to the economy?
- Based on the RDTI program classification of core and supporting activities, whether core activities have higher levels of spillovers?
- The channels of R&D spillovers and productivity transmission

This report responds directly to this challenge, undertaking a comprehensive microeconometric analysis for the Strategic Examination of R&D (SERD). We address three interconnected objectives:

1. To estimate the private and social returns to R&D investment by Australian firms, identifying how these returns and their associated spillovers vary by research field and industry.

2. To empirically test a key channel of knowledge transmission—the mobility of R&D-experienced workers—by tracking their movement and subsequent impact on firm productivity.

3. To evaluate the effectiveness of the Australian R&D Tax Incentive, moving beyond average effects to estimate its heterogeneous additionality across different firm sizes, ages, industries, and research disciplines.

For the first time, this analysis is conducted using the full census of all firms and all employees in the Australian economy. By integrating the Business Longitudinal Analysis Data Environment (BLADE) with the Person Level Integrated Data Asset (PLIDA), we leverage a world-class dataset that allows for an unprecedentedly granular and robust examination of these questions. This report provides empirical answers to the specific questions posed by the SERD. In summary, we find:

- Aggregate R&D spillovers are large and positive. On average, the annual social rate of return to $1 of business R&D is $1.49, significantly higher than the annual private return of $0.96, confirming the theoretical justification for R&D subsidies. Over the lifetime of the R&D effects this means, $1 investment in R&D results a productivity increase of $4.60 to the firm undertaking the R&D and an increase of $7.14 to the greater ecosystem (i.e. to the own firm plus firms the same ecosystem).[3]
- R&D spillovers are highly heterogeneous. They are strongest in the field of research of Information and Computing and weakest in the fields like Biology/Biotech, where knowledge may be more effectively privatized or captured by the not-for-profit sector.
- Positive R&D spillovers primarily flow from suppliers (downstream), whereas spillovers from customers (upstream) are, on average, smaller, suggesting a mix of knowledge flows and product market rivalry. However, this depends on whether the spillover recipients are R&D active or not. For R&D active firms, perhaps reflecting their higher absorptive capacity, upstream R&D spillovers from the customers tend to be more important than downstream spillovers.
- High-tech R&D labour mobility is a critical spillover channel. Hiring high-tech workers with R&D experience from other corporate firms provides a statistically significant boost to firm productivity. A 1% increase in the share of these workers is associated with a 0.267% rise in productivity. This beneficial effect is most pronounced in large firms. Notably, workers with experience in Cooperative Research Centres and Research Service Providers provide an additional, separate positive impact on the hiring firm's productivity.
- The RDTI is effective in leveraging additional R&D by firms. Using a Regression Discontinuity Design, we find the incentive generates an average of $1.57 in additional R&D for every $1 of tax revenue forgone at the $20 million turnover threshold.
- RDTI additionality is driven by specific activities and firms. This effect is concentrated entirely in Core R&D activities, with no measurable impact from Supporting R&D. In terms of industry heterogeneity, the incentive is most effective in Manufacturing and Services, and by research field, in Engineering.

The remainder of this report details the foundation for these conclusions. Section 2 provides a literature review on R&D spillovers and tax incentives, establishing the theoretical and methodological context. Section 3 reviews the key empirical findings in the existing literature. Sections 4, 5, and 6 present our three core empirical analyses: the rates of return to R&D, the labour mobility channel, and the heterogeneous additionality of the RDTI. Section 7 concludes.

[3] Assuming a depreciation rate of 15% and an interest rate of 3%.

2. R&D Spillovers, Channels of Knowledge Transmission, and R&D Tax Incentives: Literature review

The objective of this literature review is to provide a brief but relatively comprehensive overview of the economics and business literature on estimates of Research and Development (R&D) spillovers and their economic impacts. The review synthesizes the theoretical underpinnings, prevalent methods, data requirements, significant estimation challenges, key empirical findings, and policy implications associated with R&D spillovers. The findings from this review are intended to inform the empirical estimation of R&D spillover effects on Australian business performance using recently linked employer-employee data and R&D tax incentive database. Hence, the scope of the review is limited to the main econometric approaches based on the knowledge production function framework.[4]

In the review, we focus on potential data sources and measurement issues, particularly in relation to the construction of knowledge stocks and spillover pools. We pay particular attention to major estimation challenges, such as endogeneity, measurement error, the definition of proximity, heterogeneity, and spatial dependence, and discussion of common solutions. The report synthesizes key empirical regularities regarding spillover magnitude, types (intra- vs. inter-industry, domestic vs. international), the role of geography, and firm characteristics like absorptive capacity, citing seminal and representative studies. Finally, it explores the implications of these findings for innovation policy and identifies promising directions for future research.

R&D Spillovers

The existence and importance of R&D spillovers are predicted and explained by several core economic theories. These theories provide the foundation for empirical investigation and highlight the mechanisms through which spillovers might operate. Arrow (1962) provides the foundational view that knowledge as the output of R&D possesses the characteristics of a public good. It is largely non-rivalrous in consumption because the use of the knowledge by one firm does not prevent other firms from using it simultaneously. The use of knowledge is also relatively non-excludable: it is often too difficult or costly for innovators to completely prevent others from accessing and benefiting from their discoveries (even with intellectual property protections like patents). These properties imply that the creators of knowledge cannot fully appropriate the social returns generated by their R&D efforts. This incomplete appropriability leads to positive externalities, or spillovers, where other agents benefit from the knowledge generated without fully compensating the originator.[5] This underlying market failure forms the primary justification for potential market underinvestment in R&D.[6]

Research and Development (R&D) activities have been widely recognised as a major engine of long-term economic growth. They generate new knowledge to create new and improved products and processes, enhance productivity, and lower production costs. Furthermore, due to the public good characteristics of the newly generated knowledge, the potential for R&D activities to create future benefits is unlikely to be limited only to the original investing entity. The public good characteristics of knowledge generated by R&D can potentially lead to a classic market failure. If,

[4] Thus, R&D spillovers estimation studies based on patent citation analysis and utilisation of spatial econometrics, stochastic frontier analysis, and event studies are all outside the scope of this review. However, any important finding from these studies which is particularly relevant for the intended empirical analysis R&D spillovers in Australia will be included in the discussion.

[5] Thus, the social returns are the sum of the private returns captured by the knowledge creators and the spillovers.

[6] The literature, such as Czarnitzki and Kraft (2012), Jones (2019), Lychagin et al. (2016), has provided an extensive list of relevant discussions.

due to spillovers to competitors, consumers, and other industries innovators cannot fully appropriate all the benefits of their R&D investments, the private return to R&D is typically lower than the social return. The larger the wedge between private and social returns, the more likely that firms under-invest in R&D from a societal perspective if R&D investment is left to the market. Hence, governments, firms and organisations such as universities invest substantial resources in R&D to reap potentially significant future benefits. These benefits are uncertain and difficult to quantify, making investment decisions difficult.

The concept of knowledge spillovers, which includes organisational, business, technological and people knowhow, is central to modern economic thought, particularly in theories of economic growth and market failure. Whereas earlier neoclassical growth models treated technological progress as exogenous, endogenous growth theory, pioneered by Romer, Lucas, Aghion, Howitt, and Grossman and Helpman, posits that long-run growth is driven by intentional investments in knowledge creation (R&D).[7] In this theory, R&D spillovers play a crucial role because they represent the mechanism through which the aggregate stock of knowledge can continue to grow, potentially negating diminishing returns. In these models, knowledge is non-rival; as a result, ideas generated by one entity can be built upon by others, leading to increasing returns to scale at the economy-wide level. Whether the economic effects of these spillovers are strong enough to overcome diminishing returns at the firm or industry level is a central empirical question generated by this literature (Griliches, 1992).[8]

This body of endogenous growth theory explicitly incorporates technological change as an outcome of deliberate economic activities, primarily R&D. In these models, R&D spillovers are not just a market failure but a fundamental mechanism driving sustained long-run economic growth.[9] By allowing new innovations to build upon the existing stock of knowledge ("standing on the shoulders of giants"), spillovers generate dynamic increasing returns at the aggregate level, preventing the diminishing returns that would otherwise halt per capita growth. Different models emphasize different aspects, such as expanding the variety of intermediate or final goods (Keller, 2022) or improving the quality of existing goods through "creative destruction". The economy-wide rate of technological progress, and thus long-run growth, is determined by the overall level of R&D and the effectiveness of spillover mechanisms (Howitt, 2007).

Defining and Measuring R&D Spillovers

The generated knowledge from R&D activities is largely non-rivalrous (the use of the knowledge by an entity does not preclude its use by another entity) and often imperfectly excludable (if it is too difficult or costly to prevent other entity from using the newly generated knowledge). As a result, R&D activities create externalities such that the total social benefits of the activities would exceed the private benefits that could be captured by the original investing entity. In essence, R&D activities create R&D spillovers. There is an extensive and growing literature on R&D spillovers which tries to measure these spillovers as well as explain their determining channels. In their analyses, these studies start by distinguishing different types of spillovers which have important implications on the measurement of their effects.[10]

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[7] Romer (1990), Lucas (1988), Aghion and Howitt (1992), Grossman and Helpman (1991).
[8] For a recent survey, see Ugur, Churchill, and Luong (2020).
[9] The endogenous growth literature is very extensive research areas. For examples, see Aghion and Jaravel (2015) and Jones (2019).
[10] This extensive literature, providing both theoretical and empirical evidence, on R&D spillovers in domestic and international settings, includes the works of, for examples, Arrow (1962), Griliches (1979; 1992), Griffith, Redding and Van Reenen (2003), Hall, Mairesse and Mohnen (2010), Czarnitzki and Kraft (2012), Bloom, Schankerman and Van Reenen (2013), Eberhardt, Helmers and Strauss (2013), Aghion and Jaravel (2015), Lychagin et al. (2016), Lucking, Bloom and Van Reenen (2019), Belderbos and Mohnen (2020), Keller (2022). For a recent review of the literature, see Ugur, Churchill, and Luong (2020).

Knowledge Spillovers vs. Rent Spillovers

First, knowledge spillovers can be categorised into types: pure or non-pecuniary knowledge spillovers and rent or pecuniary spillovers.[11] Pure knowledge spillovers consist of knowledge spillovers that enhance the productivity or innovative capacity of recipient firms because of the flow of ideas, information, or technological know-how that is not mediated by the market. In other words, pure knowledge spillovers arise from the public good nature of knowledge itself. In contrast, "pecuniary" or "rent" spillovers arise indirectly to the recipients through market transactions. For example, when the price of quality improvements in new or improved intermediate goods or capital equipment does not fully reflect the embodied R&D outputs in the forms of quality improvements, then rent spillovers happen. This could be an actual transfer of rent spillovers because of competitive pressures such that the selling firms are unable to fully price the quality improvements. It is also possible that rent spillovers are only illusionary for the data analysts due to difficulties in measuring quality changes in price indices. In either case, it would appear that there are productivity benefits “captured” by the purchasing firms rather than the innovator.[12]

Technology Spillovers vs. Product Market Rivalry Effects

Bloom, Schankerman, and Van Reenen (2013) and other subsequent research such as Lucking, Bloom and Van Reenen (2019) distinguish R&D spillover effects into those reflecting beneficial knowledge flows and those which emanate from the competitive impacts of R&D. Technology spillovers are considered as positive externalities when they provide knowledge flows which enhance the productivity or innovation of other firms. These effects are particularly more likely to occur among firms operating in similar technological domains. Conversely, due to product market rivalry, R&D spillovers could present negative externalities when they lead to what is referred to as "business stealing" effects. Business stealing occurs when one firm’s innovations take customers away from their rivals. Much of the modern R&D spillovers literature strives to identify these effects separately to avoid incorrect policy inferences.

The choice of the R&D spillover measurement methods impacts which types of externalities are captured. It is important to exercise care in comparing different empirical approaches and evaluating empirical magnitudes across studies. Social returns incorporate positive spillovers, whereas private returns are reduced by rivalry effects. If the R&D spillover estimates conflate the two, the true social-private gap will remain unknown, potentially leading to misguided policy (e.g., subsidizing R&D that primarily fuels business stealing). Methods like Bloom, Schankerman and Van Reenen (2013) attempt this separation precisely because it is crucial for policy evaluation.[13]

The Role of Absorptive Capacity

R&D spillovers are not automatic. For firms to benefit from external knowledge, they need to be able recognise its value, assimilate it and apply it commercially. The absorptive capacity of a firm underlies this ability (Mowery 1983; Cohen and Levinthal, 1989). In other words, for firms to benefit from the positive spillovers of others’ R&D, they must have sufficient internal research expertise. This suggests that external knowledge produced by other firms is not a pure public good because to benefit from it requires investment. The interaction between internal R&D in determining a firm’s absorptive capacity and thus the extent of R&D spillovers contributes to the complexity in understanding and measuring R&D spillovers. Furthermore, the path-dependent nature of absorptive capacity means that early R&D investments can create virtuous cycles,

[11] Griliches (1979; 1992), Los (2000), Hall, Mairesse and Mohnen (2010), and Belderbos and Mohnen (2020).

[12] Los (2000), for example, has pointed out that R&D spillovers measurements based on input-output tables are likely to primarily capture rent spillovers rather than pure knowledge spillovers.

[13] See Los (2000), Li (2014), Lychagin, et al. (2016); Lucking, Bloom and Van Reenen (2019)

where firms become better at absorbing external knowledge, further boosting their innovative performance, whereas firms lagging in R&D may find it increasingly difficult to catch up. This heterogeneity in firms' ability to benefit from spillovers is a key factor complicating simple models that assume uniform spillover reception.[14]

Estimating R&D Spillovers

Accurately estimating the magnitude, channels, and determinants of R&D spillovers is of paramount importance for both academic understanding and practical policy design. As the rationale for public support relies on the magnitude of spillovers, quantifying spillovers by technology or industry can form the basis of efficient policy design. Quantifying spillovers is also essential for testing theories of endogenous growth, understanding the sources of productivity differences across firms, industries, and regions, and identifying the micro-level mechanisms driving innovation diffusion (Lychagin, et al. 2016). It helps answer fundamental questions about how knowledge is created, shared, and utilized within an economy.

Robust spillover estimates are a prerequisite for designing and evaluating public policies aimed at fostering innovation and growth (Lychagin, et al. 2016). Without knowing the magnitude of the externality (the social-private return gap), it is difficult to determine the appropriate level of R&D subsidies or tax credits (Lucking, Bloom and Van Reenen, 2019). Understanding the channels through which spillovers occur (e.g., geographic proximity, trade, labour mobility) informs the design of policies related to cluster development, trade openness, intellectual property rights, and labour market regulation (Lychagin, et al. 2016). Identifying who benefits from whose R&D is crucial for targeting policies effectively (Lychagin, et al. 2016).

Knowledge Production Function Approach

Estimating the magnitude and impact of R&D spillovers presents significant econometric challenges due to the unobservable nature of knowledge flows and the complexities of innovation processes. A variety of methodologies have been developed, each with its own strengths, weaknesses, and underlying assumptions. In this literature review, we focus on what is known as the knowledge production function (KPF) approach.[15] The standard economic model measures spillovers as the increment in a firm's turnover after holding constant its employment level, its tangible capital stock, the firm's own accumulated R&D stocks, industry specific factors and unobserved but time-invariant factors such as managerial expertise. The economic interpretation is that this measures the effect of other firms' R&D stocks on the focus firm's productivity.

This is arguably the most common framework for estimating R&D spillovers, originating from the work of Griliches (1979). The core idea is to augment a standard production function, which relates a firm's or industry's output (Y) to conventional inputs like physical capital (K) and labor (L), by including measures of knowledge capital (Hall, Mairesse and Mohnen, 2010). In this approach, knowledge capital is typically separated into two components:

1. Own R&D Capital Stock (G): Represents the knowledge accumulated by the firm/industry itself through its past R&D investments.
2. External R&D Spillover Stock (S): Represents the pool of relevant knowledge generated by other entities (firms, industries, regions, countries) that is potentially accessible to the firm/industry in question.

[14] See Griffith, Redding and Van Reenen (2003)
[15] See the Appendix for a brief discussion of other approaches to estimating R&D spillovers including patent citation analysis, spatial econometrics, and production frontier models.

The specific functional form used in estimation varies, but the Cobb-Douglas and the Translog production functions are the two most common choices. [16] The typical Cobb-Douglas Production Function in logarithmic form is specified as follows: [17]

$$ln\, Y_{it} = \alpha_i + \lambda_t + \beta_L\, ln\, L_{it} + \beta_K\, ln\, K_{it} + \beta_G\, ln\, G_{it} + \beta_S\, ln\, S_{it} + \varepsilon_{it} \qquad (1)$$

Here, i indexes the firm/industry and t indexes time period (usually year). Y is output measure (e.g., value added), L is labor input, K is physical capital stock, G is the own R&D capital stock, and S is the R&D spillover stock. The unobserved parameters include α_i which represents unit-specific fixed effects (capturing time-invariant unobserved heterogeneity), λ_t represents time fixed effects (capturing common macroeconomic shocks or trends), and ε_{it} is the idiosyncratic error term.

Output elasticities of R&D and R&D rate of returns

The coefficients (β_L, β_K, β_G, β_S) in equation (1) represent the output elasticities of the respective inputs. [18] Of our particular interest are β_G and β_S, the output elasticities of own and external R&D. A positive and statistically and economically significant β_S, for example, is interpreted as evidence of positive R&D spillovers impacting productivity.

Let us denote ρ_G as the gross private rate of returns to own R&D (i.e., how much output increases per $1 additional own R&D stock, before depreciation). Then, given an estimate of β_G, we compute the private rate of returns to own R&D as: [19]

$$\rho_G = \beta_G \times \frac{Y}{G} \qquad (3)$$

Similarly, the (gross) social rate of returns (ρ) denoted as, that is the increase in all firms' output in the whole economy per $1 increase in R&D stock, can be computed by taking into account output elasticities with respect to both own R&D stock (G) and R&D spillover stocks (S):

$$\rho = \rho_G + \rho_s = (\beta_G + \beta_S) \times \frac{Y}{G} \qquad (4)$$

Spillover Pool Construction

A critical and challenging aspect of the KPF approach is the construction of the spillover stock variable (S_{it}). This variable aims to measure the R&D performed by others that is relevant to unit

[16] Ugur, Churchill ad Luong (2020) provides the most up-to-date survey of the relevant literature.

[17] The Translog production function is a more flexible functional form than the Cobb-Douglas function. It is in essence a second-order approximation to an arbitrary production function. It includes squared terms and interaction terms for the logarithms of the inputs:

$$\ln Y_{it} = \alpha_i + \lambda_t + \sum_j \beta_j \ln X_{jit} + \frac{1}{2}\sum_j \sum_k \gamma_{jk} \ln X_{jit} \ln X_{kit} + \varepsilon_{it}$$

where X represents the vector of inputs (L, K, G, S). This allows for non-constant elasticities of substitution and more complex interactions between inputs, including potential complementarity between own R&D and spillovers (e.g., absorptive capacity effects) (Mairesse and Mulkay, 2007). However, it requires estimating significantly more parameters and is thus more demanding on data. Hence, in this review, we will focus only on the Cobb-Douglas production function approach. We should also note that the dual approach, estimating cost functions or factor demand systems, is an alternative but less common method used in the spillover literature compared to the primal production function approach (Hall, Mairesse and Mohnen, 2010).

[18] That is, percentage change in output for each percentage change in input. Mathematically, for example, $\beta_G = \frac{dY/Y}{dG/G} = \frac{dY\,G}{dG\,Y}$.

[19] $\rho_G = \beta_G \times \frac{Y}{G} = \frac{dY\,G}{dG\,Y} \times \frac{Y}{G} = \frac{dY}{dG}$ (the change in output per unit change in own R&D stock).

i. It is typically calculated as a weighted sum of the R&D capital stocks (G_{jt}) of all other relevant units j ($j \neq i$) (Lucking, Bloom and Van Reenen, 2019):

$$S_{it} = \sum_{j \neq i} w_{ij} G_{jt} \tag{5}$$

The construction of the spillover pool is not merely a technical exercise but embodies a specific hypothesis about how and from whom firms learn or benefit. The choice of the weighting scheme (w_{ij}) is crucial as it embodies the assumed channel and proximity dimension through which spillovers operate. In other words, the choice of weighting scheme reflects prior assumptions about the dominant spillover channels (technological similarity, geographic interaction, supply chain links) and significantly influences the empirical results obtained (Kim and Lester, 2019).

Input-Output (I-O) Proximity.

One frequently used approach, because data are readily available, is to derive weights (w_{ij}) from national or regional input-output tables, reflecting the flow of goods and services between industries. Pioneered by Terleckyj (1974), this approach provides detailed information on the monetary value of transactions (sales and purchases of intermediate goods) between different industries within an economy. The core idea is to use these tables to trace R&D that is embodied in goods flowing through the supply chain, thereby mapping both intra- and inter-industry spillover pathways.[20] Specifically, w_{ij} could be the share of industry i's output purchased by industry j (measuring backward R&D spillover received from suppliers) or the share of industry j's inputs supplied by industry i (measuring forward spillovers transmitted to customers).[21] Thus, by definition, this method primarily captures R&D embodied in intermediate goods and thus likely reflects rent spillovers (Los, 2000). It will only capture pure knowledge spillovers if they happen through the supply chain.

The typical application involves constructing industry-level R&D spillover pools for use within a KPF framework. The weight w_{ij} assigned to the R&D stock of industry i when calculating the spillover pool for industry j is derived from the I-O table. Common weighting schemes include:

1. Supplier-based weights: w_{ij} is the share of industry i's total intermediate inputs that are purchased from industry j. This measures spillovers received by industry i from its suppliers.
2. Customer-based weights: w_{ij} is the share of industry i's total output that is sold as intermediate input to industry j. This measures spillovers transmitted by industry i to its customers (forward linkages).

These weights are applied to the R&D stocks of the respective industries to create spillover variables (e.g., $S_{i,supplier} = \sum_{j \neq i} w_{ijsupplier} G_j$). These spillover variables are then included as regressors in production function estimations alongside own R&D stock and conventional inputs. Some studies also use capital flow matrices to account for R&D embodied in investment goods (Los, 2000).

The I-O based methods primarily capture rent spillovers or embodied R&D (Belderbos and Mohnen, 2020). The logic is that quality improvements from R&D in supplying industries may not be fully reflected in the prices of intermediate goods, leading to measured productivity gains in the purchasing industries (Los, 2000. They measure the benefits flowing through market transactions rather than pure knowledge diffusion.

One major drawback of the I-O based method is that it primarily captures rent spillovers and may only capture some pure knowledge flows.[22] It also assumes spillovers are directly proportional to

[20] Intra-industry spillovers could be captured because in the input-output table, intermediate inputs include inputs used and produced within the same industry.
[21] Some studies also incorporate weights based on capital flow matrices (Los, 2000).
[22] For example, the knowledge flows through other channels beside supply-chain.

the volume of transactions, which may not hold. Lastly, the I-O tables are typically available only at a relatively high level of industry aggregation and often with considerable time lags, limiting the granularity and timeliness of the analysis.

Industry Membership

An early and simple approach used weights based on industry classification, such as setting $w_{ij} = 1$ if firms i and j are in the same industry (e.g., 2- or 4-digit SIC/NACE) and $w_{ij} = 0$ otherwise. The spillover pool S_i then represents the total R&D stock of other firms in the same industry. A major limitation of this approach (and also the Input-Output approach) is the inability to distinguish between positive technology spillovers and negative product market rivalry effects, as both operate strongly within industries (Bloom, Schankerman and Van Reenen, 2013). Also, it rules out inter-industry knowledge flows.

Geographical Proximity

This scheme assumes spillovers decay with distance, potentially reflecting the importance of tacit knowledge and the necessity for specific knowledge spillovers channels like face-to-face communication or the importance of localised labour markets. In this case, weights are assumed to be inversely related to the physical distance between the locations of firms, plants, or regions. Common specifications include inverse distance, inverse squared distance, or negative exponential functions, often with a distance threshold beyond which the weight becomes zero. Similar to industrial classification-based proximity, others have used co-location indicators such as whether firms i and j are located in the same city or state. A significant challenge is separating the effect of geographic proximity from the tendency of technologically similar firms to cluster geographically (industrial agglomeration) (Lychagin, et al., 2016).

Technological Proximity

If the relevant data are available, a weighting scheme that can potentially better capture "pure knowledge spillovers" can be constructed based on the "similarity" of R&D activities between units i and j. For example, Jaffe (1986) pioneered the use of patent data to measure R&D similarity where each unit's distribution of patent technology classes is summarised as the unit's technology vector. The weight w_{ij} is then calculated as the uncentered correlation (that is, cosine similarity) between firms i and j's patent technology vectors. This weight ranges from 0 (no technological overlap) to 1 (identical technological focus).

Alternative metrics based on patent data, such as the min-complement distance, have also been proposed to address potential issues with the Jaffe measure (Bar and Leiponen, 2012).[23] At least in theory, these patent- or industrial metrics can better capture pure knowledge spillovers between technologically related entities compared to the input-output proximity-based metrics.

Estimation Challenges and Potential Solutions

Beyond data and measurement issues, there are significant challenges in the econometric estimation of R&D spillovers related to model specification, identification, and interpretation. Successfully addressing these challenges is crucial for obtaining credible and reliable estimates.

Estimating knowledge production function models with spillover terms as specified in equation (1) requires addressing several econometric issues, primarily unobserved heterogeneity and simultaneity/endogeneity. For example, positive productivity shocks are likely to be associated with higher level of inputs and outputs, whereas negative productivity shocks are likely to be

[23] For example, similar to the case of Industry Membership measure, Jaffe's technological distance measure rules out knowledge spillovers between different patent classes. Furthermore, the measure may overstate the technological distance of two firms when one of the firm's patent classes are a smaller subset of the other firms.

associated with lower level of outputs and inputs. If firms respond to positive productivity shocks by increasing investment in R&D, the positive correlation between the observable input levels and the unobservable productivity shocks becomes a source of bias in ordinary least squares (OLS) estimates of equation (1). Specifically, the contribution of the increase in inputs on the higher level of output will be overstated and the contribution of R&D investment to the same output increase will be understated. Another problem is that OLS estimators typically yield biased and inconsistent estimates due to the correlation between R&D inputs (own and spillover) and unobserved factors (firm ability, technological opportunities, demand shocks) and potential simultaneity (Gumprecht, Gumprecht and Muller, 2005). It is possible that R&D is planned in response to knowledge about future changes in the global trading system or emerging complementary technologies or consumer preferences.

Endogeneity

Endogeneity is arguably the most pervasive and critical challenge in estimating the causal effect of R&D investment and R&D spillovers on economic outcomes. Endogeneity arises when explanatory variables (particularly own R&D stock G and spillover stock S) are correlated with the unobservable explanators (ε) in the model. This violates core model assumptions and leads to biased and inconsistent parameter estimates. Several sources may contribute to endogeneity. First, firms' decisions regarding inputs (including R&D) and their output or productivity levels are often determined simultaneously. For instance, firms might increase R&D spending in anticipation of future high demand or productivity, or conversely, more productive firms might generate more resources to invest in R&D. This creates a correlation between G_{it} and ε_{it}. Similarly, the spillover pool S_{it} can be endogenous. Firms might strategically choose locations or technology fields to maximize exposure to beneficial spillovers, or R&D investments across firms within a technological or geographic cluster might be driven by common unobserved shocks (e.g., emergence of a new technological opportunity), leading to correlation between G_{it} and ε_{it}.

A second, related problem is omitted variable bias. Unobserved factors that influence both the outcome variable (e.g., productivity) and the R&D/spillover variables can cause bias. Examples include managerial ability and firm culture, access to finance, quality of local infrastructure, or the intensity of competition. If these factors are not included in the model (often because they are unmeasurable) and are correlated with G_{it} or S_{it}, their effects are absorbed into the unobservable explanators, creating correlation. A key manifestation is the reflection problem identified by Manski (1991). This occurs when correlated outcomes or actions within a group (e.g., firms in the same industry or region investing heavily in R&D and experiencing high productivity growth) might reflect endogenous spillovers, but could equally reflect exogenous effects (e.g., characteristics of neighbours influencing the firm) or correlated effects (e.g., all firms responding to a common external shock or opportunity). Standard regression techniques struggle to disentangle these possibilities, making it difficult to isolate the true spillover effect. Simply observing correlation between proximate firms' R&D and performance is insufficient evidence of causal spillovers.

A third problem is sample selection bias. If the sample used for estimation is not representative of the population of interest, estimates can be biased. This occurs if, for example, the analysis is restricted to firms that perform R&D, firms that survive over the entire panel period, or firms that receive foreign investment. If selection into these groups is correlated with unobserved determinants of the outcome variable, bias arises.

Broadly speaking, there are three approaches to address the endogeneity/simultaneity issue:[24]

[24] See, for example, Rovigatti and Mollisi (2018).

Fixed Effect (FE) Approach

This is the most basic approach within the broader panel data methods. The basic idea of the FE approach is to exploit the time dimension of the data by focusing on within-unit variation over time. This way, FE estimators could control for time-invariant unobserved heterogeneity (α_i), mitigating omitted variable bias (Kim and Lester, 2019). Random Effects (RE) estimators are inappropriate as they assume that firm unobserved effects are uncorrelated with inputs into production.[25] However, FE estimators may provide imprecise estimates if there is little within-unit variation over time. They also impose a very strong assumption that firm specific unobservable explanators such as managerial quality and firm culture are fixed over time.

Instrumental Variable Approach

When specific sources of endogeneity are suspected (e.g., own R&D choice, spillover pool construction), Instrumental Variable (IV) estimation can be used if valid instruments are available. Instruments must be correlated with the endogenous variable but uncorrelated with the error term ε_{it}. Plausible instruments used in the literature include changes in R&D tax incentives or user costs (Bloom, Schankerman and Van Reenen, 2013) and shifts in government or defense R&D spending that affect firms differentially (Moretti, Steinwender and Van Reenen, 2025). The validity of instruments must be tested using relevance tests (e.g., F-statistic on excluded instruments) and overidentification tests (e.g., Sargan-Hansen test) if more instruments than endogenous variables are available (Arellano and Bond, 1991; Cincera, 2005).

Generalized Method of Moments (GMM) estimators have also been proposed for dynamic panel models where regressors (like lagged output, capital, or R&D stock) may be endogenous or predetermined, and fixed effects are present. Arellano and Bond (1991) proposed the use of first differences to remove fixed effects and uses lagged levels of variables as instruments for the differenced endogenous variables. Later works including Arellano and Bover (1995) and Blundell and Bond (1998) combine the differenced equation (using lagged levels as instruments) with the equation in levels (using lagged differences as instruments). This System GMM approach may outperform the difference GMM when variables are persistent (common for R&D stocks) but requires an additional assumption that changes in instruments are uncorrelated with the fixed effects (Eberhardt, Helmers, and Strauss, 2013). Weak instrument problems can also still arise, especially with highly persistent series or large ratios of fixed effect variance to idiosyncratic error variance (Bun and Windmeijer, 2010).

The Control Function Approach

This approach aims to control for unobserved (by the economist) productivity shocks in the previous period to be correlated with the current period level of output and inputs set (and observed by the economist) by the firms. Olley and Pakes (1996) pioneered the control function approach by proposing a two-step estimation procedure to equation (1). This two-step "OP" estimator relies on an important assumption that firms are profit maximisers when making their production input and output decision dynamically. Specifically, at the beginning of each period t, firms observe their idiosyncratic productivity shocks (ξ_t) and decide accordingly the level of their "free" production inputs (e.g. labour L_t) for that period. However, ξ_t does not affect the level of period t capital stocks (K_t and G_t) because they are assumed to be "state" variables and their levels are pre-determined in period $t - b$. Thus, by assumption, current period state variables and all the lagged values of the free and state variables are uncorrelated with ξ_t and could be used as valid instruments (Rovigatti and Mollisi, 2018). Based on the above assumption, in the first step, Olley and Pakes (1996) suggest using current investment expenditure as proxy for the unobserved productivity shocks. Controlling for this proxy, an unbiased estimate for the free

[25] There is an argument that RE is theoretically wrong and that it is more likely that the Hausman test is wrong than RE being the right estimator.

factor inputs (labour in equation 1) can be obtained. Then, using the unbiased estimates of the regression coefficients for the free factor inputs in stage 1, the remaining coefficients can be obtained in the second stage.

Levinsohn and Petrin (2003) argued that due to investment expenditures decision not being made at each period, the data often show many zeros in annual investment expenditures. This could prevent the use of the OP approach. Thus, they suggested a different but similar approach (the LP approach) that is based on data on intermediate input expenditure as a proxy variable for the productivity shocks. The intuition is that decisions on intermediate input levels are more likely to be made at each period, avoiding the excessive zero observation problem.

Ackerberg, Caves, and Frazer (2015; hereafter ACF) noted that to obtain consistent coefficient of the free variable (labour) coefficient in the first stage, labour must vary independently from the proxy variable. In the LP setting, the intermediate input level and labour inputs are assumed to be allocated at the same time. This creates an identification problem between these two variables. To solve the problem, ACF suggest additional assumptions about the timing of the decisions on labour and intermediate inputs and the use of a production function specified in value added, such that the proxy variable (intermediate inputs) does not enter the production function.[26]

Heterogeneity

Spillover effects are unlikely to be uniform across all firms, industries, or regions. Ignoring this heterogeneity can lead to average estimates that are not representative and mask important variations relevant for policy. The issue here is that the impact of external R&D (S) on a unit's performance (Y) likely depends on the characteristics of both the source and the recipient.

There are a few key sources of heterogeneity that need to be considered in the estimation and analysis of R&D spillovers. First, heterogeneity arising from variation in absorptive capacity is an important source of differences across firms. As discussed earlier, firms with greater internal capabilities (higher own R&D, more skilled workforce, relevant prior knowledge) are better equipped to identify, assimilate, and exploit external knowledge. In other words, the benefits of spillovers are likely to be conditional on absorptive capacity. Second, industry characteristics may matter for spillovers. They may be stronger in high-tech industries compared to low-tech ones or differ between manufacturing and services. Furthermore, the nature of competition and technological opportunity may vary across sectors. Lastly, the type and field of R&D research may matter. Spillovers from basic research may differ from those from applied R&D or development in terms of magnitude, lag structure, and geographic reach.

Heterogeneity, particularly due to absorptive capacity, implies that the "average" spillover effect estimated in many models may not be representative for any specific firm or useful for targeted policy. Policies aiming to maximize spillover benefits need to consider which firms benefit most and why. Interventions targeting firms with low absorptive capacity might be ineffective unless they also address the capacity constraint itself.

The above potential sources of heterogeneity suggest the importance of considering the inclusion of interaction terms such as interactions between the spillover variable (S) and the moderating characteristics (e.g. $S \times AbsorptiveCapacity$) or split sample analysis. Alternatively, one can estimate the effects on firm productivity if firms hire workers from other firms with R&D experience. Similarly, subsample estimation such as estimating the model separately for

[26] Rovigatti and Molissi (2018) discusses three other refinements of the control function approaches including by Wooldridge (2009) and by themselves. The former proposed to solve OP and LP estimation problems highlighted by ACF by setting up GMM moment restrictions to estimate both models in one step. In the latter, Blundell and Bond (1998) dynamic panel instruments are implemented in Wooldridge (2009) setup to strengthen the robustness and efficiency of the estimates.

different groups of firms/industries/regions (e.g., high-tech vs. low-tech, small vs. large) could yield a more complete understanding of the variation in R&D spillovers estimates.

Data and Measures

Estimating R&D spillovers generally requires information on the R&D activities of the focal unit and potential spillover sources, measures of economic performance or innovation output for the focal unit, and variables characterizing the unit and its environment. Existing studies have been conducted using data at various levels of aggregation,[27] based on a range of measures of R&D expenditure [fundamental for constructing own R&D stocks (G) and spillover pools (S)] and on information such as the source of R&D funding (private, government, foreign), the sectors of R&D performers (business, government, higher education), and potentially granular information such as R&D personnel employed by the firm.

Despite the availability of various data sources, significant challenges remain regarding data quality, consistency, and measurement, particularly concerning the core concepts of R&D and spillovers as discussed below.

Constructing Own R&D Capital Stocks (G)

The construction of the R&D capital stock, a fundamental variable in most spillover models, rests on strong and often arbitrary assumptions, particularly regarding depreciation. These assumptions can significantly influence the final spillover estimates, as errors in measuring individual G_j components (from all firms) compound when constructing the spillover pool for firm i, G_i.

As R&D is an investment creating an intangible asset (knowledge), its contribution to production is best represented by a stock measure. However, R&D spending is often treated as a current expense in company accounts. Researchers must therefore construct the knowledge stock, typically using the Perpetual Inventory Method (PIM):

$$G_t = (1 - \delta)G_{t-1} \tag{6a}$$

or a lagged version

$$G_t = (1 - \delta)G_{t-1} + R_{t-1} \tag{6b}$$

where G_t denotes R&D capital stock at period t, R_t is R&D expenditure at period t, and δ is the depreciation rate of the R&D capital stock.

To construct R&D capital stock or knowledge stock requires some assumptions.[28] First, the rate at which knowledge becomes obsolete or loses economic value is highly uncertain and debated.[29] Unlike physical capital, knowledge doesn't necessarily wear out with use but becomes outdated due to new discoveries (creative destruction). Common practice often assumes $\delta = 15\%$, but empirical estimates vary widely (from near zero or even *appreciation*). Although some studies claim results are insensitive to δ, the substantial impact of different depreciation assumptions on the calculated stock size suggests this choice can significantly influence estimated R&D elasticities and spillover effects.

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[27] Studies using microdata at the firm or plant level include Lychagin et al. (2016), Lucking, Bloom and Van Reenen (2019), Bloom, Schankerman and Van Reenen (2013), Kim and Lester (2019), Ceccagnoli (2005), Cincera (2005), Aldieri, Sena and Vinci (2018), Cardamone (2014), Aldieri and Cincera (2009), Peters et al. (2017), and Belderbos et al. (2013). Many other studies are done at industry level (e.g., Eberhardt, Helmers, and Strauss 2013; Skully and Rakotoarisoa 2013; Acharya 2015; Grünfeld 2002; Unel 2007; Liu and Sickles, 2024; Liu, Sickles and Zhao 2022; Pieri, Vecchi and Venturini 2018). There are also many other studies done using data at the regional and country level.
[28] Ugur et al. (2016), Bitzer and Stephan (2007), Verba (2020).
[29] Hall (2005), Acharya (2015).

Second, PIM requires an estimate of the knowledge stock at the beginning of the sample period. This is often calculated using the formula

$$G_0 = \frac{R_0}{g+\delta} \tag{7}$$

where R_0 is the initial R&D flow and g is an assumed pre-sample average growth rate of R&D (e.g., 5%). This calculation is sensitive to the assumed growth rate g.

There may be a gestation lag between R&D expenditure and its impact on the usable knowledge stock or productivity (Griliches, 1991). The standard PIM often assumes immediate impact or a simple one-period lag. Results may be sensitive to this assumption as well.

Channels of Spillovers

The literature has identified numerous channels through which R&D spillovers can occur, whether market-mediated or not. The diversity of these channels suggests that no single econometric method can capture the full picture, and the relative importance of each channel and how R&D spills over are likely to vary by industry, technology, and geographic context.

In market-mediated channels, R&D spillovers can occur as embodied knowledge in production inputs. When firms purchase intermediate goods or capital equipment that incorporate R&D-driven quality improvements whose value has not been fully captured by the price the firms paid, rent spillovers occur (Belderbos and Mohnen 2020). This often happens through supplier-customer relationships and is frequently reflected in R&D spillover estimates based on input-output tables (Los, 2000).

In contrast, pure knowledge spillovers, which are separable from rent spillovers, can occur through non-market channels. There are two types of non-market channels. The first requires in-person contact, which is typically enhanced by place-based agglomerations. This includes hiring workers from related firms and participation in conferences, workshops and informal business and social networks. These channels are especially suited for tacit knowledge and broad, uncertain information. A recent study, has found that R&D investment within a firm can spur employee departures to establish new start-ups, transferring knowledge and skills developed internally (Babina and Howell, 2024). However, policies like non-compete agreements, which can restrict this channel, appear to be on the rise (El-Dardiry, Overvest and Bijlsma, 2019).

There is a growing body of studies on the impact of labour mobility due to the growth of employer-employee panel datasets and the importance of tacit knowledge for frontier innovations. The effectiveness of knowledge sharing via labour mobility can be limited by the absorptive capacity of the recipient firm as it must possess the related knowledge base and skilled colleagues to understand, integrate, and leverage the knowledge brought by the new employee;[30] and the knowledge overlap between firms which share a common labour market. Several factors can limit labour mobility – even if desired by both the worker and prospective employer: non-compete labour clauses, restrictive IP clauses, rules regarding worker secondments and internships and geographic, or commuting, distance.

The second type of non-market spillover is arm's length and includes imitation and reverse engineering and dissemination of information through publications and patent disclosures. Through imitation and reverse engineering, firms can analyse competitors' product to learn to replicate or even improve upon the underlying technologies (Lychagin et al., 2016). Less controversially, firms can share knowledge, particularly basic research findings, through scientific articles, technical reports, online conference presentations, and increasingly through open-access data repositories and open-source software platforms (Griliches, 1992).

[30] A common professional background, technical language, or cultural understanding facilitates effective communication and knowledge exchange.

R&D Tax Incentives

Australian tax subsidies for R&D were first introduced in 1985 and have undergone numerous reforms since their inception. In the context of the R&D Tax Incentive, the program being analysed was established in the 2011-12 financial year. The program originally comprised a 45% offset for small companies (aggregate turnover less than $20 million) and a 40% offset for large companies (aggregate turnover greater than $20 million). In addition, the 45% R&D tax offset was refundable, which means that if a company's tax liability is reduced to zero, companies may be entitled to a refund of any unused offset amount. In 2015, a cap on subsidized R&D spending of $100 million was introduced. In 2016, the R&DTI rates were lowered to 43.5% for the refundable scheme and 38.5% offset for large firms. Most recently, reforms in July 2021 established the offset rate based on their tax rate, aggregate turnover and for large companies, their R&D intensity.

R&D tax incentives have been used by governments worldwide, particularly in developed countries, as one of the primary policy instruments to stimulate private sector investment in research and development (R&D). This interventionist approach stems from a well-established economic consensus that market forces alone tend to result in a suboptimal level of R&D investment in the presence of market failures because of, among others, R&D spillovers (OECD, 1996; Klette, Møen and Griliches, 2000). As discussed above, knowledge generated through R&D exhibits the public good characteristics and firms undertaking R&D often cannot fully capture the economic benefits of their investment because the generated knowledge created can spill over to other firms (competitors, suppliers, and consumers) without adequate compensation to the originator. The "appropriability problem" means the social returns to R&D are likely to be greater than the private returns. Consequently, profit-maximizing firms which only care about their private returns would not invest as much as desired by society. By effectively lowering the private cost of R&D, an R&D tax incentive could potentially move business R&D investments closer to the socially optimal level.

Yet Akcigit, Hanley, and Stantcheva (2022) develop a theoretical model suggesting that subsidies do not impact firms' behaviours and productivity uniformly. They show that large, high-productivity firms convert R&D spending into innovations much more effectively than smaller or less productive ones. Because governments cannot perfectly observe which firms are genuinely innovative, policies must balance rewarding R&D with preventing wasteful subsidies. Their main takeaway is that optimal R&D support should taper off for higher R&D levels—larger, more productive firms already have strong innovation incentives—while smaller or less efficient firms may warrant proportionally higher support to offset disadvantages.

3. Review of Empirical Findings

Private and Social Returns to R&D

Decades of empirical research have generated over a hundred empirical studies on R&D spillovers (Hall, Mairesse and Mohnen 2010; Frontier Economics 2023) but very few using Australian data (Bakhtiari and Breunig 2018; Palangkaraya, Balaguer and Webster 2024). Although findings vary according to method, data, and context, several key patterns and outstanding questions emerge. First, a broad consensus exists that R&D spillovers generate positive externalities, leading to social rates of return that generally exceed private rates of return. Also, it is reasonable to assume that R&D spillovers are largely localised within agglomerations (Bode 2004; Carboni 2013; Fischer, Scherngell and Jansenberger 2006; Gumprecht, Gumprecht, and Müller 2005; Lopez-Garcia and Montero 2012; Aldieri and Cincera 2007; Cardamone 2017; Giroud, Liu and Muller 2025; Jaffe, Trajtenberg and Henderson, 1993; Lychagin et al 2016).

Early reviews and many individual studies suggested substantial spillover effects, with social returns potentially being two to four times higher than private returns. However, more recent meta-analyses, which systematically synthesize results from numerous studies while controlling for publication bias and method differences, tend to find more modest average spillover effects. These analyses often report that the average output elasticity of spillover R&D is positive but smaller than the elasticity of own R&D. Furthermore, a significant portion of the reported estimates in the literature may lack adequate statistical power, and when focusing on adequately powered studies, the practical significance of the average spillover effect appears to be small.

Overall gap between private and social returns

Estimates of the gap between social and private returns to R&D inform the overall level of support required to align private incentives with social benefits. Support can come in the form of tax incentives, loans, warrantees, equity, regulations (including intellectual property) or grants. The larger the gap, the greater is the required level of support needed to optimise the level of R&D in an economy. Furthermore, more information on the technologies or industries that produce higher rates of R&D spillovers, allows governments to more carefully target this support. Precise calibration is arguably not feasible, but it is possible to have broad bands of support, such as low, medium and high levels of support. Targeted policies are more complex to administer and easier for firms to game.

In their meta-analysis of 63 recent empirical studies, Frontier Economics (2023) estimate that the average private rate of return to R&D (ρ_G) is at least 14% but is likely to be 20%. The same study concluded that conservatively, social returns to R&D (ρ) are twice those of the private returns – which implies a gap of between 14 to 20%. They also conclude that where there is evidence of market-stealing effects of R&D, this is more than offset by knowledge spillover benefits.

Assuming the bulk of recent empirical studies are valid, and there remains a gap between social and private returns, then the current 2-3% R&D of GDP in advanced economies remains insufficient from the standpoint of societal well-being. This is true even with the current wide array of R&D incentives in place.

The significance and magnitude of estimated spillovers are sensitive to the method employed. Studies using cross-sectional data or simple KPF models often find larger effects than time-series studies or studies that rigorously control for endogeneity and common factors using advanced panel techniques (like GMM or common factor models). These latter studies sometimes find spillover effects to be insignificant or very small. Some studies even report negative spillover effects, potentially reflecting dominant product market rivalry, adjustment costs, or creative destruction dynamics.[31]

Differences by firm size

The relationship between firm size and spillover benefits is less clear-cut, with mixed empirical findings. Some studies suggest larger firms benefit more from spillovers, potentially due to greater absorptive capacity, economies of scope in research, or ability to internalize external knowledge. However, other influential work (e.g., Bloom, Schankerman and Van Reenen (2013)) finds that smaller firms may generate lower social returns because they tend to operate in technological niches with fewer relevant spillover sources, even if their private returns are high. Some evidence also suggests smaller firms might be more reliant on external knowledge or respond more strongly to certain types of spillovers or R&D support. This heterogeneity complicates policy discussions regarding targeted support for small and medium-sized enterprises (SMEs) based on spillover arguments.[32]

Differences between industries and technologies

Despite the quantity of studies, there is scant evidence to indicate which industry, or technology produces the most benefits. A recent Australian study by Palangkaraya, Balaguer and Webster (2024) only considered the third-party effects on other R&D active firms. Overseas, a few existing studies disaggregate source R&D by manufacturing industry (Bernstein and Nadiri (1991); whether it is basic or applied (Akcigit, Hanley, and Serrano-Velarde 2021) and whether it is intra-mural or extra-mural (Crespi et al. 2020).

An accumulation of R&D stocks by one firm may have positive effects on peers through the direct exchange of knowledge (called R&D spillovers), or, through the deepening of ancillary industries and labour markets to support the successful use of knowledge (called external economies). The latter can be instrumental in reducing the risk of further R&D investment or aiding the transfer of new ideas across industries.

To our knowledge, there are no comprehensive studies that have compared spillovers between different classes of technology. Some studies use technology similarity to weighted R&D from neighbouring firms (e.g. Bloom, Schankerman and Van Reenen 2013; Lucking, Bloom and Van Reneen 2019; Kim and Lester 2019). Others examine the channels through which spillovers travel, such as imported inputs of foreign direct investment (e.g. Griffith, Harrison and Van Reneen 2006; Zhu and Jeon 2007; Belderbos, Lykogianni and Veugelers 2008; Lööf and Anderson 2010; Zaclicever and Pellandra 2018; Liu and Fan 2020). But no other studies have undertaken and across the board comparison of R&D disaggregated by technology. Our dataset is the recently developed Australian Business Longitudinal Analysis Data Environment (BLADE) which is a census of unit record firm data over a 20-year period and includes R&D expenditure data which the firms has coded to 4-digit technology areas.

Channels of transmission

Whereas the existence of knowledge spillovers has been well established both in Australia and overseas, there is limited representative modelling on the actual channels of spillover transmission. Early work tracing channels of transmission has focused on data from surveys (e.g. Harabi 1997); the geographic proximity of foreign/multinational firms; the movement or inventors nominated on patent applications and suppliers of R&D intensive inputs. More robust evidence

[31] See, for examples, Ugur et al. (2020), Cincera (2005), Griliches (1992, 1995), Mohnen (1996), Bloom, Schankerman and Van Reenen (2013).
[32] See Bloom, Schankerman and Van Reenen (2013).

rests on population-level, linked employer-employee datasets and datasets linking intermediate input sales.

Below we summarise recent evidence on the main channels of transmission of R&D or knowledge spillovers.

Via the supply chain

Studies using narrow industry definitions or technological proximity measures often find stronger intra-industry effects (Cardamone, 2014). Spillovers appear largest among close technological neighbours (Orlando, 2004). Other studies, particularly those using I-O tables or broader definitions of proximity, find significant inter-industry spillovers, sometimes exceeding intra-industry effects (Autant-Bernard and LeSage, 2011). Spillovers flowing through vertical supply chains (supplier-customer linkages) are also found to be important.

Via internal R&D capacity

Empirical work strongly supports the Mowery-Cohen-Levinthal hypothesis that a firm's ability to benefit from R&D spillovers depends on its internal capabilities. Firms with higher own R&D intensity, larger stocks of human capital (skilled labour), or specific learning routines and organizational practices demonstrate a greater capacity to identify, assimilate, and exploit external knowledge. This is often evidenced by positive and significant coefficients on interaction terms between spillover measures and proxies for internal research expertise (like own R&D stock or R&D personnel share) in KPF models. The implication is that R&D investment has a dual role: generating innovation directly and building the capacity to learn from others (Griffith, Redding, and Van Reenen 2003; Mikhailov and Reichert 2020; Audretsch and Belitski 2022).

Via labour mobility

The aphorism goes…'the best way to send information is to wrap it up in a person' [33] has long been understood by economists studying knowledge and innovation (Marshall 1890; Arrow 1962; Geroski, 1995; Stephan 1996). The data to establish clear tractable evidence for this person-to-person transmission however has been emerging slowly.

The earlier literature seeking evidence of labour mobility as a knowledge transmission channel used data on the migration of inventors (Almeida and Kogut 1999; Kim and Marschke 2005; Agrawal et al. 2006; Hoisl 2007; Giuri and Mariani 2013; Miguélez and Moreno. 2013; Drivas et al 2016; Wang and Zheng 2022; Bergeaud et al 2025; Chang 2024; Giroud et al 2024). They defined mobility as a person who had been assigned to different organisations on a patent document. This is clearly a restricted view of mobility but was the best available data at the time. The recent study by Giroud et al (2024) found that whereas larger technology clusters make local inventors more productive, they raise the productivity of firms in other clusters, which are connected to the focal cluster through their parent firms' networks. Inter-cluster innovation spillovers depend less on the physical distance than these networks. A related literature Ozgen (2021) reviews 9 relatively recent studies that examine the impact of immigrant skilled workers on patent activity – as a measure of innovation.

Studies with clearer identification methods use linked employer-employee datasets (LEED) – typically found in the Scandinavian countries. Martins (2006) used Portuguese LEED data to show that people with previous foreign firm work experience earned a wage premia compared with those without, and these premia was higher the greater was the foreign-firm experience. Kaiser, Kongsted, and Ronde (2008) used the Danish LEED linked to patent data to find positive effects of skilled worker mobility on patenting in the receiving firm and, a positive effect of patenting in

[33] Attributed to Robert Oppenhiemer.

the sending firm (but only if it was patent active). They attribute the latter effect to reverse knowledge flow coming back to them from their ex-employee.

Perhaps the first study to investigate the impact of labour movement on firm productivity was by Maliranta et al (2009) who used the Finnish LEED to trace the impact on firms hiring R&D workers from other firms.[34] They found a positive impact on the receiving firm's productivity only if the moving worker takes a non-R&D job in the new firm. Subsequently, Stoyanov and Zubanov (2012) used Danish manufacturing data and estimated that hiring a worker from a more productive firm led to a 0.35% increase in the receiving firm's productivity the next year. The effect lasts 4 years. Although the productivity boost was highest for more skilled workers, evidence of a boost from medium-skilled workers suggests that a focus on patenting firms may miss much knowledge transfer. Balsvik (2011) used Norwegian manufacturing LEED data and estimates that workers with foreign multinational firm experience contribute 20% more to the productivity of their receiving plant than workers without such experience.

The management literature has conducted several studies using less regular bespoke datasets. For example, Rao and Drazin (2002) use financial industry data to find evidence that younger firms and poorly connected firms poach experienced employees from large firms. However, recruit characteristics have stronger effects on product innovation in poorly connected organisations.

The impact of R&D tax incentives

Most research suggests business R&D investment responds to tax subsidies, though results vary. However, estimating the causal impact is challenging because a firm's R&D investment and its effective subsidy through tax deductions are jointly determined: higher R&D spending generates larger tax benefits and correspondingly greater revenue forgone by government.

Estimating the additionality effect of R&D tax subsidies requires exogenous variation in the rates of the subsidy—either across firms, industries, or time. In practice, firm-level data typically show substantial variation in R&D demand but limited exogenous variation in subsidy rates. The empirical challenge is isolating the effect of the subsidy while controlling for factors that influence R&D demand.

Methodological Challenges

Causal firm-level analysis faces a fundamental identification problem: all firms performing eligible R&D can access the subsidy, making it difficult to construct appropriate control groups. This problem is particularly acute for incremental R&D tax incentives, where the effective subsidy rate increases with R&D expenditure by design. Compelling external instrumental variables are rarely available, forcing researchers toward 'internal' instrumentation approaches (Hall, 1992; Dagenais et al., 1997).

An alternative approach exploits inter-jurisdictional variation in tax policy using panel data across countries or subnational regions (see Bloom et al., 2002; Guellec & Van Pottelsberghe, 2003; Falk, 2006; Wilson, 2009; Thomson and Jensen, 2013). However, this approach faces its own limitations: relatively few observations, infrequent policy reforms, and difficulty ruling out that policy changes correlate with unobserved factors influencing R&D investment. Early studies using policy shift dummies faced similar concerns (e.g., Eisner et al., 1984; Bernstein, 1986; Thomas et al., 2003).

[34] Earlier papers by Moen (2005) and Magnani (2006) used the Norwegian and US manufacturing LEEDs (respectively) but did not look at the effect of R&D worker mobility on firm productivity (only wages).

Quasi-Experimental Evidence

Recent quasi-experimental approaches represent an important methodological advance. Dechezleprêtre et al. (2023) and Guceri and Liu (2019) provide compelling examples, both analysing a 2008 UK reform. Using regression discontinuity and difference-in-differences designs respectively, both studies exploit changes in asset-based size thresholds that made medium-sized firms eligible for more generous R&D tax credits than large firms. Both find significant positive effects on innovation.

Despite over 30 years of R&D tax support in Australia, rigorous statistical evidence on program effectiveness emerged only recently. Early research failed to establish that the incentive induced additional R&D investment by Australian firms (see Thomson, 2010). Holt, Skali and Thomson (2016) provided the first quasi-experimental Australian evidence, using a difference-in-differences design to estimate that the R&D Tax Incentive induces an additional $1.90 per $1.00 of forgone tax revenue. More recently, Thomson, Kollmann and Yamashita (2025) employed a regression discontinuity design exploiting the $20 million turnover eligibility threshold, finding additionality of 1.68.

Sectoral Heterogeneity

A key limitation of existing research is that most studies estimate economy-wide average additionality without systematically investigating sectoral differences. The few studies controlling for sectoral characteristics have typically treated these as secondary rather than examining whether sectoral patterns are systematic or what explains them.

Castellacci and Lie (2015) addressed this gap through a meta-regression analysis of 34 microeconometric studies on R&D tax credits. Their central finding: sectors matter significantly. Studies focusing on high-tech industries found smaller additionality effects on average, particularly in countries with incremental schemes. Conversely, additionality is stronger for SMEs, service sectors, and low-tech sectors under incremental systems. They propose two explanations: first, firms with lower R&D intensity may find it easier to scale up from a smaller base (a mean reversion effect); second, these firms may seek the incentive primarily for fiscal relief and to ease financial constraints rather than to permanently expand R&D investment.

Bodas Freitas et al. (2017) provide cross-country empirical evidence on sectoral patterns using innovation survey data from Norway, Italy, and France (2004-2008). They examined how input and output additionality vary across sectors with different R&D orientations (using Pavitt's taxonomy) and market concentration levels.

Their results show that firms in high R&D-oriented industries—particularly science-based and specialized supplier sectors—have both a higher propensity to receive R&D tax credits and stronger input additionality compared to other sectors. This pattern holds across all three countries. The authors attribute this to formalized R&D strategies and stronger managerial capabilities in these sectors, improving both application propensity and quality.

In terms of the efficacy at inducing firms to invest in R&D, numerous studies have found evidence that smaller firms experience larger program effects such as Howell (2017), OECD (2020) and Dechezleprêtre et al. (2023). However, in the context of Australian firm sizes, these studies often define firms with fewer than 500 employees as small- and medium-sized firms.

The pattern of heterogeneity extends beyond sector to firm size. Numerous studies have found evidence that smaller firms experience larger program effects, including Howell (2017), OECD (2020), and Dechezleprêtre et al. (2023), though these studies often define firms with fewer than 500 employees as small- and medium-sized. The OECD study finds that R&D tax incentives are most effective for smaller, less research-intensive firms, while large or already R&D-heavy

companies show little change in behaviour. When governments make R&D tax credits more generous, small and medium businesses tend to invest noticeably more in research and development—often adding more than a dollar of private R&D for each dollar of public support—whereas big firms mostly keep spending at their previous levels. Much of this difference comes not from size alone but from how much R&D firms were doing to begin with: those starting from a low base respond the most. The study also shows that once a company already spends heavily on R&D, further tax breaks make little difference. This echoes Castellacci and Lie's proposed mean reversion effect and suggests that well-designed tax incentives can encourage innovation by helping smaller or less established firms overcome funding barriers, while effects on mature, high-R&D industries are limited.

For output additionality (measured by turnover from new products), effects were positive across all countries, but sectoral patterns differed markedly. Industries with large economies of scale showed the highest output additionality in Norway, specialized suppliers in Italy, and both specialized suppliers and supplier-dominated industries in France. These cross-country differences suggest output additionality depends on country-specific factors such as program design (volume-based versus incremental) and industrial specialization patterns. In Australia, output additionality has proven difficult to identify; Thomson et al. (2025) find little evidence using RDD, potentially due to the relatively small size of firms near the threshold.

Policy Implications

These studies demonstrate that horizontally-defined R&D tax incentive schemes—offering uniform fiscal benefits across sectors—produce systematically different effects across industries. This has important policy implications: fiscal resources intended to stimulate R&D and economic competitiveness may disproportionately benefit sectors with lower technological opportunities and weaker spillover effects. As Castellacci and Lie (2015) conclude, if these patterns persist, R&D tax incentive mechanisms may need redesigning to account for sector-specific innovation dynamics, potentially directing greater fiscal support toward high-opportunity and technologically dynamic sectors.

4. The Rate of Returns to Australian Business R&D

As discussed in the literature review, optimising the level of R&D in an economy requires a good understanding on the extent of the gap between social (ρ) and private returns (ρ_G) to R&D. Knowing the level of the gap informs the overall level of support required to align private incentives with social benefits. Furthermore, knowing how the gap varies across firm, technology, and industry characteristics informs which bands of support, such as low, medium and high levels of support, to be used. This sections of the report provide estimates of both the internal (own) and external effects of R&D on firm productivity according to the technology of the R&D expenditure and other firm characteristics including size and age. Note, we are only modelling the impact of R&D coming from the for-profit sector. As such we do not model the effects of higher education sector and non-profit sector R&D.

Empirical framework

Economic models, constructed to reflect the effects of accumulated knowledge, usually begin by estimating (firm, industry or national) productivity and then proceed to model the impact of their own stock of knowledge, and related firms' stock of knowledge on this productivity. We follow this approach. Specifically, we follow the dominant method of augmenting the production–function framework to include own-firm R&D and related firms' R&D as per Griliches (1979) and specified in equation (1).[35] Due to lack of data and our inclusion of non-R&D active firms in the analysis, we do not use direct and indirect patent citations as measures of spillovers (e.g. Jaffe, Trajtenberg, Henderson 1993; Belenzon and Schankerman 2013; Colino 2016; Akcigit, Hanley, and Serrano-Velarde 2021). However, we do consider both horizontal and vertical spillovers and the influence of absorptive capacity as reflected by firm size or and firm size in the absorption of knowledge. Like Audretsch and Belitski (2020), we focus on the effect of knowledge flows on firm productivity rather than intermediate stages such as firm innovation.[36]

Novel contributions

Unlike most if not all existing studies, we consider several novel aspects in the estimations of R&D spillovers and the returns to R&D. First, we account for both the intensive and extensive margins by estimation our econometrics model like the one specified in equation (1) using samples consisting of both R&D performing firms and non-R&D performing firms. All existing estimates discussed in the literature review earlier are based only on samples of R&D firms and thus rule out any potential R&D returns at the extensive margins (i.e., the gains from having no R&D to doing R&D). Furthermore, non-R&D firms may also benefit from the knowledge spillovers. Excluding them from R&D spillover analysis will underestimate the social returns to R&D. Besides, if absorptive capacity is critical for firms to benefit from R&D spillovers, then the effect of doing R&D at the extensive margins could be significant. A focus only on the intensive margins will underestimate the private returns to R&D.

Secondly, we study heterogeneity in R&D spillovers over dimensions which have not received as much attention in the literature. Specifically, we distinguish different types of R&D activities in terms of the field or research and whether the R&D investment is for activities classified as core R&D activities or as supporting activities such as spending on infrastructures to set up research labs.

Core R&D is an activity whose outcome cannot be known or determined in advance on the basis of current knowledge, information or experience, but can only be determined by applying a systematic progression of work that: (i) is based on principles of established science; and (ii)

[35] According to Brown (2008), Cobb and Douglas suggested the common multiplicative form following Wicksteed and Wicksell.
[36] For a short history of including technological change into the production function see Griliches (1996).

proceeds from hypothesis to experiment, observation and evaluation, and leads to logical conclusions; and (b) that are conducted for the purpose of generating new knowledge (including new knowledge in the form of new or improved materials, products, devices, processes or services).

Supporting R&D activities are activities directly related to core R&D activities and examples include a literature review to refine the hypothesis; clean and maintaining the equipment used during experiments; and the decommissioning and dismantling of equipment used for core experiments.[37]

These distinctions of R&D investment could potentially reveal the reason for why we have widely varying estimates of the rate of returns to R&D. For example, supporting R&D activities are unlikely to have the same knowledge spillover effects as core R&D activities, since the latter are more likely to involve knowledge generation. Distinction by field of research could highlight, for example, the influence of intellectual property rights (IPR) in preventing knowledge spillovers in areas such as biotechnology and pharmaceuticals in which IPR protection tends to more effective.

Lastly, we contribute to the literature by providing a more comprehensive analysis on how the social rate of returns to R&D varies by the characteristics of the sources of R&D spillovers. For example, in addition to separating R&D spillovers from a firm's customers and suppliers, we also investigate how the spillovers vary when the sources are exporters or are new firms.

The basic model

Our basic model is the augmented Cobb-Douglas production function as specified in equation (1) and reproduced in equation (8) below using the corresponding lower-case letters to denote the logarithmic values of the inputs and output:[38]

$$y_{it} = \alpha_i + \beta_L l_{it} + \beta_K k_{it} + \beta_G g_{it-1} + \beta_S s_{it-1} + \lambda \bar{y}_t + \alpha_t + \alpha_s + \varepsilon_{it} \quad (8)$$

We estimate our basic model specified in equation (8) with the available data on value-added (sales less cost of sales) of each firm i in year t (Y_{it}), the accounting value of the tangible capital stock or non-current assets (K_{it}), the level of employment in terms of head counts (L_{it},), the firm's stock of R&D capital (G_{it-1}) constructed using the perpetual inventory method described in the literature review (equations 6a and b),[39] and the weighted sum of the stocks of R&D capital of all other firms ($S_{it-1} = \sum_{j \neq i} w_{ij} G_{jt}$); where w_{ij} is a weight which reflects the strength of the channels of knowledge transmission between the R&D generating firm and the receiving firm as discussed earlier and further detailed below.[40]

As discussed in depth in Bloom, Schankerman and Van Reenen (2013), there are three issues that could potentially result in biased estimates of the main parameters in equation (8): unobserved heterogeneity, endogeneity of external R&D and dynamics. We attempt to address each of these issues though not by using the identical approaches as proposed by them due to different nature

[37] These are different definitions from the Frascati Manual.

[38] We use lagged values for the R&D stock variables to account for one-period delay before R&D activities could affect output. In addition, we add economy wide average output ($\bar{y}$), period-fixed effects (α_t) and industry fixed effects (α_s) capture potential time-varying economy trend and other period and industry specific differences.

[39] In constructing the R&D stock (g_{it-1}) based on annual R&D expenditure data, we assume an R&D depreciation rate of 15% and a time lag of up to 15 years (common estimates by several studies range from 15% to 36% (Hall, Mairesse and Mohnen (2010)).

[40] Appendix Table 1 provides more details on the source of the data.

of our data. Thus, to make estimation and interpretation of equation (8) more tractable we have made several assumptions and assessments as detailed below.

First, we note that estimating the rates of return of R&D based on (8) in a first-difference model to control for the unobserved permanent productivity differences across firms may be difficult because of cyclical and measurement errors.[41] Specifically, our raw business tax filing data may have non-negligible measurement errors which appear to exacerbate the attenuation bias from implementing a firm fixed effect model specification.[42] Accordingly, we assume our intangible residual includes α_t, α_s and $\lambda\bar{y}_t$, which are respectively, year dummy variables, State dummy variables and 4-digit ANZSIC average value added to capture general economy, regional and sub-industry time-specific common shocks.

Secondly, since we do not have enough information to measure firm-specific unit cost of R&D for each different field of research nor do we observe any significant R&D policy variation across Australian states, we can only address any potential impact of endogeneity arising from unobserved transitory shocks on firm factor input decision indirectly in three ways:

a) We used one-period lagged internal and external R&D stocks to rule out contemporaneous shocks.
b) To assess any forward-looking implication on the estimated production function, we implement the Olley and Pakes (1996) control function estimator with ACF correction using value added as the dependent variable.
c) We also include in equation (2) a four-digit industry time varying control variable, defined as the annual average turnover in each industry, to capture common transitory shocks that might affect industry level unit cost of R&D.

Lastly, we include an 'error' term, ε_{it}, to capture all other determinants of firm productivity that are uncorrelated with the explanatory variables but collectively follow a normal distribution. Equation (8) also includes dummy variables if there is zero own R&D or zero external R&D in each firm/year.

External R&D measure

As discussed in Bloom, Schankerman and Van Reenen (2013), by only estimating a single production function such as equation (8), we abstract from the potential different channels for how external R&D affects any firm's productivity. For example, it is plausible that firm j's R&D affects firm i through G_{it} such as when firm j's R&D acts as a substitute to firm i's R&D. Another plausible channel of the external benefit is through the product market where firm j's R&D shifts the market demand for firm i's product. In this case, even if there is no knowledge spillover between the two firms, the ultimate effect may be captured by the external benefit parameter estimate of β_S in our reduced form equation.

Our approach also differs from Bloom, Schankerman and Van Reenen (2013) in one important way. As we do not have patenting information, we only use a product proximity weight based on input-output table. This means, our spillover estimates would capture the positive knowledge spillover effects and negative business stealing effects. If the latter dominates the former, then we may obtain a negative "knowledge spillovers" estimates.

[41] Hall, Mairesse and Mohnen (2010).
[42] Under constant returns to scale, the elasticities, parameters (α, β_L, β_K, β_G and β_S), would sum to one. However, if unobservable intangibles, which are typically non-rivalrous, play important roles in production, then the sum of the observed elasticities may be less than one but not significantly so.

Furthermore, we differ by distinguishing upstream and downstream spillovers by constructing two separate external R&D measures according to the use and supply intermediate input coefficients of the input-output table as described below.

Upstream spillovers (or spillovers from customers)

For the upstream spillovers, the knowledge spillovers come from the customers of the focal firm (firm i). In this case, the weighting matrix w_{ij} varies by how relevant business j's R&D is to business i, where relevance is measured by the input-output "use" coefficients (the proportion of firm i's industry outputs which are used by firm j's as industry input). For example, let say firm i produces steel which is used by firms in many different manufacturing and construction industries. Those firms are firm i customers. If they generate new knowledge from their R&D and if it spills over to firm i, then firm i may benefit more from the knowledge of those customer firms which use firm i's output relatively more intensively.[43]

Formally, the upstream external R&D is defined as:[44]

$$S^{U}_{it-1} = \sum_{j \neq i} w^{use}_{ij} G_{jt} \tag{9a}$$

where w^{use}_{ij} is the "use" input-output coefficients.

Downstream spillovers (or spillovers from suppliers)

The downstream spillovers measure the impact of knowledge spillovers coming from the suppliers of the focal firm. In this case, the weighting matrix w_{ij} is defined as w^{supply}_{ij}, constructed from the input-output supply coefficient (the proportion of firm i's industry <u>inputs</u> which are supplied by firm j). Formally, the downstream external R&D is defined as:[45]

$$S^{D}_{it-1} = \sum_{j \neq i} w^{supply}_{ij} G_{jt} \tag{9b}$$

where w^{use}_{ij} is the "use" input-output coefficients.

<u>The extended model</u>

To assess heterogeneity in R&D spillovers and returns to R&D, we further extend our basic model by distinguishing R&D stock according to the field of research and the characteristics for the firms receiving and sending the spillovers.

Field of research

The extension in terms of field of research is shown in equation (10) in which a new subscript f has been added to the R&D stock variables and parameters:[46]

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + \beta_{fG} g_{f,it-1} + \beta^{U}_{fs} s^{U}_{f,it-1} + \beta^{D}_{fs} s^{D}_{f,it-1} + \delta \bar{y}_t + \gamma_t + \gamma_s + \varepsilon_{it} \tag{10}$$

Where $g_{f,it-1}$ is the log of the firm i's own R&D capital stock in time t-1; $s^{U}_{f,it-1}$ is the log of spillover knowledge stocks in time $t-1$ coming from firm i's customers; and $s^{D}_{f,it-1}$ is the log of

[43] Ideally, if the data are available, we would want to use a firm-to-firm supply chain relationship. Here, we use the input-output coefficients as proxies for such supply chain relationship.

[44] To increase cross-firm variation with respect to $S_{f,it-1}$, we also impose a condition that the spillover effects is geographically bounded at the State level.

[45] We again impose a condition that the spillover effects is geographically bounded at the State level.

[46] We also distinguish between upstream and downstream.

spillover knowledge stocks in time $t-1$ coming from firm i's suppliers. Equation (10) allows us to estimate private and social returns to R&D in each field of research f. Recall from equation (4), total social returns from R&D in a field of research f is

$$\rho^{f} = (\beta_{fG} + \beta_{fs}^{U} + \beta_{fs}^{D}) \times \frac{Y}{G} \tag{11}$$

where $\beta_{fG} \times \frac{Y}{G}$ is private returns to R&D in field of research f and $(\beta_{fs}^{U} + \beta_{fs}^{D}) \times \frac{Y}{G}$ is the spillover returns from R&D in field of research f.[47]

For the field of research, we use the Australian and New Zealand Standard Research Classification (ANZSRC) information in the RDTI Program database to classify R&D engaged firms into its main field of research (defined as the field of research with the largest amount of R&D expenditure). The ANZSRC information is available up to four-digit classification. However, to ensure that we have a sufficient sample in each field of research to estimate equation (10) and to avoid potential multicollinearity if we have too many different fields in the same regression, we classify firms into five broad fields of research.[48] Following the research discipline classification of the Australian Research Council, we have classified the fields of research as:[49]

- **Bio**: Biology and Biotechnology
- **Eng**: Engineering
- **HCSE**: Humanities, Creative Arts, Social, Behaviour, Economics
- **IC**: Information and Computing
- **Pure**: Math, Physics, Chemistry, Earth science.

Source of spillovers

Like our upstream spillover measures ($s_{f,it-1}^{U}$) in equation (10) which construct external R&D measure coming from the customers of firm i as the source of spillovers, we construct alternative external R&D measures depending on the characteristics of the source firms. These characteristics include industry, export status, cohort year, and type of R&D activities (core or supporting). For example, we construct $s_{f,it-1}^{U,exporter}$ as a measure of external R&D from firm i's customers who are exporters and $s_{f,it-1}^{U,non\text{-}exporter}$ as the measure of external R&D from firm i's customers who are not exporters. Similarly, for example, we construct $s_{f,it-1}^{U,A}$ as the measure of external R&D from firm i's customers who are in industry division A (Agriculture, forestry and fishing).

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[47] In the review by Hall, Mairesse and Mohnen (2010, Tables 2a and 2b), studies used different assumptions with regards to $\frac{Y}{G}$ ratio and the value can range from 1 to 14. Bloom, Schankerman and Van Reenen (2013, 1383) assumed a value of 2.48; whereas, Goto and Suzuki (1989, Table 4) assumed a value in the range of 8 to 100 depending on the 2-digit industry. In our estimates, we use the median value-added to median R&D stocks.

[48] To avoid multicollinearity and omitted variable bias in equation (10), we include $\beta_{f's}^{U} s_{f',it-1}^{U} + \beta_{f's}^{D} s_{f',it-1}^{D}$. The subscript f' represent all other fields of research beside f, thus the variable $s_{f',it-1}^{U}$ represents the external R&D from all fields of research other than f. Thus, $\beta_{f's}^{U}$ and $\beta_{f's}^{D}$, capture the variation in the external R&D in the field of research of interest f while controlling for variation in all other types of technologies.

[49] Appendix Table 1 provides the ANZSRC codes for each of these broad fields of research.

Split-sample analysis

To examine potential heterogeneity in R&D spillovers, we estimate equations (10) and its various extensions as discussed above using several split samples:

- Industry division: 20 one-digit ANZSIC (exc. P) and Knowledge Intensive Sectors (KIS)[50]
- R&D status: all firms, R&D firms, and non-R&D firms
- Firm size: small (10-19 workers), medium (20-199 workers), and large (200+ workers)
- Type of R&D activities: core and supporting
- Firm age: startup (<= 5 years old) and established (6+ years old)
- Firm size and cohort: old large firms (born prior to 2000) and new large firms (born in 2000 or later)

The split sample analysis can potentially reveal, for example, the importance of absorptive capacity if the estimated spillover effects on R&D firms are larger than those on non-R&D firms.[51]

Data

BLADE: BAS, BIT, and RDTI Databases

Our empirical analysis uses a combination of databases available in the Business Longitudinal Analysis Data Environment (BLADE). These include three administrative databases from the Australian Taxation Office, the Australian Business Activity Statement (BAS), Business Income Tax records (BIT) and the Pay-as-You-Go records (PAYG) covering the universe of Australian businesses since the 2001/02 financial year.

To identify R&D active firms, we use the R&D expenditure values from the R&D Tax Incentive Program (RDTI) program database of the Department of Industry Science and Resources (DISR). This database covers all Australian Businesses that participated in the RDTI program. Significantly, the data include project-level information such as the four-digit Field of Research (FoR) classification and the type of R&D activities which allows us to investigate their role as mediating factor to R&D spillovers.

Sample Descriptives

Our main empirical analysis is based on both non-R&D active firms and R&D active firms who are registered with DISR's RDTI program. The sample period of our empirical analysis spans between 2002/3 and 2020/21. Because of missing values in key variables for estimating the regression models such as in equation (10), our full estimating sample consists of 146,814 distinct firms in our "All firms" sample. Out of these firms, 5,449 firms are R&D active.

Table 1 provides a descriptive statistics summary of the estimating sample.[52] Overall, if we considered all firms (with non-R&D active firms having $0 R&D investment), the average value of own R&D capital stock is $246,000.[53] However, if we restrict the sample only to R&D active firms, the average increases to $4,344,000. It is clear from Table 1 that large firms with more than 200 employees account for most of the R&D investment.

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[50] The Knowledge Intensive Services industry is defined following Eurostat's definition as listed in Appendix Table 2.

[51] See for example Mowery (1983) and Cohen and Levinthal (1989).

[52] As our estimating sample excludes micro firms as well as firms missing key variables required for analysis, we cannot be fully confident that Table 1 provides representative measures for the population.

[53] This is a panel average across firm-year observation. The value is in constant price.

In terms of field of research, Table 1 shows that approximately 85% of R&D active firms are investing in R&D in the fields of EN (Engineering) and IC (Information and Computing). Furthermore, these two fields of research received the highest average level of investment with own R&D stock with a value of $3,702,000 and $7,235,000 per firm per year, respectively.

Lastly, Table 1 also shows the average value of external R&D stock (external R&D of customers and external R&D of suppliers). Interestingly, the external R&D of suppliers is higher than the external R&D of customers, suggesting that supplier firm's R&D is higher.

Table 1: Estimating sample descriptive summary, annual average per firm, 2002/3 to 2020/21

Firm characteristic	Firm-year (observa-tions)	Turnover ($000)	Fixed assets ($000)	Employ-ment (FTE head count)	Own R&D stock ($000)	Supplier External R&D stock ($000)	Customer External R&D stock ($000
All firms	1,000,427	77,500	76,400	86	246	1,760,000	1,070,000
Small	463,356	2,945	7,523	12	42	1,930,000	1,120,000
Medium	487,678	15,700	17,900	49	146	1,590,000	1,020,000
Large	49,393	1,390,000	1,300,000	1,145	3,142	1,840,000	1,160,000
R&D firms	56,553	270,000	737,000	370	4,344	1,890,000	1,000,000
Small	15,831	5,081	6,956	12	1,214	2,650,000	1,370,000
Medium	29,844	25,600	37,800	60	2,388	1,550,000	814,000
Large	10,878	1,330,000	3,720,000	1,741	14,300	1,730,000	997,000
Main Field of Research							
Bio (Biology and Biotechnology)	4,755	89,200	98,500	224	2,092	1,320,000	607,000
Eng (Engineering)	33,001	149,000	285,000	271	3,702	1,380,000	689,000
HCSE (Humanities, Creative Arts, Social, Behaviour, Economics)	958	99,700	569,000	218	1,626	2,720,000	1,530,000
IC (Information and Computing)	14,674	658,000	2,110,000	702	7,235	3,300,333	1,880,000
Pure (Mathematics, Physics, Chemistry and Earth Science)	3,165	60,200	96,800	122	1,845	1,360,000	651,000

Note: There are 146,814 distinct firms in our "All firms" sample and 5,449 distinct firms in our "R&D"-firms sample. All R&D stock values are in constant prices; turnover and fixed assets are in current prices. External R&D stock is defined as the total own R&D stock of all other firms in the same state and subdivision, weighted by two-digit industry supply input-output coefficients. For Supplier External R&D stock, supply intermediate coefficients are used as the weights. For Customer External R&D stock, intermediate coefficients are used as the weights. Employment head count is based on Full-Time Employment equivalent.

Estimation results

Rate of returns to R&D by fields of research

We estimate equation (10) using three separate samples: all firms, R&D firms only, and non-R&D firms only. The output elasticity estimates with respect to own R&D stock and external R&D stocks (downstream and upstream) are summarised in Appendix Tables 3-5. We then use those elasticities estimate and equation (11), with a firm-level average value added to R&D stock ratio $\frac{Y}{G}$ = 20.2 to compute the annual (gross) rate of returns of own R&D (i.e., the private returns) and the annual (gross) rate of returns of spillovers R&D.[54] Table 2 summarises the average annual gross private and spillover returns to R&D received by firm in each estimating subsample (All firms, R&D firms and non-R&D firms) and the main field of research of the firm receiving the returns to R&D.[55]

Table 2: Estimates of rate of returns to R&D

Sample and Fields of Research which generate the returns	Gross annual return to R&D ($) per $1 R&D spent				
	Private returns	Upstream spillover returns (from customers' R&D)	Downstream spillover returns (from suppliers' R&D)	Total spillover returns	Total social returns
	(1)	(2)	(3)	(4) = (2) + (3)	(5) = (1) + (4)
Sample: All firms					
All fields of research	0.96	0.13	0.40	0.53	1.49
Biology/Biotech	0.86	0.18	-0.84	-0.66	0.20
Engineering	0.76	0.08	0.35	0.43	1.19
Humanities/Creative Arts/Social	1.06	-0.03	0.24	0.21	1.27
Information and Computing	1.03	0.09	0.52	0.61	1.64
Math, Physics, Chemistry, Earth	0.96	-0.14	-0.02	-0.16	0.81
Sample: R&D firms					
All fields of research	0.23	0.74	0.05	0.79	1.02
Biology/Biotech	0.25	0.21	-0.61	-0.40	-0.14
Engineering	0.14	0.25	0.20	0.45	0.59
Humanities/Creative Arts/Social	0.34	0.56	-0.32	0.24	0.58
Information and Computing	0.26	0.80	0.21	1.01	1.27
Math, Physics, Chemistry, Earth	0.26	0.20	-0.12	0.08	0.34
Sample: Non-R&D firms					
All fields of research		0.05	0.28	0.33	0.33
Biology/Biotech		0.12	-0.82	-0.70	-0.70
Engineering		0.00	0.41	0.41	0.41
Humanities/Creative Arts/Social		-0.07	0.26	0.20	0.20
Information and Computing		-0.05	0.61	0.56	0.56
Math, Physics, Chemistry, Earth		-0.11	-0.02	-0.13	-0.13

Notes: Private and social rates of returns to R&D are computed using the formula in equation (11): $\rho^f = (\beta_{fG} + \beta_{fs}^U + \beta_{fs}^D) \times \frac{Y}{G}$ with a $\frac{Y}{G}$ value of 20.2 and R&D capital stock elasticity estimates (the βs) presented in Appendix Tables 3-5.
Source: Processed from BLADE and RDTI databases.

In Table 2, column (1) presents the estimates of the average annual gross private returns to R&D. Looking at the All-firms sample and for All fields of research, a $1 R&D investment in year t-1 is associated with an annual increase in productivity of $0.96 in year t, all else equal. As we use

[54] That is, we have not accounted for annual depreciation in the R&D capital.
[55] Some firms may engage in more than one fields of research. In that case, we assign their main field of research as the field of research with the highest R&D investment.

both R&D active firms and non-R&D active firms, this private rate of returns reflects both intensive and extensive margins. A private rate of return of $0.96 per $1 investment is higher than estimates in existing studies discussed in the literature review section. As the literature estimates are based only on a R&D-firms dataset, they only capture returns at the intensive margins. In fact, if we now look at our private returns estimates based only on our R&D-firm sample, the rate of return is only $0.23. This rate of returns is more comparable to those estimates in the literature. This lower rate of return suggests that the rate of return to $1 R&D investment measured at the extensive margins (that is, comparing non-R&D firms to R&D firms) is significant. This measured impact of R&D at the extensive margins is not available when the sample consists of only R&D firms.

Column (4) in Table 2, defined as column (2) + column (3), provides the total R&D spillover effects. Thus, looking at the All-firms sample and All fields of research, the total annual R&D spillovers return to the whole private economy is estimated as $0.53 per $1 R&D investment. Given the total social returns of $1.49 (column 5 – which is private return plus spillovers), the spillover returns accounts approximately 36%. This suggests, a gap of at least 36% between the socially optimal level of R&D investment and the current level of private R&D investment.

Columns (2) and (3) in Table 2 splits the rate of returns from external R&D into the sources of the external R&D: customers (column 2) and suppliers (column 3). So, to use the above example, the overall average gross annual R&D spillover returns of $0.53 comes from customers' R&D ($0.13) and suppliers' R&D ($0.40). It is clear here that R&D investment by suppliers in the value chain generates most of the spillovers return. This suggests that rent spillovers are likely to be important if suppliers are unable to fully capture the rent from producing cheaper or higher quality inputs as a result of their R&D.

Depending on the relative importance of knowledge or rent spillovers and the business stealing effect, the spillover returns may be negative. This is especially the case if we consider R&D at a specific field of research. For example, if we look at Biology and Biotech and the All firms sample, column (3) shows a negative spillover rate of returns of -$0.84 for external R&D from suppliers.56 This may reflect the ability of R&D investment by supplier firms in this research field to use patent protection, as it is an effective way to protect expropriation in this field of research, to extract value from their R&D investment which could present as a negative shock to their customers (due to, say, monopoly pricing). A patent holder has the right to exclude others from using the embodied ideas for commercial use for up to 20 years. This includes building on the patented idea and improving it. As such, a third-party firm wishing to benefit from patented R&D stocks will need permission from the patent holder to commercially benefit from this idea. Typically, this is done through licensing, the revenue which is then captured in the patent holder's turnover data. Alternatively, as our method does not allow us to estimate the impact of R&D on organisations such as hospitals, not-for-profit agencies and governments, we may be understating spillover effects of the knowledge generated in physical and biological sciences.

In contrast, looking at the All-firms sample and "Math, Physics, Chemistry, and Earth science", the estimates in column (2) suggest a negative spillover returns of $-0.14. Given their private returns are positive (column 1), the firms who are engaged in these the Maths/Physics etc and Biology/Biotech fields of research are likely to have captured most of the short-term returns to R&D privately. 57

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[56] Implicit in the model is an assumption that the commercial return from R&D depreciates by 15% a year and that the discount rate on the use of funds is 3% a year. This means that 95% of all the benefits from the R&D investment accrue within 10 years. Patent protection lasts up to 20 years. If for example we assume R&D depreciates at 5% a year, then the 10-year return would only capture 58% of the lifetime returns.

[57] In general terms, the activity of one firm, whether it is about new skilled labour hiring, additional material purchases or new machinery installation, may affect the business performance of other firms

Table 2 shows that R&D spillovers from Information and Computing appears to be the highest among the fields of research. This finding is consistent with the characteristic of general-purpose technologies being pervasive and enabling. We note that Zhu and Jeon (2007) found that effect of inter-country information technology transmission on OECD productivity growth had been growing over the 1990s. Lucking, Bloom and Van Reenen (2019) found a positive bump in spillovers as a result of the millennial dot.com boom.

The fifth column of Table 2 presents the total social rate of returns, which represent how much the society benefit from $1 R&D investment after one year. Looking at all firms and all fields of research, a $1 R&D investment yield an average total social gross return of $1.49 in the following year. Assuming a depreciation rate of 15% and an interest rate of 3%, the average total private and social returns of $1 investment in R&D (in net present value term) are $4.60 and $7.14, respectively.

Lastly, before we move on to comparisons of spillover effects received by different industries, we note that the average spillover rates of returns received by R&D firms ($0.79 in column 4) is higher than the average spillover rates of returns received by non-R&D firms ($0.33). This indicates that absorptive capacity is potentially important for firms to benefit from external knowledge, as R&D firms are more likely to have a higher level of absorptive capacity. Furthermore, we also note that R&D firms appear to differ from non-R&D firms in terms of the vertical source of spillovers. R&D firms tend to benefit from positive R&D spillovers coming from their customers. In contrast, non-R&D firms tend to benefit from positive R&D spillovers from the suppliers.

Rates of returns to R&D by recipient industry

We also estimate a simplified version of equation (10) where we drop the subscript f to focus only on total R&D investment (regardless of fields of research) for each industry division separately. For the sample of all firms, the computed rate of returns based on the estimated R&D capital stock elasticities (the βs) are summarised in Table 3.[58]

Before proceeding with our interpretation of the estimates in Table 3, we note that some services industries only have a small number of R&D firms and they are thus combined as one: H, O, P, Q, R, S, which includes industries such as H (Accommodation and food services) and S (Other services). Having said that, we notice significant heterogeneity across industries in terms of the private returns to R&D. To some extent, this reflects inter-industry variation in the importance of R&D activities. It also indicates that a one size fit all policy across industries to increase R&D investment is likely to be suboptimal. This is even more clearly seen when we consider the variation in the total social returns to R&D enjoyed by firms in different industry.

The roles of firm size and age and the types of R&D activities

We also estimate a variant of equation (10) using split samples in terms of firm age and size. The resulting estimates, summarised in Table 4, reveal different aspects in the heterogeneity in the returns to R&D. First, comparing start-ups younger than five years to established firms six years and older, we can conclude that non-R&D start-up firms do not benefit as much in terms of total R&D spillovers. This is probably a story of inadequate absorptive capacity. However, they do still

through different channels. In the case of R&D, for firms in the same industry, R&D activities may increase the performance of the businesses performing R&D at the expense of its local competitors (Bloom, Schankerman and Van Reenen 2013). This may be by stealing market share as result of competition (de Bondt 1996) or by creating scarcity of inputs including those required in R&D production (McGahan and Silverman 2006; Buckley and Kafouros 2008; Kaneva and Untura 2018).

[58] The corresponding estimates for R&D-firms sample and non-R&D-firms sample are provided in Appendix Tables 6-7.

benefit from higher spillover effects from their suppliers, which is likely to reflect rent spillovers. Furthermore, established firms appear to have better ability to capture private returns to R&D.

Comparing the average total social rate of returns to R&D of the recipient firms across size categories (small, medium and large) reveals an inverted U relationship where medium sized firms with 20-199 workers appear to benefit most from R&D investment. The relationship is not as clear cut however if we consider upstream and downstream spillovers separately and the R&D activity status.

Table 3: Estimates of rate of returns to R&D by Receiving Industry, Sample = All firms

Receiving Industry Division	Gross annual return to R&D ($) per $1 R&D spent				
	Private returns	Upstream spillover returns (from customers' R&D)	Downstream spillover returns (from suppliers' R&D)	Total spillover returns	Total social returns
	(1)	(2)	(3)	(4) = (2) + (3)	(5) = (1) + (4)
All Divisions	0.96	0.13	0.40	0.53	1.49
A Agriculture, forestry, fishing	1.06	-0.63	0.35	-0.28	0.78
B Mining	1.15	-0.23	-0.23	-0.45	0.70
C Manufacturing	0.72	0.60	0.25	0.85	1.57
D Electricity, Gas, Water, Waste	-0.05	-0.47	0.92	0.45	0.39
E Construction	0.94	-0.40	0.67	0.27	1.21
F Wholesale trade	0.91	0.75	-0.02	0.73	1.64
G Retail trade	0.40	0.81	-0.14	0.67	1.07
I Transport, postal, warehousing	0.10	-0.69	0.99	0.30	0.40
J Information media, telecommunication	-0.03	2.02	-1.74	0.27	0.25
K Financial & insurance services	0.31	-0.03	1.05	1.02	1.33
L Rental, hiring, real estate	0.80	0.03	0.36	0.39	1.19
M Professional, scientific, technical services	0.30	-0.27	0.63	0.35	0.65
N Administrative and support	0.97	-1.58	1.76	0.17	1.14
H, O, P, Q, R and S (see Notes below)	1.82	-1.35	1.78	0.43	2.24
KIS (Knowledge intensive services)	0.73	0.62	0.01	0.63	1.36

Notes: Private and social rates of returns to R&D are computed using the formula in equation (11): $\rho^f = (\beta_{fG} + \beta^U_{fs} + \beta^D_{fs}) \times \frac{Y}{G}$ with a $\frac{Y}{G}$ value of 20.2 and R&D capital stock elasticity estimates (the βs) from the estimated model similar to equation (10). HOPQRS is H (Accommodation and food services), O (Public administration, safety), P (Education and Training), Q (Health care and Social Assistance), R (Arts and recreation), and S (Other services). These services divisions are aggregated due to their low level of R&D activities.
Source: Processed from BLADE and RDTI databases.

Table 4: Estimates of rate of returns to R&D by spillover receiving firms characteristics and the R&D status

Spillover Recipient Firm's characteristics and R&D status	Gross annual return to R&D ($) per $1 R&D spent				
	Private returns	Upstream spillover returns (from customers' R&D)	Downstream spillover returns (from suppliers' R&D)	Total spillover returns	Total social returns
	(1)	(2)	(3)	(4) = (2) + (3)	(5) = (1) + (4)
Recipient: start up (<=5 years old)					
All firms	0.46	-0.30	0.81	0.51	0.97
R&D firms	0.23	0.64	0.05	0.68	0.91
Non-R&D firms		-0.39	0.60	0.22	0.22
Recipient: established firms (6+ years old)					
All firms	0.92	0.41	0.17	0.58	1.50
R&D firms	0.15	0.70	0.12	0.82	0.94
Non-R&D firms		0.35	0.14	0.49	0.49
Recipient: large firms (200+ workers)					
All firms	-0.04	0.69	-0.15	0.54	0.50
R&D firms	-0.04	0.91	-0.30	0.61	0.57
Non-R&D firms		0.79	-0.37	0.41	0.41
Recipient: medium firms (20-199 workers)					
All firms	0.74	0.06	0.51	0.57	1.31
R&D firms	0.46	0.64	0.22	0.85	1.31
Non-R&D firms		0.01	0.35	0.36	0.36
Recipient: small firms (10-19 workers)					
All firms	0.19	-0.15	0.63	0.47	0.66
R&D firms	0.13	0.06	0.40	0.46	0.59
Non-R&D firms		-0.23	0.50	0.28	0.28

Notes: Private and social rates of returns to R&D are computed using the formula in equation (11): $\rho^{f} = (\beta_{fG} + \beta_{fs}^{U} + \beta_{fs}^{D}) \times \frac{Y}{G}$ with a $\frac{Y}{G}$ value of 20.2 and R&D capital stock elasticity estimates (the βs) from the estimated model similar to equation (10).

Source: Processed from BLADE and RDTI databases.

Source of spillovers

In the discussion so far, we mostly look at R&D spillovers from the perspective of the firms who are receiving R&D spillovers. It is also important for policy design and implementation to understand how R&D spillovers vary from the point of view of the source of the spillovers. We have considered the spillover source angle when we include two measures of external R&D depending on whether the R&D activities are done by supplier firms or customer firms along the value chains. In this section, we analyse additional dimensions of the source of R&D spillovers to get a better understanding of the extent of heterogeneity in the returns to R&D. Using the same strategy as the upstream and downstream distinction of the source of R&D spillovers, we construct separate external R&D capital stock measures depending on the industry of the firms doing the R&D activities and whether those firms are exporters or non-exporters. For example, in a modified form of equation (10), we may use $\beta_s^A s_{it-1}^{U,A} + \beta_s^{notA} s_{it-1}^{U,notA}$ to determine whether firms in ANZSIC Division A are an important source of R&D spillovers.[59] Table 5 summarises the estimation results.

Table 5: Estimates of spillover returns generated by $1 R&D in the source industry

Source Industry Division	Gross annual spillover returns from $1 R&D spent		
	Upstream spillover returns (from customers' R&D)	Downstream spillover returns (from suppliers' R&D)	Total spillover returns
	(1)	(2)	(3) = (1) + (2)
All Divisions	0.13	0.40	0.53
A Agriculture, forestry, fishing	0.50	-0.99	-0.48
B Mining	0.01	0.06	0.07
C Manufacturing	-0.21	-0.69	-0.91
D Electricity, Gas, Water, Waste	0.39	-0.55	-0.16
E Construction	0.28	0.10	0.38
F Wholesale trade	0.38	-1.06	-0.69
G Retail trade	0.12	-0.72	-0.60
I Transport, postal, warehousing	0.13	-0.06	0.07
J Information media, telecommunication	0.02	0.14	0.17
K Financial insurance services	-0.35	1.07	0.71
L Rental, hiring, real estate	0.19	0.20	0.40
M Professional, scientific, technical services	-0.29	0.99	0.70
N Administrative and support	-0.39	0.26	-0.14
H, O, P, Q, R, S (see Notes below)	-0.99	0.95	-0.04
KIS (Knowledge intensive services)	-0.32	1.00	0.68

Notes: Private and social rates of returns to R&D are computed using the formula in equation (11): $\rho^f = (\beta_{fG} + \beta_{fs}^U + \beta_{fs}^D) \times \frac{Y}{G}$ with a $\frac{Y}{G}$ value of 20.2 and R&D capital stock elasticity estimates (the βs) from the estimated model similar to equation (10). HOPQRS is H (Accommodation and food services), O (Public administration, safety), P (Education and Training), Q (Health care and Social Assistance), R (Arts and recreation), and S (Other services). These services divisions are aggregated due to their low level of R&D activities.
Source: Processed from BLADE and RDTI databases.

From Table 5, like all previous results, we see significant heterogeneity in terms of sources of positive spillovers. The R&D spillover estimates in Table 5 indicate that in general the services sector is the one that provides positive R&D spillovers in particular Financial insurance services;

[59] Note that this is different from the analysis in Table 3 where each row represent the industry of R&D spillover recipients.

Professional, scientific, technical services; Rental, hiring, real estate; and Information media, telecommunication. Surprisingly, Manufacturing appears to be a source of negative spillovers, suggesting a more dominant market stealing effect by R&D activities in that industry. The mining sector serves as a positive source of R&D spillovers, but the value of the spillovers is small ($0.07 per $1 R&D investment).

In Table 6 below, we further see heterogeneity in the source of R&D spillovers in terms of the characteristics of the R&D firms. First, based on export status, exporting firms provide positive R&D spillovers if they are the suppliers in the value chain (i.e., the R&D spillovers going downstream).[60] However, the estimates in Table 6 suggest that exporting firms provide negative R&D spillovers if they are the customers (column 1). This might reflect those exporters' need to find cheaper inputs as they compete in the world market.

Table 6: Estimates of spillover returns generated by $1 R&D, by the characteristics of the source firms and type of R&D activities

Firm and R&D types	Gross annual spillover returns from $1 R&D spent		
	Upstream spillover returns (from customers' R&D)	Downstream spillover returns (from suppliers' R&D)	Total spillover returns
	(1)	(2)	(3) = (1) + (2)
Source firm export status			
Exporter	-0.08	0.63	0.55
Non-exporter	0.37	-0.08	0.29
Source firm establishment year			
After 2000 (inclusive)	-0.20	1.25	1.05
Before 2000	0.19	0.07	0.26
Type of R&D activities			
Core R&D activities	0.23	0.19	0.42
Supporting R&D activities	0.16	0.09	0.25

Notes: Private and social rates of returns to R&D are computed using the formula in equation (11): $\rho^f = (\beta_{fG} + \beta_{fs}^U + \beta_{fs}^D) \times \frac{Y}{G}$ with a $\frac{Y}{G}$ value of 20.2 and R&D capital stock elasticity estimates (the βs) from the estimated model similar to equation (10). HOPQRS is H (Accommodation and food services), O (Public administration, safety), P (Education and Training), Q (Health care and Social Assistance), R (Arts and recreation), and S (Other services). These services divisions are aggregated due to their low level of R&D activities.
Source: Processed from BLADE and RDTI databases.

Secondly, from Table 6, we could see that the cohort of recently established firms (born after they year 2000, inclusive) appears to be a much more important source of positive R&D spillovers, particularly if the firms are suppliers. The estimate suggests as much as $1.05 worth of R&D spillover rate of returns generated by $1 R&D investment from the new firm cohort. This is almost 4 times as much R&D spillovers as those generated by the older cohort of firms established prior to the year 2000.

[60] That is we can use $\beta_s^{exporter} s_{it-1}^{U,exporter} + \beta_s^{notexporter} s_{it-1}^{U,notexporter}$

Lastly, Table 6 shows a comparison of two types of R&D activities: core and supporting. Included in core activities are all R&D and innovative activities. Supporting activities include expenditures to setup, for example, laboratories facility. In theory, the first type of activities is more likely to be associated with knowledge generating activities and thus can potentially provide a higher level of beneficial R&D spillovers. If we look at the bottom panel in Table 6, this appears to be the case. Total spillover rate of returns to Core R&D is $0.42, which is much higher than that of supporting activities at $0.25.

5. Australian Labour Mobility Channel of Knowledge Transmission

Introduction

It has long been understood that critical business information and knowledge spreads across organisations with staff movement. Agrawal, Cockburn and McHale (2006) find evidence supporting the view that personal relationships formed through co-location within an organisation can endure over time, space, and organizational boundaries. However, it is not until the event of comprehensive employer-employee longitudinal datasets that we have been able to get robust quantitative evidence on the impact of people movement. Australian employer-employee data sets have only been made available to researchers in the last couple of years.

Below we present estimates of the effect which employees, who had worked for an R&D active public or corporate sector organisation in the last 2 years, have on a private-sector firm that subsequently hires them.

Impact of hiring high-tech workers from R&D active firms

In this section we assess the importance of worker mobility as a channel of R&D generated knowledge transmission among Australian businesses. To do that, we use linked employer-employee database (PLIDA and BLADE) to identify for-profit firms who hired high-tech employees from other R&D active firms or organisations. These R&D active firms or organisations include for profit firms in the corporate sector or government or not-for-profit organisations which had been R&D active in the previous two decades. The latter include all tertiary education organisations such as universities and TAFE colleges. We use the occupation information as two-digit ANZSCO occupation codes to identify high-tech employees. These codes include: 11 Chief Executives, General Managers and Legislators; 13 Specialist Managers; 23 Design, Engineering, Science and Transport Professionals; 26 ICT Professionals; 31 Engineering, ICT and Science Technicians; 34 Electrotechnology and Telecommunications Trades Workers.

We then estimate an augmented Cobb-Douglass production function panel regression model like the one specified in equation (1) with a slightly different set of explanatory variables. The basic specification of the estimating equation (Model 1) in log-linear format is:

Model 1:

$$y_{it} = \alpha + \beta_L l_{it} + \beta_K k_{it} + \beta_g g_{it-1} + \beta_m m_{it} + \beta_R r_{it-1} + \gamma_N new\text{-}nonRD_{it} + \gamma_R new\text{-}RD_{it} + \alpha_t + \alpha_i + \varepsilon_{it} \tag{12}$$

where i indexes firm and t indexes year and y denotes sales turnover (log), l denotes number of employees (log), k denotes total assets, g denotes total intangible assets, m denotes operating expenses, r denotes R&D spending, $new\text{-}nonRD$ denotes share of newly hired employees from non R&D active firms, and $new\text{-}RD$ denotes share of newly hired high-tech employees from R&D active firms; and α_t and α_i are year and firm fixed effects. [61]

We estimate Model 1 as specified in equation (12) using data from a sample of for-profit firms with over 20 employees. The estimation results are shown in Column (1) of Table 7 below which reveals that all the expected variables are significant and correctly signed – and notably the coefficients on own R&D and intangible assets show that both have a positive effect on firm labour productivity after controlling for the level of tangible assets. Importantly for the purpose of knowing whether worker mobility is a conduit for R&D know-how, we find that whereas hiring new non-R&D workers has a negative effect on productivity (possibly due to the costs of induction and training), new R&D active workers have a positive effect on productivity. There is considerable

[61] See Appendix Table 8 on the data definition of these explanatory variables.

agreement in the literature that for firms to fully absorb the know-how from other agencies, it should employ high-tech employees.

In Columns 2 and 3, we extend Model 1 into Model 2 and Model 3 by including a variable that measures the percentage of the receiving firm's employees who are defined as a high-tech employee. In Column 2, we include this high-tech employee variable and its interaction with the percentage of new R&D active employees. Column 2 shows that both the percentage of high-tech employees and its interaction with new R&D active employee are positive and significant, *ceteris paribus*. This supports the absorptive capacity theory.

Table 7: Estimate of the impact of hiring high-tech workers from R&D firms[62]

Dep. Variable = $log(Turnover)_{it}$

Explanatory variables	Model 1	Model 2	Model 3
	(1)	(2)	(3)
$log(Employment)_{it}$	0.750^{***}	0.750^{***}	0.750^{***}
	(0.002)	(0.002)	(0.002)
$log(Total\ assets)_{it}$	0.009^{***}	0.009^{***}	0.009^{***}
	(0.002)	(0.000)	(0.000)
$log(Intangible\ assets)_{i,t-1}$	0.002^{***}	0.002^{***}	0.002^{***}
	(0.000)	(0.000)	(0.000)
$log(Operating\ expenses)_{t}$	0.011^{***}	0.011^{***}	0.011^{***}
	(0.001)	(0.000)	(0.000)
$log(R\&D\ spending)_{i,t-1}$	0.002^{***}	0.002^{***}	0.002^{***}
	(0.000)	(0.000)	(0.000)
$log(Share\ of\ new\ nonR\&D\ workers)_{it}$	-0.010^{***}	-0.009^{***}	-0.009^{***}
	(0.001)	(0.001)	(0.001)
$log(Share\ of\ new\ R\&D\ workers)_{it}$	0.002^{***}	-0.012^{***}	
	(0.001)	(0.003)	
$log(Share\ of\ high\text{-}tech\ workers)_{it}$		0.010^{***}	0.009^{***}
		(0.008)	(0.001)
$log(Share\ of\ new\ R\&D\ workers)_{it}$		0.004^{***}	
$\times\ log(Share\ of\ hightech\ workers)_{it}$		(0.001)	
$log(Share\ of\ new\ R\&D\ workers\ ex\text{-}public)_{it}$			-0.015^{**}
			(0.006)
$log(Share\ of\ new\ R\&D\ workers\ ex\text{-}corporate)_{it}$			-0.012^{***}
			(0.003)
$log(Share\ of\ new\ R\&D\ workers\ ex\text{-}public)_{it}$			0.002
$\times\ log(Share\ of\ hightech\ workers)_{it}$			(0.002)
$log(Share\ of\ new\ R\&D\ workers\ ex\text{-}corporate)_{it}$			0.004^{***}
$\times\ log(Share\ of\ hightech\ workers)_{it}$			(0.001)
Observations	1,044,561	1,044,561	1,044,561
R^2	0.328	0.328	0.328

Notes: Firm is indexed by i and year is indexed by t. Sample consists of for-profit firms in Australia over 2001-02 to 2021-22. Standard errors in parentheses. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Regression model is panel with firm fixed effects and includes, but not shown, year dummy variables to account for inflation and a constant.

In Column 3, we disaggregate the new R&D active employees into those coming from a public-sector organisation and those coming from a corporate-sector firm. As before, to test for the

[62] A high-tech worker is defined as ANZSCO 11 Chief Executives, General Managers and Legislators; 13 Specialist Managers; 23 Design, Engineering, Science and Transport Professionals; 26 ICT Professionals; 31 Engineering, ICT and Science Technicians; 34 Electrotechnology and Telecommunications Trades Workers.

impact of both these new hires given the level of high-tech employees in the hiring firm, we include interaction terms. The coefficients in Column 3 suggest that it is only new R&D active employees who previously worked in the corporate sector have a positive effect on the receiving firm's productivity.

To estimate the impact on productivity (i.e., turnover after accounting for other inputs) of hiring R&D active employees from other firms we simulate the marginal effects within the model. These simulations assume 50% of the workforce in receiving firms are from high-tech occupations and all other inputs are held at their actual values. The results from these simulations are shown in Table 8. They reveal that if a firm's new R&D active hires from corporate sector increases from zero to 1% of their workforce, their productivity will rise by 0.267%. The effect on productivity from the same rise in public sector R&D active new hires is negligible.

Table 8: Simulated marginal effects (Increase new R&D active employees from 0% to 1%) implied by Table 7, Columns 2 and 3

Previously worked in...	Annual turnover increases (%)
Both sectors	0.058***
Corporate sector	0.267***
Public sector	-0.355

Note: Estimated from Table 7, Columns 2 and 3

Heterogeneity in labour mobility effect

Does the size of the receiving firm matter?

There are several reasons to expect that the size of the receiving firm affects how impactful new R&D active employees will be – even after we account for the level of R&D being undertaken in this firm. Larger firms are more likely to have economies of scale and scope and therefore be able to successfully integrate new R&D active employees. Table 9 re-estimates the basic model (Model 1) with four separate subsamples according to the receiving firm's employment size. It shows that larger firms have the greater impacts from hiring new R&D active workers than small and micro firms.

Table 9: Determinants of firm productivity by firm size; Dep. Variable = Ln(Turnover), for-profit firms only, Australia, 2001-02 to 2021-22

Explanatory variables	**5-9 employees**	**10-19 employees**	**20-199 employees**	**Over 200 employees**
	(1)	(2)	(3)	(4)
$log(Employment)_{it}$	0.573***	0.646***	0.768***	0.731***
	(0.002)	(0.003)	(0.002)	(0.005)
$log(Total\ assets)_{it}$	0.016***	0.013***	0.009***	0.006***
	(0.000)	(0.000)	(0.000)	(0.001)
$log(Intangible\ assets)_{i,t-1}$	0.005***	0.004***	0.003***	0.001***
	(0.001)	(0.001)	(0.000)	(0.000)
$log(Operating\ expenses)_{t}$	0.016***	0.012***	0.010***	0.048***
	(0.000)	(0.000)	(0.000)	(0.001)
$log(R\&D\ spending)_{i,t-1}$	0.002***	0.000	0.002***	0.001***
	(0.001)	(0.000)	(0.000)	(0.000)
$log(Share\ of\ new\ nonR\&D\ workers)_{it}$	-0.005***	-0.010***	-0.014***	0.014**

	(0.000)	(0.001)	(0.001)	(0.006)
$log(Share\ of\ new\ R\&D\ workers)_{it}$	-0.000	0.000	0.001*	0.011**
	(0.001)	(0.001)	(0.001)	(0.005)
Observations	2,057,981	1,228,512	967,170	77,391
R2	0.083	0.123	0.293	0.411

Notes: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Includes year dummy variables to account for inflation and constant. The 5-9 employees and 10-19 employees subsamples were not part of the estimating sample for the regression estimates in Table 7.

Table 10 converts the coefficients into simulated marginal effects of a 1 percentage point increase (from 0 to 1) in new-to-the-firm R&D active employees on the firm's annual turnover. It shows that the greatest impact is on large firms with over 200 employees. A change in new hires from zero to 1% of the workforce, increases productivity in marge firms (over 200 employees) by 1.435%. The impact on smaller firms is negligible.

Table 10: Simulated marginal effects (Increase new R&D active employees from 0% to 1%) implied by Table 9

Size of firm	Annual turnover increases (%)
5-9 employees	-0.027
10-19 employees	-0.060
20-199 employees	-0.112*
Over 200 employees	1.435**

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Does the industry of the receiving firm matter?

As it is plausible that the impact on new hires depends on the market and technology of the receiving firm and accordingly, we estimate the extended model (disaggregating whether the new hires came from the public or corporate sectors) by broad industry group. The estimation results based on broad industry group split-sample are presented in Appendix Table 10 and, similar to the previous results, supports the theory that to benefit from external research one needs to have considerable absorptive capacity within the receiving firm and that the R&D active workers who gained their experience from the corporate sector have most impact.

In addition, we can see from the corresponding simulated marginal shown in Table 11, receiving firms in 'Transport; postal and warehousing; Information media and telecommunications; Financial and insurance services; Rental, hiring and real estate services; Professional, scientific and technical services' gain the most from hiring R&D active employees. This broad industry sector was also the only sector to register a positive and significant impact from public sector R&D new hires.

Table 11: Simulated marginal effects (Increase new R&D active employees from 0% to 1%)

Broad industry sector (receiving firm), for profit	Previously worked in…	Annual turnover increases (%)
Agriculture	Public sector	-0.098
	Corporate sector	0.244
Mining; Manufacturing, Electricity, gas and water; Construction; and Wholesale trade	Public sector	-0.118
	Corporate sector	0.0173
Transport; postal and warehousing; Information, media and telecommunications; Financial and insurance services; Rental, hiring and real estate services; Professional, scientific and technical services	Public sector	0.082*
	Corporate sector	0.505***
Administrative and support services; Public administration and safety; Health care and social assistance; Education and training	Public sector	-0.447**
	Corporate sector	0.328**
Retail trade; Accommodation and food services; Arts and recreation services; Other services	Public sector	-0.192
	Corporate sector	0.192***

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Only includes firms with over 20 employees

Do CRC or RSP experienced workers have a different impact?

We have information on whether mobile workers have come from an entity registered as a Cooperative Research Centre (CRC) or Research Service Provider (RSP). CRCs are collaborative university-industry programs that are funded roughly a third from each industry, government and universities. They last up to 10 years in duration, have a typical income in the $20 million to $70 million range and are predominantly from the science, technology, engineering and medical fields of research. RSPs are specialist organisations (registered with the Government) to undertake research and development on behalf of, or under contract to other companies.

Compared with the Government's R&D program, which is entitlement based, the CRC program is competitive. Its distinguishing feature is its emphasis on quality research to solve industry-identified problems and outcome-focused collaborative research partnerships between industry and research organisations. It encourages collaboration with small and medium enterprises. RSPs are commercial businesses that live or die by their research quality. Accordingly, we expect that workers experienced in both the CRC and RSP organisations will be highly skilled in producing commercially impactful research.

In Appendix Table 11, we estimate the same model as in Table 7 but include a variable to indicate whether the employee had experienced working in a CRC or RSP in the prior 2 years (noting that a given employee can be classified as both R&D active and CRC/RSP active). As before, this indicator only applies to workers in the high-tech occupations. The results suggest that employees who previously worked in either a CRC or RSP has an impact on the receiving firm's productivity over and above having worked in a R&D active firm.[63] In Table 12, we present the simulated effects of CRC/RSP experience.

[63] Note that due to data limitations the time period for Appendix Table 11 is shorter than Table 7 and is not strictly comparable.

Table 12: Simulated marginal effects (increase new CRC/RSP active employees from 0% to 1%) implied by Appendix Table 11, Columns 2 and 3

Previously worked in...	Annual turnover increases (%)
Both corporate and public sectors	0.587

Note: Holds constant the number of R&D workers

Table 13 (marginal effects based on the regression estimates in Appendix Table 12) show that the greatest impact of hiring an CRC/RSP worker is in medium size firms (20-199 employees). An increase new CRC/RSP active employees from 0% to 1% will raise productivity by 0.339%. The impact on smaller firms is positive but the impact on firms over 200 employees is negative.

Table 13: Simulated marginal effects (increase new CRC/RSP active employees from 0% to 1%)

Size of firm	Annual turnover increases (%)
All sizes	0.587
5-9 employees	0.076
10-19 employees	0.035
20-199 employees	0.339***
Over 200 employees	-0.406

Note: Holds constant the number of R&D workers

We then estimate the same productivity model separately for 5 broad for-profit-sector industry groups (1) Agriculture; (2) Mining; Manufacturing, Electricity, gas and water; Construction; and Wholesale trade;[64] (3) Transport; postal and warehousing; Information, media and telecommunications; Financial and insurance services; Rental, hiring and real estate services; Professional, scientific and technical services; (4) Administrative and support services; Public administration and safety; Health care and social assistance; Education and training; (5) Retail trade; Accommodation and food services; Arts and recreation services; Other services.

The estimation results for these five broad industry sectors separately are not presented but the simulated effects are presented in Table 14. It reveals that former CRC/RSP employees had the largest impact in the broad for-profit sector consisting of Administrative and support services; Public administration and safety; Health care and social assistance; Education and training. Former CRC/RSP employees were also influential in Retail trade; Accommodation and food services; Arts and recreation services; Other services. The effects on Agriculture; Mining, Manufacturing, Electricity, gas and water; Construction; and Wholesale trade; Transport; postal and warehousing; Information, media and telecommunications; Financial and insurance services; Rental, hiring and real estate services; Professional, scientific and technical services, were negligible.

Table 14: Simulated marginal effects (Increase new R&D active employees from 0% to 1%) (regression table not shown)

Broad industry sector (receiving firm), for profit	Previously worked in...	Annual turnover increases (%)
Agriculture	CRC/RSP	0.400
Mining; Manufacturing, Electricity, gas and water; Construction; and Wholesale trade	CRC/RSP	0.183
Transport; postal and warehousing; Information, media and telecommunications; Financial and insurance services; Rental, hiring and real estate	CRC/RSP	0.488

[64] We include Wholesale trade in this group as our previous research has revealed that many good producing firms are classified as wholesale trade if they outsource the processing or manufacture of the product (but undertake design, R&D and sales in-house).

services; Professional, scientific and technical services		
Administrative and support services; Public administration and safety; Health care and social assistance; Education and training	CRC/RSP	1.378***
Retail trade; Accommodation and food services; Arts and recreation services; Other services	CRC/RSP	1.063*

Note: * p < 0.10, ** p < 0.05, *** p < 0.01. Only includes firms with over 20 employees; holds constant the number of R&D workers

6. Heterogeneous Additionality of Australian R&D Tax Incentives

Introduction

We extend Thomson et al. (2025)'s recent assessment of the Australian R&D Tax Incentive (RDTI) program by using the same established Regression Discontinuity Design (RDD) framework to examine heterogeneous treatment effects across multiple dimensions of interest to policymakers. In particular, these treatment effects will allow us to causally estimate how responsive firms are to the R&D tax incentive program.

Our fundamental identification strategy remains unchanged: we compare firms just below and just above the $20 million aggregate turnover threshold, exploiting the discontinuous change in tax offset rates at this threshold between the 2013/14 and 2020/21 financial years. The key innovation is allowing the treatment effect—the causal impact of receiving the higher refundable offset rate—to vary systematically with pre-treatment firm and sectoral characteristics.

Following the framework developed by Calonico et al. (2025), we estimate conditional average treatment effects (CATEs) that capture how the program's impact differs across subpopulations. The empirical specification builds naturally on the baseline RDD model shown in Equation (1). Our heterogeneous effects specification extends this to allow the treatment effect to vary with observed subsamples. Although too complex to represent in a simple equation, it functionally amounts to a fully interacted model for a firm's treatment status, its running variable, and the set of subsamples.

Our extension focuses on pre-determined subsamples that can be partitioned into distinct, non-overlapping subgroups. This corresponds to familiar subgroup analysis where we estimate separate treatment effects for different categories of firms. For instance, we might classify firms as operating in distinct ANZSIC divisions, or as young versus mature firms. In this case, the heterogeneity analysis amounts to estimating the RDD separately for each subgroup, with appropriate adjustments to ensure valid inference when making comparisons across groups. This subgroup approach is particularly well-suited to categorical distinctions that map naturally onto the policy questions discussed in the spillover analysis. Nevertheless, it is important to note that these estimates are "local," insofar as they may only apply to the set of firms around the threshold for the given the subgroup being analysed. We recommend caution on extending the analysis to firms outside of the aggregate turnover bandwidth being analysed.

Empirical Approach

The R&D Tax Incentive has a well-defined treatment discontinuity at an aggregate turnover of $20 million. Firms below this threshold are eligible to claim a 43.5% refundable tax offset (45% prior to the 2016/17 financial year), whereas firms above the threshold can claim a 38.5% non-refundable tax offset (40% prior to 2016/17). Hence, as in Thomson et al. (2025), our approach to identifying the additionality achieved by the Australian R&D Tax Incentive follows a (RDD). Outside of randomized interventions, RDD is a powerful quasi-experimental method for establishing causality (Cattaneo, Idrobo and Titiunik, 2020).

The Regression Discontinuity Design

The core logic of RDD is to compare firms just on either side of the policy threshold. The estimated difference in R&D at this threshold can be causally attributed to the differential offset rates, under the assumption that firms just on either side are otherwise comparable.

To describe this approach more formally, we first introduce some key concepts:

- Running variable: The variable determining treatment status which in this context is aggregate turnover.

- Cut-off: The value of the running variable determining treatment status—in this case, $20 million in aggregate turnover.
- Bandwidth: The range on either side of the cut-off that the researcher considers comparable.

To estimate the policy impact statistically, RDD involves modelling the relationship between the running variable and the outcome (R&D) while allowing for a discontinuity at the cut-off. The estimate can be interpreted as the causal effect of the treatment provided firms cannot manipulate their classification—that is, manipulate their reported turnover to place themselves on one side of the threshold (Lee, 2008).

Validity of the No Manipulation Assumption

We believe this no-manipulation assumption is reasonable in this context. Persistent, systematic manipulation of reported turnover is difficult, and suppressing real sales to qualify for a higher R&D tax offset rate is unlikely to serve shareholders' interests—especially given that the value of the R&D Tax Incentive typically constitutes a small fraction of the overall balance sheet for the overwhelming majority of firms.

We distinguish this from simple timing manipulations, such as end-of-year delays in invoicing to reduce revenue in a particular period. Such practices are unlikely to be effective for achieving a particular turnover figure over a full income year. These arguments are supported by statistical tests and robustness checks described below.

Baseline Estimation

The simplest method of estimating the RDD statistically is a OLS regression of the form:

$$\begin{aligned} \ln(\mathrm{R\&D}) = \beta_0 + \beta_1(Running - CutOff) + \beta_2 Refundable \\ + \beta_3(Running - CutOff) \times Refundable + \varepsilon \end{aligned} \tag{13}$$

where $ln(R\&D)$ is the log of a firms R&D expenditures subject to the tax incentive, $Running$ is a firms log aggregate turnover and the $CutOff$ is the log of $20 million and $Refundable$ is an indicator variable whether a firm is below the threshold and therefore claiming the higher, refundable offset. β_2 is the key coefficient of interest as it is the estimated treatment effect of the R&D Tax policy and will be used as the basis for determining additionality.

We follow convention of modelling R&D demand against turnover in logs, which also accounts for the skewed values of R&D and turnover values within the data. Our main findings are robust to variation in bandwidth employed, but our primary findings use a data-driven bandwidth selection technique described in Calonico et al. (2014).

Extending the Analysis to Heterogeneous Treatment Effects

Our analysis extends the established RDD framework to examine heterogeneous treatment effects across multiple dimensions of interest to policymakers. The fundamental identification strategy remains unchanged: we compare firms just below and just above the $20 million aggregate turnover threshold, exploiting the discontinuous change in tax offset rates at this threshold.[65] The key innovation is allowing the treatment effect—the causal impact of receiving

[65] A key identifying assumption of our RDD approach is that the discontinuity in R&D expenditure at the $20 million threshold is caused by the differential tax offset rates, rather than other factors that might change discontinuously at this threshold. To assess the validity of this assumption, omitted from this report, we examined whether other firm-level outcomes exhibit similar discontinuities at the $20 million cutoff. We examine six alternative outcome variables: capital expenditures, employment, profit, asset,

the higher refundable offset rate—to vary systematically with pre-treatment firm and sectoral characteristics.

Following the methodological framework developed by Calonico et al. (2025), we estimate conditional average treatment effects (CATEs) that capture how the program's impact differs across subpopulations. The empirical specification builds naturally on the baseline RDD model shown in equation (13). Our heterogeneous effects specification extends this to allow the treatment effect to vary with observed subsamples. While too complex to represent in a simple equation, it functionally amounts to a fully interacted model for a firm's treatment status, its running variable, and the set of subsamples.

Our extension focuses on pre-determined subsamples that can be partitioned into distinct, non-overlapping subgroups. This corresponds to familiar subgroup analysis where we estimate separate treatment effects for different categories of firms. For instance, we might classify firms as operating in distinct ANZSIC divisions, or as young versus mature firms. In this case, the heterogeneity analysis amounts to estimating the RDD separately for each subgroup, with appropriate adjustments to ensure valid inference when making comparisons across groups.

This subgroup approach is particularly well-suited to categorical distinctions that map naturally onto the policy questions discussed in the spillover analysis.

Estimation and Inference

Implementation of the heterogeneous effects RDD follows the robust bias-correction framework first developed by Calonico et al. (2014) and extended to the CATE context by Calonico et al. (2025). Several technical features of this approach warrant brief mention for transparency, though the underlying statistical theory is beyond the scope of this policy-oriented report.

The estimation employs local polynomial regression, which fits separate flexible polynomial functions to the relationship between the running variable (aggregate turnover) and the outcome (R&D expenditure) on each side of the threshold, while allowing these relationships to interact with the heterogeneity covariates. We follow standard practice by using local linear regression (first-order polynomials) as the baseline specification, which balances bias and variance considerations and has well-understood theoretical properties.

The bandwidth—the window around the $20 million threshold within which we include observations—is selected using data-driven, mean squared error optimal procedures. Importantly, when conducting subgroup analysis with binary orthogonal covariates, we allow the optimal bandwidth to differ across subgroups as well as on both sides of the threshold. This recognizes that the optimal comparison window need not be identical across different subsets of the data, just as it need not be identical across different datasets.

Inference incorporates robust bias correction, which addresses the fact that the local polynomial estimator is biased in finite samples. Standard confidence intervals that ignore this bias have incorrect coverage rates. The bias-corrected approach constructs confidence intervals that maintain valid coverage while preserving the desirable power properties of the point estimator. Standard errors are adjusted for clustering at the enterprise group level, recognizing that firms within the same corporate structure may exhibit correlated R&D investment decisions.

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income and wages and find no statistically significant discontinuities. The absence of discontinuities in these alternative outcomes provides strong support for the validity of our identification strategy.

Calculating Input Additionality from Treatment Effects

Input additionality measures the amount of new R&D investment induced per dollar of tax revenue forgone.[66] Our RDD approach estimates the treatment effect of receiving the more generous refundable offset (43.5% or 45% depending on year) compared to the less generous non-refundable offset (38.5% or 40%). We derive implied additionality from these regression estimates using counterfactual analysis for a representative firm near the $20 million threshold.

The treatment effect from our RDD estimates represents the percentage increase in R&D expenditure associated with receiving the higher offset rate. To convert this into an additionality measure, we calculate the additional R&D investment per dollar of additional tax revenue forgone when shifting a firm from the lower to the higher offset rate.

The increase in forgone tax revenue from this shift reflects two components:

- **Inframarginal effect**: R&D that would have occurred anyway now receives a higher offset rate (e.g., 45% instead of 40%)
- **Marginal effect**: Additional R&D induced by the higher offset rate is eligible for that higher rate

For a representative firm at the threshold with baseline R&D expenditure R_0, receiving the lower offset rate r_L, the additionality when shifting to the higher offset rate r_H can be calculated as:

$$\text{Additionality} = \frac{\delta \times R_0}{(r_H - r_L) \times R_0 + r_H \times \delta \times R_0} \tag{14}$$

where δ represents the proportional increase in R&D (the treatment effect from our RDD estimates). The numerator captures the additional R&D investment induced by the policy, while the denominator represents the total increase in forgone tax revenue from both inframarginal and marginal R&D.

This formula simplifies to:

$$\text{Additionality} = \frac{\delta}{(r_H - r_L) + r_H \times \delta}$$

For example, if our RDD estimates indicate that the higher offset rate induces a 30% increase in R&D ($\delta = 0.30$), and the offset rates are 40% and 45%, the implied additionality would be:

$$\text{Additionality} = \frac{\delta}{(r_H - r_L) + r_H \times \delta} = \frac{0.30}{0.185} = 1.62$$

This means that for every dollar of additional tax revenue forgone, firms invest $1.62 in additional R&D.

[66] Omitted from this report, we also conducted output additionality of Australian R&D tax incentives using data on patent and trademark filing by the R&D performing firms. We found no detectable output additionality, a result that is consistent with the Thomson et al. (2025) who similarly found little evidence of output additionality. It is important to note, however, that the absence of measurable output additionality does not necessarily imply the policy is ineffective. Input additionality—documented clearly in our results discussed in this report—indicates firms are genuinely increasing R&D investment in response to the incentive. Whether this translates to economically valuable innovation may not be fully captured by patent and trademark measures, particularly for the types of firms and R&D activities prevalent near the $20 million threshold or within the timeframes easily measured using this approach.

Important Caveats

Several caveats should be acknowledged when interpreting these additionality estimates:

Refundability versus rate effects: Our calculation assumes the difference in investment is entirely attributable to the higher offset rate, not the refundability per se. For firms with sufficient tax liability, this is appropriate. However, for firms with exhausted tax liabilities, non-refundable offsets must be carried forward to future years, reducing their present value. We cannot separately identify how much of the treatment effect stems from the 5 percentage point rate difference versus the refundability feature.

Real versus reported R&D: We cannot directly assess the extent to which reported R&D expenditure for tax purposes corresponds to variation in real R&D activity. Two concerns arise: relabelling existing activities as R&D to access the incentive, and input price inflation (paying more for the same inputs without increasing real R&D). Evidence on R&D tax incentives and input price inflation can be found in Thomson and Jensen (2013).

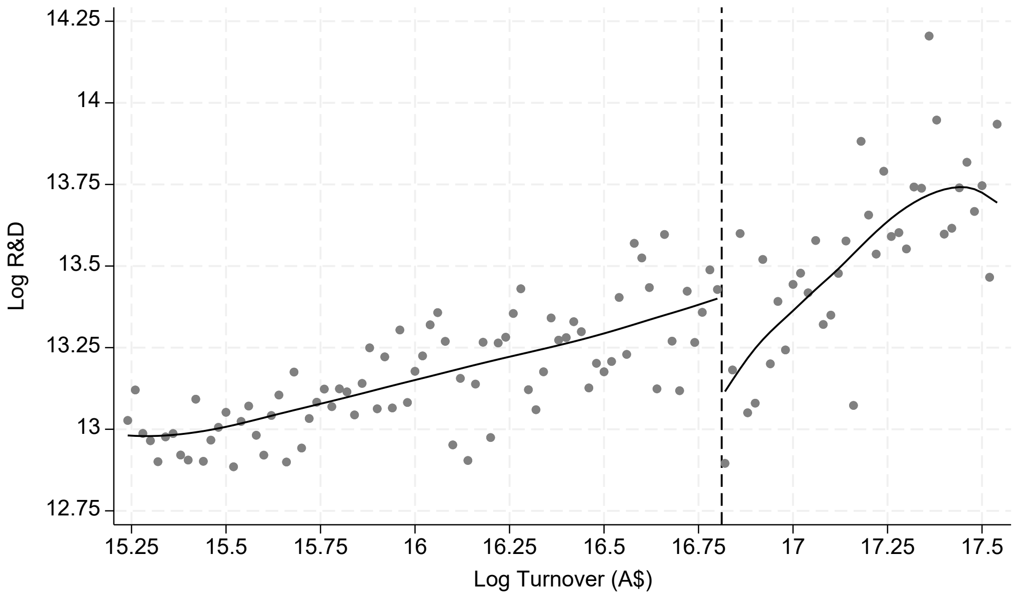
External validity: While RDD is a powerful technique for identifying causal effects for firms near the policy threshold, it has well-known limitations in external validity. We cannot assess whether firms distant from the $20 million threshold would respond similarly to changes in offset rates. Our estimates are most directly applicable to firms near this threshold.

Results

Discontinuity and Treatment Effect Estimate

We first visually explore for evidence of a discontinuity at the $20 million turnover threshold. Figure 1 depicts the relationship between turnover and R&D (both in logs) for our primary regression sample found in column (3) of Table 15. Following standard practice, we aggregate 10,140 firms into turnover bins with a fixed width of 0.02 log points, representing on average 87 firms per bin whose turnover ranged from $4.1 million to $42.3 aggregate turnover. The fitted lines illustrate predictions from locally weighted scatterplot smoothing (*LOWESS*) regression on either side of the $20 million threshold, shown as the vertical dashed line.

Figure 1: Discontinuous Relationship Between Turnover and R&D Expenditure



Notes: Figure 1 depicts the relationship between aggregate turnover and R&D expenditure (both in natural logs) for the primary regression sample reported in column 3 of Table 15. Each point represents the mean log R&D spend for firms within a turnover bin with a fixed width of 0.02 log points, averaging 87 firms per bin. The fitted lines show predictions from locally weighted scatterplot smoothing (LOWESS) regression estimated separately on either side of the $20 million threshold. The vertical dashed line indicates the threshold at log($20 million) ≈ 16.811. Aggregate turnover ranged from $4.1 million to $42.3 million.

The *LOWESS* regression lines reveal a steady positive relationship between turnover and R&D on both sides of the threshold. Critically, there is a clear discontinuous drop in average R&D spending at the threshold—firms just above $20 million (receiving the less generous non-refundable offset) exhibit markedly lower R&D than firms just below the threshold (receiving the more generous refundable offset). Average R&D for firms above the threshold quickly returns to follow the same upward trend observed below the threshold. This visual evidence suggests a discontinuity at the $20 million eligibility threshold, which we formally test using the econometric RD design described above.

We now turn to formal estimation of the treatment effect using the RDD approach. Table 15 reports our baseline estimates across six specifications that vary the sample restrictions and R&D measurement approach. All estimates implement the local polynomial method with robust bias correction developed by Cattaneo et al. (2020), using a data-driven optimal bandwidth selection.

Column (1) provides our initial estimate using total registered R&D expenditure from the R&D Tax Incentive program database against the aggregate turnover measure reported at registration from the same database. The estimated treatment effect is 0.176 (statistically significant at the 10% level), implying an additionality of 1.36—that is, each dollar of forgone tax revenue induces an additional $1.36 in R&D spending by firms receiving the more generous offset.

Column (2) replaces the registered R&D measure with total R&D expenditure reported in Business Income Tax (BIT) returns. Although the point estimate remains positive (0.144), it is not statistically significant. This may reflect measurement differences between registration intentions and actual expenditure, or potential noise in BIT reporting.

Moreover, for approximately 10% of firms where the data is available, the reported aggregate turnover measure in the RDTI database is significantly different than the firms reported sales in BIT. Based on our manual review of the figures in RDTI, it appears apparent that some of the figures are estimates based on obvious rounding. However, the difference may indicate that for some of the observed firms, we are missing important ownership data that would allow us to aggregate the correct R&D expenditure data from BIT.

Primary Specification

Our primary specification, reported in column (3), addresses the potential measurement error in the aggregate turnover variable discussed above. At registration, firms report expected aggregate turnover, which may differ from actual turnover. We therefore restrict the sample to observations where reported aggregate turnover at registration falls within ±20% of total sales reported in BIT returns for the same financial year. This restriction ensures we compare firms whose registration-time turnover closely matches their actual turnover, improving the validity of our threshold-based identification.

Under this tighter sample restriction, the treatment effect increases to 0.268 (significant at the 1% level), corresponding to an additionality of 1.57. This suggests that firms receiving the higher refundable offset invest $1.57 in R&D for every dollar of forgone tax revenue. The stronger result in this specification reinforces that measurement error in the running variable can attenuate treatment effect estimates.

Table 15: RDTI Additionality Estimates

	R&D Expenditure					
	Total R&D	Total R&D	Total R&D	Total R&D	Core	Support
R&D Data Source	RDTI	BIT	RDTI	BIT	RDTI	RDTI
Sample	All	All	Restricted	Restricted	Restricted	Restricted
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment Effect	0.176*	0.144	0.268***	0.233**	0.274***	0.060
	(0.096)	(0.098)	(0.092)	(0.101)	(0.096)	(0.122)
Additionality	1.36	--	1.57	1.51	1.58	--
Treated	9,680	9,131	8,522	7,517	8,616	7,520
Control	3,138	2,383	1,618	1,426	1,755	1,543
Bandwidth (Treated)	1.28	1.31	1.56	1.49	1.59	1.58
Bandwidth (Control)	1.03	0.93	0.75	0.76	0.84	0.82
Density Test	0.0017	0.0002	0.7358	0.5098	0.3664	0.3293

Notes: All specifications use local polynomial regression with robust bias correction (Cattaneo et al., 2020) and data-driven optimal bandwidth selection. The treatment effect represents the log-point difference in R&D at the $20 million threshold. Additionality is calculated as in Equation 2 where the treatment effect is statistically significant. Treated (Control) reports the number of observations below (above) the threshold within the optimal bandwidth. Bandwidth values are in log points. Density test reports p-values from Cattaneo et al. (2020) tests of discontinuity in firm density at the threshold. Standard errors (in parentheses) are clustered at the enterprise group level. *** p<0.01, ** p<0.05, * p<0.10. R&D Expenditure: RDTI = total registered R&D from R&D Tax Incentive data; BIT = total R&D from Business Income Tax returns; Core = registered core R&D activities only; Support = registered supporting R&D activities only.

Robustness and R&D Components

Columns (4)-(6) explore the robustness of our primary result. Column (4) combines the sample restriction from column (3) with the BIT-based total R&D measure, yielding a treatment effect of

0.233 (significant at the 5% level) and additionality of 1.51. The similarity to column (3) suggests our results are not driven by the choice between registered versus reported R&D measures.

Using the sample restrictions from column (3), columns (5) and (6) show registered R&D for core and supporting activities, respectively. The treatment effect for core R&D is 0.274 (significant at the 1% level, additionality of 1.58), nearly identical to the overall effect in column (3). In contrast, the effect for supporting R&D is small (0.060) and statistically insignificant. This indicates that the additional R&D induced by the more generous offset is concentrated in core research activities rather than supporting activities.

Diagnostic Tests

The density tests reported in the bottom row examine whether firms manipulate their turnover to fall just below the $20 million threshold (Cattaneo et al., 2020). For our primary specification (column 3) and all subsequent specifications, we cannot reject the null hypothesis of no discontinuity in the density of firms at the threshold (p-values > 0.32), supporting the validity of our identification strategy.

The bandwidth values indicate the range around the $20 million threshold within which observations are included. The asymmetric bandwidths—larger for treated firms (below threshold) than control firms (above threshold)—are optimally selected to balance bias and variance considerations on each side of the threshold. The larger sample of treated firms reflects their greater prevalence in the economy.

Heterogeneity Analysis of RDTI Additionality

Research Disciplines

Having established a positive overall treatment effect of 0.268 and additionality of 1.57 for R&D, we now examine whether this effect varies across research disciplines. Understanding sectoral heterogeneity is crucial for policy design, as discussed in our literature review—existing evidence suggests R&D tax incentives may have systematically different effects across industries with different technological characteristics and innovation dynamics. As discussed in Section 4, using the core R&D expenditure data and the firms main (largest) field of research, we classify firms into five separate Australian Research Council (ARC) Field of Research classifications:: **Bio**: Biology and Biotechnology; **Eng**: Engineering; **HCSE**: Humanities, Creative Arts, Social, Economics; **IC**: Information and Computing; **Pure**: Math, Physics, Chemistry, Earth science.

Table 16 reveals substantial heterogeneity in the point estimates of the treatment effect. The most striking finding is for Engineering (Eng), which shows a statistically significant treatment effect of 0.317 ($p<0.05$), corresponding to an additionality of 1.65. The large effect is generally consistent with our earlier spillover analysis that suggested Engineering and to a similar extent HCSE have significant spillovers in the Australian economy.

For the remaining disciplines, point estimates are positive but not statistically significant. Humanities, Creative Arts, Social, Economics (HCSE) shows a treatment effect of 0.215, Information and Computing (IC) shows 0.182, and Biology and Biotechnology (Bio) shows 0.092. The lack of statistical significance may reflect both genuine heterogeneity in policy responsiveness and the smaller sample sizes for these disciplines compared to Engineering.

Firms doing R&D in pure sciences (Pure) show a very large point estimate of 0.826, but with an extremely large standard error (0.983), rendering it statistically insignificant. This imprecision reflects the very small sample size for this discipline (220 treated firms, 40 control firms), which limits our ability to draw reliable inferences about the firms' responsiveness to the incentive.

Table 16: Regression Discontinuity Estimates by ARC Discipline (Core R&D)

	Bio	Eng	HCSE	IC	Pure
Treatment Effect	0.092	0.317**	0.215	0.182	0.826
	(0.334)	(0.125)	(0.234)	(0.360)	(0.983)
Additionality	--	1.65	--	--	--
Treated	928	4,554	2,615	756	220
Control	151	984	362	167	40
Bandwidth (Treated)	1.91	1.48	1.78	1.75	2.07
Bandwidth (Control)	0.78	0.77	0.86	0.91	0.99

Notes: All specifications use local polynomial regression with robust bias correction (Cattaneo et al., 2020) and data-driven optimal bandwidth selection. The treatment effect represents the log-point difference in R&D at the $20 million threshold. Additionality is calculated as in Equation 2 where the treatment effect is statistically significant. Treated (Control) reports the number of observations below (above) the threshold within the optimal bandwidth. Bandwidth values are in log points. Standard errors (in parentheses) are clustered at the enterprise group level. *** p<0.01, ** p<0.05, * p<0.10.

Supporting R&D Shows No Effects

Table 17 confirms that supporting R&D activities show no significant treatment effects across any discipline. All point estimates are small in magnitude and statistically insignificant, with some even negative (though not statistically significantly different from 0). This reinforces our earlier finding that the R&D Tax Incentive's impact operates primarily through core research activities.

Table 17: Regression Discontinuity Estimates by ARC Discipline (Supporting R&D)

	Bio	Eng	HCSE	IC	Pure
Treatment Effect	-0.133	-0.035	0.017	0.032	-0.347
	(0.362)	(0.161)	(0.284)	(0.453)	(1.208)
Additionality	--	--	--	--	--
Treated	649	4,156	1,728	977	164
Control	136	1,029	359	168	33
Bandwidth (Treated)	1.63	1.54	1.45	2.71	1.96
Bandwidth (Control)	0.90	0.95	0.95	1.25	1.38

Notes: All specifications use local polynomial regression with robust bias correction (Cattaneo et al., 2020) and data-driven optimal bandwidth selection. The treatment effect represents the log-point difference in R&D at the $20 million threshold. Additionality is calculated as in Equation 2 where the treatment effect is statistically significant. Treated (Control) reports the number of observations below (above) the threshold within the optimal bandwidth. Bandwidth values are in log points. Standard errors (in parentheses) are clustered at the enterprise group level. *** p<0.01, ** p<0.05, * p<0.10.

Interpretation and Policy Implications

The concentration of significant effects in Engineering is noteworthy and has important policy implications. Engineering represents the largest discipline in our sample (4,554 treated firms). The finding that engineering firms are particularly responsive to the incentive suggests the program is effective at stimulating R&D in that fields of research. These results partially align with the international evidence discussed earlier. Bodas Freitas et al. (2017) found that specialized supplier sectors (which overlap substantially with engineering) showed strong input additionality effects. However, our results differ somewhat from Castellacci and Lie (2015), who found that high-tech sectors showed smaller average effects. The difference may reflect Australia's specific industrial composition of Australian firms near the $20 million threshold.

The absence of significant effects in other disciplines should be interpreted cautiously given the smaller sample sizes and wider confidence intervals. The point estimates remain positive (except for supporting activities), suggesting the incentive may still induce additional R&D in these sectors, even if we cannot precisely estimate the magnitude with our current sample and identification strategy.

Heterogeneity across Industries

While ARC disciplines classify firms by the type of research they conduct, industry sectors capture differences in business models, market structures, and innovation processes. We therefore examine heterogeneity using aggregated ANZSIC Divisions, which group firms by their primary economic activity provided in BLADE's Indicative Data Items.

Balancing the need to capture meaningful economic distinctions while maintaining sufficient sample sizes for reliable estimation within each category, we classify firms into four industry groups: (i) **Primary**: Agriculture, Forestry, Fishing (ANZSIC Division A excluding Subdivision 5) and Mining (Division B); (ii) M**anufacturing**: Manufacturing (Division C) and Wholesale Trade (Division F); (iii) **Knowledge Intensive Services**: Professional, Scientific and Technical Services (Division M), Information Media and Telecommunications (Division J), Education and Training (Division P), Arts and Recreation Services (Division R), selected subdivisions (72, 85, 5); **Other Services**: All remaining ANZSIC codes (including Retail, Healthcare, Finance, etc.).

Table 18 reports RDD estimates by aggregated ANZSIC division for core R&D activities. The results reveal substantial and statistically significant heterogeneity across industries, with two sectors showing strong positive effects.

Table 18: Regression Discontinuity Estimates by Aggregated ANZSIC Divisions (Core)

	Primary	Manufacturing	Knowledge Intensive	Services
Treatment Effect	-0.091	0.308**	0.331	0.502**
	(0.440)	(0.136)	(0.229)	(0.211)
Additionality	--	1.63	--	1.82
Treated	379	3,728	3,292	1,978
Control	140	991	370	421
Bandwidth (Treated)	1.69	1.44	1.91	1.79
Bandwidth (Control)	1.34	0.87	0.90	1.23

Notes: All specifications use local polynomial regression with robust bias correction (Cattaneo et al., 2020) and data-driven optimal bandwidth selection. The treatment effect represents the log-point difference in R&D at the $20 million threshold. Additionality is calculated as in Equation 2 where the treatment effect is statistically significant. Treated (Control) reports the number of observations below (above) the threshold within the optimal bandwidth. Bandwidth values are in log points. Standard errors (in parentheses) are clustered at the enterprise group level. *** p<0.01, ** p<0.05, * p<0.10.

First, from Table 18, manufacturing firms exhibit a treatment effect of 0.308 ($p<0.05$), implying an additionality of 1.63. This finding is consistent with our ARC discipline results, as Manufacturing overlaps substantially with Engineering research activities. Manufacturing represents the largest sector in our sample (3,728 treated firms) and is a traditional focus of innovation policy given its role in technological development and productivity growth.

Secondly, service firms show an even larger treatment effect of 0.502 ($p<0.05$), corresponding to an additionality of 1.82—the highest across all sectors examined. This indicates that service sector firms receiving the more generous offset invest $1.82 in additional core R&D for every dollar of forgone tax revenue. This strong responsiveness among service firms is particularly noteworthy given the growing importance of R&D and innovation in service industries, including areas such as software development, business analytics, and service innovation that may not fit traditional notions of R&D. Nevertheless, those firms may partial be classified within the Knowledge Intensive Services sector.

Third, knowledge intensives service firms show a positive but statistically insignificant treatment effect of 0.331. While the point estimate suggests some responsiveness to the incentive, the wider confidence interval (standard error of 0.229) prevents us from drawing firm conclusions. This sector includes professional, scientific and technical services, which might be expected to show strong effects, but the heterogeneity within this broad category may contribute to the imprecision. It may be the case that given the nature of activities within the sector, the firms are more likely to engage in R&D activities regardless of the incremental incentive from the tax scheme to do so.

Last, primary sector firms show a small negative point estimate (-0.091), though it is not statistically significant and the standard error (0.440) is relatively large given the smaller sample (379 treated firms). The lack of a positive effect in primary industries may reflect the nature of R&D in these sectors, which may be less responsive to tax incentives or may face other binding constraints on innovation investment.

Heterogeneity across Firm Size

Firm size is an interesting dimension for understanding R&D tax incentive effectiveness. Smaller firms may face greater financial constraints that make tax incentives particularly valuable, but may also have less capacity to scale up R&D activities. Larger firms may have more stable R&D programs but face fewer financial constraints, potentially making them less responsive to marginal changes in tax treatment.

To investigate heterogeneity in input additionality, we classify firms into three size categories based on employment (measured using PAYG head count data): (i) Small: 5–19 employees; (ii) Medium: 20–199 employees; and, (iii) 200+ employees. The results are summarised in Table 19.

Table 19: Regression Discontinuity Estimates by Firm Size (Core)

	Small	Medium	Large
Treatment Effect	-0.152	0.306***	0.068
	(0.418)	(0.117)	(0.522)
Additionality	--	1.63	--
Treated	8,436	5,280	65
Control	100	1,226	543
Bandwidth (Treated)	3.14	1.21	1.15
Bandwidth (Control)	1.11	0.65	1.43

Notes: All specifications use local polynomial regression with robust bias correction (Cattaneo et al., 2020) and data-driven optimal bandwidth selection. The treatment effect represents the log-point difference in R&D at the $20 million threshold. Additionality is calculated as in Equation 2 where the treatment effect is statistically significant. Treated

(Control) reports the number of observations below (above) the threshold within the optimal bandwidth. Bandwidth values are in log points. Standard errors (in parentheses) are clustered at the enterprise group level. *** p<0.01, ** p<0.05, * p<0.10.

Table 19 reveals a striking pattern: the treatment effect is concentrated entirely in medium-sized firms. Medium firms show a highly significant treatment effect of 0.306 (p<0.01), corresponding to an additionality of 1.63. This indicates medium-sized firms are highly responsive to the more generous offset, investing an additional $1.63 in R&D for every dollar of forgone tax revenue.

In contrast, both small and large firms show no significant treatment effects. Small firms exhibit a small negative point estimate (-0.152, not significant), while large firms show a modest positive estimate (0.068, also not significant). However, these null results should be interpreted extremely cautiously given the sample compositions.

For small firms, there are 8,436 treated observations but only 100 control observations within the optimal bandwidth. This extreme imbalance reflects the fact that most small firms naturally fall below the $20 million threshold, leaving very few small firms above the threshold for comparison. The very wide bandwidth on the treated side (3.14 log points) relative to the control side (1.11 log points) further indicates the scarcity of comparable small firms just above the threshold.

For large firms, the sample is extremely limited (only 65 treated firms), severely limiting statistical power. Large firms with turnover under $20 million are relatively rare, making it difficult to reliably estimate treatment effects for this group.

The concentration of effects among medium-sized firms has important policy implications. These firms appear to be at an optimal stage where they have sufficient organizational capacity to scale up R&D in response to incentives, while still facing financial constraints that make the tax offset meaningful for investment decisions. This finding aligns with the broader innovation literature suggesting that medium-sized firms occupy a "sweet spot" for policy responsiveness.

Heterogeneity across Age and Cohort

Like firm size, a firm's age represents another important dimension of heterogeneity. Younger firms may be more dynamic and responsive to incentives but may also face greater uncertainty and resource constraints. Older, more established firms may have more stable R&D programs but potentially less flexibility to adjust investment in response to policy changes.

We examine heterogeneity along two related dimensions. First, we split firms by age, classifying firms under 15 years old as "young" and those 15 years or older as "old." Age is determined using the Birth Module in BLADE, which tracks firm entry. The data is further supplemented based on the date of first reported financial data in BAS or BIT. Second, we examine cohort effects by comparing firms that began operations before versus after 2005, restricted to observations when these firms were still classified as young (under 15 years old). This cohort analysis helps identify whether the responsiveness of young firms has changed over time. The results are summarised in Table 20.

Table 20: Regression Discontinuity Estimates by Age and Cohort (Core)

	Firm Age		Cohort	
	Young	**Old**	**Prior to 2005**	**After 2005**
Treatment Effect	0.282*	0.336**	0.244	-0.159
	(0.148)	(0.143)	(0.188)	(0.177)
Additionality	1.59	1.67	--	--

Treated	5,168	4,086	5,382	2,638
Control	705	1,060	629	977
Bandwidth (Treated)	1.78	1.50	1.98	1.15
Bandwidth (Control)	0.89	0.81	0.90	0.86

Notes: All specifications use local polynomial regression with robust bias correction (Cattaneo et al., 2020) and data-driven optimal bandwidth selection. The treatment effect represents the log-point difference in R&D at the $20 million threshold. Additionality is calculated as in Equation 2 where the treatment effect is statistically significant. Treated (Control) reports the number of observations below (above) the threshold within the optimal bandwidth. Bandwidth values are in log points. Standard errors (in parentheses) are clustered at the enterprise group level. *** p<0.01, ** p<0.05, * p<0.10.

Heterogeneity across Age

Table 20 shows that both young and old firms exhibit significant positive treatment effects. Young firms show a treatment effect of 0.282 (p<0.10), implying an additionality of 1.59. Old firms show a slightly larger effect of 0.336 (p<0.05) and additionality of 1.67.

The similarity in treatment effects across age groups suggests the R&D Tax Incentive is broadly effective regardless of firm age. Both young and established firms near the $20 million threshold increase their R&D investment substantially in response to the more generous offset. The slightly larger (and more precisely estimated) effect for older firms may reflect their greater organizational stability and capacity to implement R&D programs, though the confidence intervals for the two estimates overlap considerably.

Heterogeneity across Cohort

The cohort analysis reveals an intriguing, though statistically insignificant, pattern. Young firms that began operations prior to 2005 show a positive treatment effect of 0.244, while young firms that began after 2005 show a small negative effect of -0.159. Neither estimate is statistically significant, preventing strong conclusions.

However, the contrast is suggestive. If the pattern were statistically robust, it might indicate that young firms founding after 2005 are less responsive to the R&D Tax Incentive. This could reflect changes in the innovation landscape, such as the rise of digital and software-based business models where R&D boundaries are less clear, or changes in the competitive environment facing new entrants. Alternatively, it may simply reflect sampling variation or differences in the types of young firms operating near the $20 million threshold in different time periods.

7. Concluding Remarks

The analysis in this report addressed a fundamental economic challenge: quantifying the magnitude of R&D spillovers and identifying the specific channels through which they flow in the Australian economy. Although the theoretical justification for R&D subsidies—that the social return to innovation exceeds the private return due to positive externalities—is well-established, empirical estimates in the Australian context have historically been constrained by data limitations.

Our analysis confirmed that aggregate R&D spillovers in Australia are large and positive. We estimated an average annual social rate of return to business R&D of $1.49 per dollar invested, significantly exceeding the private return of $0.96. This gap confirms the existence of a market failure that justifies government intervention. Moreover, those R&D spillovers are highly heterogeneous across fields of research. They are strongest in Information and Computing, consistent with its nature as a general-purpose technology. Conversely, spillovers are lowest in Biology/Biotech, where negative spillover estimates suggest that effective patent protection allows firms to privatize returns and potentially exert pricing power over customers and significant business stealing effects. Finally, spillovers flow primarily from suppliers (downstream) rather than customers, indicating that firms benefit most from R&D embodied in better or cheaper intermediate inputs. However, firms that are themselves R&D active—possessing higher absorptive capacity—are better able to harvest knowledge spillovers from their customers.

We provided robust evidence that knowledge is transmitted through the movement of high-tech workers. Hiring R&D-experienced workers from the corporate sector drives significant productivity gains; a 1% increase in the share of these workers raises productivity by 0.267%. Workers with experience in Cooperative Research Centres (CRCs) and Research Service Providers (RSPs) provide an additional productivity boost, particularly for medium-sized firms. These benefits of labour mobility are most pronounced in large firms (>200 employees), likely due to their superior scale and absorptive capacity to integrate new knowledge.

Using a Regression Discontinuity Design (RDD) at the $20 million turnover threshold, we find the RDTI is effective but appears to act through specific channels. Overall, the program generates $1.57 in additional R&D for every $1 of tax revenue forgone. This additionality is driven entirely by Core R&D activities (1.58 additionality). Supporting R&D activities show no measurable additionality, suggesting they are either unresponsive to the incentive or susceptible to reclassification.

A cross-examination of the findings from the above analysis reveals a high degree of structural consistency. The results mutually reinforce the conclusion that R&D policy is most effective when targeting specific types of activities and firms with specific capabilities, rather than applying blunt, economy-wide instruments. For example, in the spillover analysis, Core R&D activities generate significantly higher spillover returns. In the RDTI analysis, we found that input additionality is concentrated entirely in Core R&D activities. This suggests a virtuous policy cycle: the RDTI is effectively stimulating precisely the type of R&D (Core) that generates the highest positive externalities for the broader economy. Conversely, the lack of additionality in Supporting R&D aligns with its lower social value, suggesting these expenditures may be more susceptible to reclassification or less driven by market failures.

The sectoral heterogeneity observed in spillover generation is mirrored to a certain extent in the responsiveness to tax incentives. For example, Engineering generates substantial positive spillovers and exhibits strong responsiveness to the RDTI. In contrast, Biology/Biotechnology exhibits negative spillovers (likely due to strong IP protections and privatization of returns) and shows statistically insignificant responsiveness to the RDTI. This finding is consistent with the economic theory of appropriability. In sectors like Biotech, where firms can fully capture returns (hence low/negative spillovers) via patent protection, tax incentives may be less critical for stimulating investment compared to sectors like Engineering, where knowledge leaks more easily (high spillovers) and market failure is more acute. In areas, where the impact is most felt organisations such as hospitals, not-for-profit agencies and governments, the RDTI remains important for incentivising activity.

Furthermore, both the spillover and labour mobility analyses independently validate the "absorptive capacity" hypothesis. The spillover analysis shows that R&D active firms benefit significantly more from customer spillovers than non-R&D firms. Similarly, the labour mobility analysis finds that hiring new R&D workers only boosts productivity if the receiving firm already possesses a high share of high-tech workers. Thus, external knowledge—whether embodied in supply chains or mobile workers—is not a free public good. Firms must possess their own internal R&D capabilities to unlock the value of the Australian innovation ecosystem.

However, our analysis also revealed a notable nuance, especially with regards to firm size, where the "sweet spot" for policy intervention may differ from the "sweet spot" for knowledge absorption. For example, the spillover analysis suggests that medium-sized firms (20–199 employees) appear to benefit the most from external R&D. The labour mobility analysis finds that large firms (200+ employees) derive the greatest productivity boost from hiring R&D workers from other firms. This is perhaps a reflection of different economic constraints. Large firms may possess the organizational scale and diverse complementary assets required to attract and integrate and leverage complex tacit knowledge brought by new employees.[37]

The empirical evidence presented suggests that a "one-size-fits-all" approach to innovation policy may be suboptimal. The sharp disparity in additionality between Core and Supporting R&D suggests that policy definitions should be more targeted. Fiscal resources may be more efficiently deployed by focusing incentives strictly on Core activities where genuine behavioural additionality occurs and spillover returns are maximised. The variation in social returns—high in Engineering and ICT, lower in Biotech due to strong appropriability—implies that uniform subsidies may over-subsidise sectors where private returns are already sufficient (due to IP protection) and under-subsidize those with high public good characteristics.

Whereas this analysis utilised the most comprehensive data available, several caveats remain. First, the measurement of R&D stocks, a key variable in the estimation of returns to R&D, rely on the basic Perpetual Inventory Method (PIM) with an assumed uniform depreciation rates which may indeed vary significantly across industries. Second, the additionality estimates rely on, and thus are most robust for firms near, the discontinuity around the $20 million turnover threshold.[44] Extrapolating these results to very small start-ups or very large multinationals requires caution. Third, although we distinguish between upstream and downstream flows, fully disentangling pure knowledge spillovers from pecuniary (rent) spillovers and business stealing effects remains an econometric challenge. Our estimates of the R&D spillovers mixed two effects which work in the opposite direction: business stealing effect and knowledge spillovers effect.

Lastly, analysing the underlying factors driving our estimates is beyond the scope of this report. More in-depth case studies of business R&D or empirical analyses based on more nuanced data could potentially reveal insights of utmost value for innovation policy design. An analysis of the long-term dynamics, for example, using the lag structures of R&D additionality could help in a better understanding on whether the RDTI pulls forward investment or creates sustained capability improvements. Furthermore, analysing how the RDTI interacts with direct grant funding (e.g., CRC grants) can help identify potential complementarities or crowding-out effects. Finally, incorporating patent data will allow us to better map the "pure" knowledge flows in the high-tech sectors where IPRs are prevalent.

To conclude, by moving beyond average effects to uncover the heterogeneous drivers of innovation, this report provided a micro-economic foundation for refining Australia's industrial policy to better capture the social value of R&D.

Appendices

Appendix Table 1: Fields of Research

Fields of Research	Description	ANZSRC Codes
Bio	Biology and Biotechnology	600-799, 1100-1199, 3000-3299, 4100-4199, 4201, 4205, 4208, 4299 (not Language and Culture), 4503, 4509, 4515
Eng	Engineering	800-1099, 1200-1299 (exc. 1201), 2800-2999, 3302-3303, 4000-4099, 4505, 4512, 4515, 4600-4699
HCSE	Humanities, Creative Arts, Social, Behaviour, Economics	115, 1201, 1205, 1300-1899, 1601, 1900-2199, 2439, 3301, 3304, 3399, 3500-3599, 3600-3699, 3800-3999, 4200-4299, 4300-4399, 4401,4405,4499, 4400-4599, 4501, 4505, 4513, 4519, 4599, 4500-4799, 4800-4899, 5000-5099, 5200-5299, 9204, 9305 (and anything in ANZSRC Division "Education", "History and Archaeology", "Language and Culture")
IC	Information and Computing	800-899, 4600-4699, (and ANZSRC Division "Information and Computing Sciences" and "Information, Computing and Communication Sciences")
Pure	Mathematics, Physics, Chemistry and Earth Science	100-599, 2300-2799, 3400-3499, 3500-3799, 4900-4999, 5100-5199

Note: The ANZSRC codes are mixed of 2008 and 2020 versions.

Appendix Table 2: Knowledge Intensive Services Industry

ANZSIC 2006 Subdivision	Description
55	Motion Picture and Sound Recording Activities
56	Broadcasting (except Internet)
57	Internet Publishing and Broadcasting
58	Telecommunications Services
70	Computer System Design and Related Services
59	Internet Service Providers, Web Search Portals and Data Processing Services
60	Library and Other Information Services
48	Water Transport
49	Air and Space Transport
69	Professional, Scientific and Technical Services (Except Computer System Design and Related Services)
72	Administrative Services
62	Finance
63	Insurance and Superannuation Funds
64	Auxiliary Finance and Insurance Services
54	Publishing (except Internet and Music Publishing)
75	Public Administration
76	Defence
84	Hospitals
85	Medical and Other Health Care Services
86	Residential Care Services
87	Social Assistance Services
90	Creative and Performing Arts Activities
89	Heritage Activities
92	Gambling Activities
91	Sport and Recreation Activities
77	Public Order, Safety and Regulatory Services

Source: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Knowledge-intensive_services_(KIS) (Accessed on 06-Nov-2025).

Appendix Table 3: Production function elasticity estimates of R&D stocks, All firms

Estimating Sample and Fields of Research	Own R&D elasticity	External R&D elasticity	
		Upstream spillovers from customers	Downstream spillovers from suppliers
	β_{fG}	β_{fs}^{U}	β_{fs}^{D}
	(1)	(2)	(3)
All fields of research	0.077	0.011	0.032
	(0.001)	(0.001)	(0.001)
Biology/Biotech	0.069	0.015	-0.067
	(0.004)	(0.006)	(0.004)
Engineering	0.061	0.006	0.028
	(0.005)	(0.002)	(0.003)
Humanities/Creative Arts/Social	0.084	-0.002	0.019
	(0.001)	(0.000)	(0.000)
Information and Computing	0.083	0.007	0.041
	(0.001)	(0.001)	(0.005)
Math, Physics, Chemistry, Earth science	0.077	-0.011	-0.001
	(0.002)	(0.001)	(0.003)

Notes: These are elasticities estimates from regression equation (10), reproduced here:

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + \beta_{fG}\, g_{f,it-1} + \beta_{fs}^{U} s_{f,it-1}^{U} + \beta_{fs}^{D} s_{f,it-1}^{D} + \delta \bar{y}_t + \gamma_t + \gamma_s + \varepsilon_{it}$$

() Standard Errors.

Appendix Table 4: Production function elasticity estimates of R&D stocks, R&D firms

Estimating Sample and Fields of Research	Own R&D elasticity	External R&D elasticity	
		Upstream spillovers from customers	Downstream spillovers from suppliers
	β_{fG}	β^{U}_{fs}	β^{D}_{fs}
	(1)	(2)	(3)
All fields of research	0.018	0.059	0.004
	(0.002)	(0.001)	(0.001)
Biology/Biotech	0.020	0.017	-0.049
	(0.001)	(0.001)	(0.001)
Engineering	0.011	0.020	0.016
	(0.001)	(0.001)	(0.001)
Humanities/Creative Arts/Social	0.027	0.045	-0.026
	(0.004)	(0.003)	(0.004)
Information and Computing	0.021	0.064	0.017
	(0.002)	(0.001)	(0.001)
Math, Physics, Chemistry, Earth science	0.021	0.016	-0.010
	(0.001)	(0.001)	(0.001)

Notes: These are elasticities estimates from regression equation (10), reproduced here:

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + \beta_{fG}\, g_{f,it-1} + \beta^{U}_{fs} s^{U}_{f,it-1} + \beta^{D}_{fs} s^{D}_{f,it-1} + \delta \bar{y}_t + \gamma_t + \gamma_s + \varepsilon_{it}$$

() Standard Errors.

Appendix Table 5: Production function elasticity estimates of R&D stocks, Non-R&D firms

Estimating Sample and Fields of Research	External R&D elasticity	
	Upstream spillovers from customers	Downstream spillovers from suppliers
	β_{fs}^{U}	β_{fs}^{D}
	(1)	(2)
All fields of research	0.004	0.022
	(0.000)	(0.000)
Biology/Biotech	0.009	-0.065
	(0.001)	(0.005)
Engineering	0.000	0.033
	(0.002)	(0.001)
Humanities/Creative Arts/Social	-0.005	0.021
	(0.000)	(0.001)
Information and Computing	-0.004	0.049
	(0.003)	(0.005)
Math, Physics, Chemistry, Earth science	-0.009	-0.002
	(0.005)	(0.006)

Notes: These are elasticities estimates from regression equation (10), reproduced here:

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + \beta_{fG}\, g_{f,it-1} + \beta_{fs}^{U} s_{f,it-1}^{U} + \beta_{fs}^{D} s_{f,it-1}^{D} + \delta \bar{y}_t + \gamma_t + \gamma_s + \varepsilon_{it}$$

() Standard Errors.

Appendix Table 6: Estimates of rate of returns to R&D by Receiving Industry, R&D firms

Receiving Industry Division	Annual return to R&D ($) per $1 R&D spent				
	Private returns	Upstream spillover returns (from customers' R&D)	Downstream spillovers returns (from suppliers' R&D)	Total spillover returns	Total social returns
	(1)	(2)	(3)	(4) = (2) + (3)	(5) = (1) + (4)
All Divisions	0.23	0.74	0.05	0.79	1.02
A Agriculture, forestry, fishing	1.03	-0.66	-0.58	-1.24	-0.21
B Mining	0.37	-1.69	1.22	-0.47	-0.10
C Manufacturing	0.35	0.16	0.28	0.43	0.79
D Electricity, Gas, Water, Waste	-0.34	-0.26	0.14	-0.12	-0.46
E Construction	-0.10	0.65	0.18	0.83	0.73
F Wholesale trade	0.51	-0.04	0.64	0.59	1.10
G Retail trade	-0.47	0.71	-0.49	0.21	-0.25
I Transport, postal, warehousing	-0.46	-0.22	0.50	0.31	-0.15
J Information media, telecommunication	-0.28	-0.08	-0.06	-0.14	-0.43
K Financial insurance services	-0.27	0.17	0.77	0.93	0.66
L Rental, hiring, real estate	0.29	2.07	-1.58	0.49	0.78
M Professional, scientific, technical services	0.01	-0.33	0.47	0.14	0.14
N Administrative and support	-0.25	-1.97	2.23	0.25	0.00
H, O, P, Q, R and S (see Notes below)	0.67	0.86	-0.51	0.35	1.02
KIS (Knowledge intensive services)	-0.20	-0.29	0.47	0.18	-0.02

Notes: Private and social rates of returns to R&D are computed using the formula in equation (11): $\rho^f = (\beta_{fG} + \beta_{fs}^U + \beta_{fs}^D) \times \frac{Y}{G}$ with a $\frac{Y}{G}$ value of 20.2 and R&D capital stock elasticity estimates (the βs) from the estimated model similar to equation (10). HOPQRS is H (Accommodation and food services), O (Public administration, safety), P (Education and Training), Q (Health care and Social Assistance), R (Arts and recreation), and S (Other services). These services divisions are aggregated due to their low level of R&D activities.
Source: Processed from BLADE and RDTI databases.

Appendix Table 7: Estimates of rate of returns to R&D by Receiving Industry, Non-R&D firms

Receiving Industry Division	Annual return to R&D ($) per $1 R&D spent		
	Upstream spillover returns (from customers' R&D)	Downstream spillover returns (from suppliers' R&D)	Total spillover returns
	(1)	(2)	(3) = (1) + (2)
All Divisions	0.05	0.28	0.33
A Agriculture, forestry, fishing	-0.50	0.27	-0.24
B Mining	0.00	-0.44	-0.44
C Manufacturing	0.40	0.15	0.55
D Electricity, Gas, Water, Waste	-0.67	0.91	0.24
E Construction	-0.44	0.49	0.05
F Wholesale trade	0.72	-0.51	0.21
G Retail trade	0.47	-0.35	0.12
I Transport, postal, warehousing	-0.64	0.80	0.17
J Information media, telecommunication	2.20	-2.13	0.07
K Financial insurance services	-0.27	0.83	0.56
L Rental, hiring, real estate	-0.22	0.29	0.07
M Professional, scientific, technical services	-0.37	0.49	0.12
N Administrative and support	-1.25	1.34	0.10
H, O, P, Q, R and S (see Notes below)	-1.61	1.84	0.23
KIS (Knowledge intensive services)	0.64	-0.11	0.52

Notes: Private and social rates of returns to R&D are computed using the formula in equation (11): $\rho^f = (\beta_{fG} + \beta_{fs}^U + \beta_{fs}^D) \times \frac{Y}{G}$ with a $\frac{Y}{G}$ value of 20.2 and R&D capital stock elasticity estimates (the βs) from the estimated model similar to equation (10). HOPQRS is H (Accommodation and food services), O (Public administration, safety), P (Education and Training), Q (Health care and Social Assistance), R (Arts and recreation), and S (Other services). These services divisions are aggregated due to their low level of R&D activities.
Source: Processed from BLADE and RDTI databases.

Appendix Table 8: Definition of Explanatory Variables in Table 7

Explanatory Variable	Definition
Turnover	Current value of total sales turnover
Intangible assets	Two-year moving average of factor of patent trademark design rights filed and the reported level of intangible assets
Operating expenses	Current value of operating expenses
Employment	Total employment count (constructed from PLIDA database)
R&D spending	Two-year moving average of R&D spending
Total assets	Current value of total tangible assets
Share of new non-R&D workers	New employees from non-R&D active firms as percentage of total employment count
Share of new R&D workers	New employees who were high-tech workers from R&D active firms as percentage of total employment count Note: A high-tech worker is defined as ANZSCO 11 Chief Executives, General Managers and Legislators; 13 Specialist Managers; 23 Design, Engineering, Science and Transport Professionals; 26 ICT Professionals; 31 Engineering, ICT and Science Technicians; 34 Electrotechnology and Telecommunications Trades Workers.
Share of high-tech workers	High-tech workers as percentage of total employment count
Share of new R&D workers ex-public	New employees who were high-tech workers from R&D active public firms as percentage of total employment count
Share of new R&D workers ex-corporate	New employees who were high-tech workers from R&D active firms from the corporate sector as percentage of total employment count

Appendix Table 9: Descriptive statistics for the estimating sample of Table 7

Explanatory variable	Mean	P1	P5	P10	P95	P99
Turnover ($000)	104,240	259	724	1,104	91,561	635,442
Operating expenses ($000)	85,509	0	0	0	67,337	460,699
R&D expenditure ($000)	145	0	0	0	0	1,852
Intangible assets (factor)	0.58	0	0	0	2.9	11.3
Total assets($000)	121,435	0	0	0	56,262	725,027
Total employment (persons)	137.3	20	20	21	294	1,546
New non-R&D workers (%)	38.9	8.3	16	20	84.6	95.8
High-tech workers (%)	25.9	0	0	1.8	76.1	89.2
New R&D workers (%)	1.6	0	0	0	7	12.9
New R&D workers ex-public	0.3	0	0	0	2.3	4.5
New R&D workers ex-corporate	1.2	0	0	0	5.7	11.4

n = 1,044,561

Appendix Table 10: Determinants of firm productivity including effects of absorptive capacity; Dep. Variable = Ln(Turnover), for-profit firms, by broad industry sector of receiving firm, Australia, 2005-06 to 2021-22

Explanatory variables	Agriculture	Mining; Manufacturing, Electricity, gas and water; Construction; and Wholesale trade	Transport; postal and warehousing; Information, media, telecommunications; Financial insurance services; Rental, hiring and real estate services; Professional, scientific technical services	Administrative and support services; Public administration and safety; Health care and social assistance; Education and training	Retail trade; Accommodation and food services; Arts and recreation services; Other services
$log(Employment)_{it}$	0.539***	0.778***	0.759***	0.747***	0.731***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
$log(Total\ assets)_{it}$	0.003***	0.011***	0.009***	0.017***	0.010***
	(0.000)	(0.000)	(0.001)	(0.001	(0.000)
$log(Intangible\ assets)_{i.t-1}$	0.000	0.002***	0.004***	0.006***	0.004***
	(0.0001)	(0.000)	(0.001)	(0.002)	(0.001)
$log(Operating\ expenses)_{t}$	0.019***	0.008***	0.008***	0.008***	0.007***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
$log(R\&D\ spending)_{i.t-1}$	0.007***	0.002***	-0.001	-0.000	-0.000
	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)
$log(Share\ of\ new\ nonR\&D\ workers)_{it}$	0.011***	-0.010***	-0.019***	-0.022***	-0.010***
	(0.003)	(0.002)	(0.003)	(0.004)	(0.002)
$log(Share\ of\ high\text{-}tech\ workers)_{it}$	0.038***	0.011***	0.009***	0.012***	0.006***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
$log(Share\ of\ new\ R\&D\ workers\ ex\text{-}public)_{it}$	-0.015	0.010	-0.022	-0.041**	-0.033***
	(0.021)	(0.014)	(0.016)	(0.017)	(0.011)
$log(Share\ of\ new\ R\&D\ workers\ ex\text{-}corporate)_{it}$	-0.014	0.001	-0.021***	-0.023**	-0.019***
	(0.013)	(0.006)	(0.008)	(0.009)	(0.005)
$log(Share\ of\ new\ R\&D\ workers\ ex\text{-}public)_{it} \times log(Share\ of\ hightech\ workers)_{it}$	0.0035	-0.003	0.0059	0.009*	0.008**
	(0.005)	(0.004	(0.004)	(0.005)	(0.003)
$log(Share\ of\ new\ R\&D\ workers\ ex\text{-}corporate)_{it} \times log(Share\ of\ hightech\ workers)_{it}$	0.0045	0.000	0.007***	0.007**	0.006***
	(0.004)	(0.002)	(0.00214)	(0.003)	(0.002)
Observations	165,056	274,116	180,672	157,750	266,967
R^2	0.208	0.331	0.280	0.300	0.279

Note: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Only includes firms with over 20 employees and constant

Appendix Table 11: Determinants of firm productivity, R&D and CRC workers; Dep. Variable = Ln(turnover), for-profit firms only, Australia, 2015-16 to 2021-22

Explanatory variables	(1)	(2)	(3)
$log(Employment)_{it}$	0.748***	0.749***	0.749***
	(0.003)	(0.003)	(0.003)
$log(Total\ assets)_{it}$	0.009***	0.009***	0.009***
	(0.000)	(0.000)	(0.000)
$log(Intangible\ assets)_{i,t-1}$	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)
$log(Operating\ expenses)_{t}$	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)
$log(R\&D\ spending)_{i,t-1}$	-0.001	-0.001	-0.006
	(0.000)	(0.000)	(0.000)
$log(Share\ of\ new\ nonR\&D\ workers)_{it}$	-0.013***	-0.013***	-0.013***
	(0.002)	(0.002)	(0.0023)
$log(Share\ of\ new\ R\&D\ workers)_{it}$	0.006	-0.015***	
	(0.001)	(0.005)	
$log(Share\ of\ new\ CRC/RSP\ workers)_{it}$	0.006***	-0.020**	-0.020**
	(0.002)	(0.009)	(0.010)
$log(Share\ of\ high\text{-}tech\ workers)_{it}$		0.011***	0.011***
		(0.001)	(0.001)
$log(Share\ of\ new\ R\&D\ workers)_{it} \times log(Share\ of\ hightech\ workers)_{it}$		0.004***	
		(0.001)	
$log(Share\ of\ new\ CRC/RSP\ workers)_{it} \times log(Share\ of\ hightech\ workers)_{it}$		0.007***	0.007***
		(0.003)	(0.003)
$log(Share\ of\ new\ R\&D\ workers\ ex\text{-}public)_{it}$			-0.011
			(0.011)
$log(Share\ of\ new\ R\&D\ workers\ ex\text{-}corporate)_{it}$			-0.015***
			(0.005)
$log(Share\ of\ new\ R\&D\ workers\ ex\text{-}public)_{it} \times log(Share\ of\ hightech\ workers)_{it}$			0.003
			(0.003)
$log(Share\ of\ new\ R\&D\ workers\ ex\text{-}corporate)_{it} \times log(Share\ of\ hightech\ workers)_{it}$			0.005***
			(0.001)
Observations	426,367	426,367	426,367
R2	0.211	0.211	0.211

Notes: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Includes year dummy variables to account for inflation and constant.

Appendix Table 12: Determinants of firm productivity by firm size; Dep. Variable = Ln(Turnover), for-profit firms only, Australia, 2001-02 to 2021-22

Explanatory variables	5-9 employees	10-19 employees	20-199 employees	Over 200 employees
	(1)	(2)	(3)	(4)
$log(Employment)_{it}$	0.490***	0.564***	0.754***	0.800***
	(0.004)	(0.004)	(0.003)	(0.011)
$log(Total\ assets)_{it}$	0.013***	0.011***	0.008***	0.011***
	(0.000)	(0.000)	(0.000)	(0.001)
$log(Intangible\ assets)_{i,t-1}$	0.005***	0.006***	0.003***	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
$log(Operating\ expenses)_{t}$	0.001***	0.001***	0.002***	0.018***
	(0.000)	(0.000)	(0.000)	(0.001)
$log(R\&D\ spending)_{i,t-1}$	-0.001	-0.001	-0.002***	0.001
	(0.001)	(0.004)	(0.001)	(0.001)
$log(Share\ of\ new\ nonR\&D\ workers)_{it}$	-0.005***	-0.008***	-0.014***	0.002
	(0.001)	(0.001)	(0.002)	(0.011)
$log(Share\ of\ new\ R\&D\ workers)_{it}$	0.000	-0.001	-0.001	0.028***
	(0.001)	(0.001)	(0.001)	(0.009)
$log(Share\ of\ new\ CRC/RSP\ workers)_{it}$	0.001	0.001	0.005**	-0.003
	(0.002)	(0.002)	(0.002)	(0.014)
Observations	802,742	494,914	394,492	31,875
R2	0.045	0.073	0.193	0.243

Notes: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Includes year dummy variables to account for inflation and constant.

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