# Channels of Knowledge Spillover: An Australian Perspective

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**Abstract**

Using a survey of R&D conducting firms in Australia, we study the significance of various channels through which knowledge leaks among firms. We implement a very rich set of proxies that account for peers, suppliers, clients, institutes of higher education and government agencies as potential sources of knowledge spillover. We additionally apply geographic weights to investigate whether the impacts depend on physical proximity. The results show that R&D in a firm is being influenced by peer and client firms in its proximity, but spillover form suppliers is not necessarily confined to close distances. Our interpretation is that interactions between R&D staffs are the main channel for knowledge leakage from peers and clients, whereas with suppliers the procured good or service by itself is conduit for knowledge transfer. Additionally, we find that expenditures by local academic institutions are supportive of R&D among private firms, but expenditures by state and commonwealth government seem to be a disincentive possibly due to their applied nature.

**Keywords:** R&D, Innovation, Knowledge Production, Subsidies.

**JEL:** D22, O31, O38.

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# 1 Introduction

An important feature of a vibrant and progressive economy is its rate of innovation and entrepreneurship. Both forces are strongly tied to the national productivity growth and also to the competitiveness of domestic firms in comparison to their foreign counterparts. That is why many governments in the world have initiatives in place to boost innovation-related expenditures among domestic companies through providing various forms of assistance including R&D subsidies. Such initiatives seam to attract more urgency now that mounting evidence points to an alarming decline in the rate of entrepreneurship and business dynamism; see Decker et al. (2014) and Hathaway & Litan (2014) for evidence in the US and Talimanidis (2014) for evidence on Australia.

Such initiative turn out ot be very costly in terms of bygone tax revenues. For instance, in fiscal year 2011–2012, the subsidies offered as part of the R&D Tax Concession program amounted to about \$2bil.; that is about 0.14% of the Australian GDP during the same period. Given the costliness of such initiatives, it is necessary to get the maximum impact out of these programs which. In turn, one needs to understand how businesses innovate, so that financial aid can be targeted to those areas that bear influence in the innovation process. In this paper, we focus on a certain aspect of the R&D process, and that is the channels through which knowledge can leak between firms. Widespread spillover of knowledge among firms can be a powerful driver of innovation across businesses and, more importantly, generate a multiplier effect for government R&D subsidies. At the same time, spillovers could also discourage firms from carrying out innovation-related activities in the absence of government subsidies.

For in insight into this issue, we construct an array of proxies to model external sources for knowledge that are available to a firm. The list includes peer firms that compete in the same industry, supplying firms, and client firms. We also account for a few public sources of knowledge to better differentiated between private and public channels.

We use data on Australian firms that registered for R&D Tax Concession program to analyze the presence and importance of each channel. Firms in this data are geocoded, and we use the geographic coordinates of firms to further study the role of physical distance in the leakage of knowledge. For our purpose, we investigate whether leakage of knowledge from each source instigates any private R&D expenditures above and beyond the normal course. As a result, we end up with a dynamic panel model with selection, since our data is imbalanced and firms can drop out of the panel when they conclude their R&D project. We use a recently developed method by Semykina & Wooldridge (2013) to address both issues simultaneously.

Our results show that much of the knowledge spillover originates from peer firms and clients in the close proximity of a firm. We also find a strong spillover link from suppliers, however, the strength of this link does not fade with distance. As per this evidence, we theorize that knowledge spillover from peers and clients requires contact between the R&D staff of two firms, hence, is greatly facilitated by closeness in distance. On the other hand, knowledge spillover from suppliers is probably embodied in the product or service itself, hence distance is not a hindrance.

We also find that institutes of higher education have been a driver for R&D among private companies, whereas R&D conducted by government mostly discourages private R&D. We notice that most of the research carried out by universities are of basic type, as opposed to government institutes that mostly undertake applied research. We believe this distinction helps to explain the difference in our finding regarding universities versus government.

In the next section, we describe the existing literature on knowledge spillover. Next we introduce R&D Tax Concession data and illustrate the composition of the data. In Section 4 we formulate our proxies that measure knowledge spillover from horizontal and vertical links and additionally discuss the geographic weights that we will use to distinguish firms in a near and far distance context. Section 5 explains our econometric approach to estimating a dynamic panel model with sample selection. In Section 6 we present and discuss our findings. The paper is concluded in Section 7.

## 2 Literature

A comprehensive survey by (Chatterji et al., 2013) investigates the role of clustering and geographic proximity in spillover as evidenced by many works in the iterature. The collection of evidence supports the notion that innovation is mostly localized and happens among firms that are geographically close to each other.

Australia: (Elnasri, 2014) use aggregate time series and finds no role for government spending on innovation (and tax subsidies) on improving productivity of private firms. This paper addresses a similar issue but using a firm-level data. Moreover, we are able to distinguish between R&D tax subsidiy and other government R&D expenditures. Our results suggest that R&D tax concessions have mostly boosted R&D expenditures among firms, especially among the smaller businesses, and it is the expenditures by government agencies that act as a disincentive.

Bloom et al. (2013) study the effect of spillover on output and productivity of other firms using Mahalanobis measure of proximity. They propose that the mechanism through which knowledge leaks from one firm to the other is through the random encounters between the R&D staff of the two firms. We build on their approach to model knowledge spillover in our model.

Acs et al. (1994) and later Acs et al. (2013) argue that knowledge spillover from large incumbent firms are a significant driver of entrepreneurship in any economy. Their theory is based on the proposition that "entrepreneurial behavior is a response to profitable opportunities from knowledge spillover".

There is also a subset of this literature that is mostly dedicated to the international aspects of spillover by looking at the impact of Foreign Direct Investment (FDI) on domestic firms through the lens of economic development. Havranek & Irsova (2011) survey a series of works on this issue, and they find that the implications for spillover effects vary from work to work but on aggregate the results point to a positive and significant impact from foreign firms on domestic suppliers but very small or no effect regarding spillovers to customers and firms in the same sector. In a follow up work, Irsova (2013) again find close to zero effect from FDI on firms in the same sector. Although we are aware of this literature, we do not find it directly related to our main theme which investigates the spillover channels only in a domestic context.

# 3 Data

Since 1985, the Australian Department of Industry has been running a R&D Tax Concession program in collaboration with the Australian Taxation Office in order to promote R&D and innovation among Australian businesses, especially small businesses, by offering them a tax subsidy payable on eligible expenditures for research and innovation projects. As part of this program, the department conducts a survey of the recipient firms in each year. The resulting panel forms the basis of our study. Despite the fact that the panel only represents a selected subset of firms in Australia, the coverage includes almost all the R&D active firms and accounts for the vast majority of private R&D expenditure in Australia, hence, we are able to assume an air of generality about our results.

R&D Tax Concession program has not been a static set of regulations but has evolved over the years to provide better and more effective incentives to firms. As of 2001, the program offered (ATO, 2009):

- a 125% tax concession that applies to all firms,[1]
- a R&D tax offset to small businesses in case they incurred tax losses,
- a 175% tax concession that applies to the incremental part of R&D expenditures. The incremental part is defined as any R&D expenditure above the average expenditure over the preceding three years.

In 2007, the commonwealth government of Australia further extended the 175% tax concession for incremental R&D to the subsidiaries of multinational firms operating in Australia.[2]

There are three main eligibility criteria that need to be met before a firm can claim R&D tax concession. First, the business or the subsidiary must be registered in Australia. Second, at least 90 percent of R&D expenditure must be incurred on Australian soil. Third, the annual R&D expenditure has to be at least $20,000 (all monetary values are in AUD) with the exception of when R&D is conducted jointly with an approved research institute. The department also has a guideline for what constitutes research and development and defines R&D as (ATO, 2009):

1. Systemic, investigative and experimental activities that involve innovation or high levels of technical risk and are carried on for the purpose of

[1] In the US taxation system, the equivalent of a tax concession is income credit; a deduction from income that will result in a reduction in taxes. In Australia, there is also a *tax offset* that is equivalent to a tax credit in the US system.

[2] Note that the years stated in this text are financial years and not calendar years. In Australia, financial year begins on 1st of July and ends on 30th June of the following year. Therefore, 2007 in this context means July 2006 to June 2007.

(a) acquiring new knowledge (whether or not that knowledge will have a specific practical application); or

(b) creating new or improved material, products, devices, processes or services; or

2. other activities that are carried on for a purpose directly related to the carrying on of activities of the kind referred to in paragraph (1).

Only those costs conforming to the guideline above are considered eligible expenses.

Firms that satisfy these eligibility conditions then have to register with the Department of Industry no later than 10 months after the end of the fiscal year in which the expenses were incurred in order to claim the benefits. As of 2011, there were 9,281 firms across Australia that were registered for the program. In 2012, the program was replaced with a R&D tax incentive scheme that changed the tax concessions into tax offsets and also extended most of the size-dependent benefits to medium-sized businesses.

For our study, we focus on the period of 2001 to 2011 as the most stable stretch of the program with the least number of major regulatory changes. The data in particular record the name and business number of firms, annual turnover, annual R&D expenditure, number of employees and the number of R&D staff. The survey reports the number of employees in absolute numbers, but the number of R&D staff are reported in full-time equivalent for a better and more accurate measurement of R&D activity. In addition to operational information, the data also provides information on the geographic location of the firm and the country of headquarter in case the firm is a subsidiary of a foreign multinational company. Through a Department of Industry initiative, most of the firms in the data have their location matched to a geocode providing the longitude and latitude coordinates of the firm.

### 3.1 Composition of the Sample

The annual participation of firms in the program during the period 2001–2011 is illustrated in Table 1. The panel of firms in the data is not balanced and there is a constant flow of entries into and exits from the program in every year. However, the inflow of entrants out-paces the number of exits in each year, so that the scale of program in absolute numbers has been constantly expanding through the years. We find that 1,568 firms in our data are part of

| | Number of | | | | |
|---|---|---|---|---|---|
| Year | Firms | Exits | Entries | Temporary Exits | Re-entries |
| 2001 | 3,732 | 699 | 0 | 196 | 0 |
| 2002 | 4,755 | 1,050 | 1,722 | 261 | 0 |
| 2003 | 5,097 | 975 | 1,392 | 252 | 75 |
| 2004 | 5,646 | 1,160 | 1,524 | 278 | 129 |
| 2005 | 5,997 | 1,123 | 1,511 | 277 | 192 |
| 2006 | 6,421 | 1,183 | 1,547 | 282 | 236 |
| 2007 | 6,967 | 1,277 | 1,729 | 228 | 230 |
| 2008 | 7,911 | 1,537 | 2,221 | 225 | 326 |
| 2009 | 8,582 | 1,769 | 2,208 | 184 | 302 |
| 2010 | 8,767 | 1,755 | 1,954 | 0 | 302 |
| 2011 | 9,281 | 0 | 2,269 | 0 | 391 |
| Total | 73,156 | 12,528 | 18,077 | 2,183 | 2,183 |

Table 1: The annual count of firms, entries and exits. Exit is a firm that is not observed the following year. Entry is a firm that was not observed the preceding year.

the balanced sample appearing in all ten years of the data, whereas 2,140 firms in our data appear in at least nine years. These numbers point to a good deal of continuity in the R&D activities of the participating firms, however, there is a size bias and the larger proportion of firms in the balanced panel are large in size.

The table also shows that about a quarter of exiting firms in every year re-appear in some later year of our observed data as a re-entry. We explain this pattern as firms concluding an innovation project which causes R&D expenditure to fall below the required threshold and forces the firm to drop out of the program until the commencement of a new project followed by a re-registration in the program. This patten is most conspicuous among smaller firms which lack a dedicated research division and a constant flow of R&D expenditures.

These outreach of the program has been quite diverse, and firms from a wide array of industries ranging from manufacturing to mining, construction and services have been recipient of the subsidies. This diversity is illustrated in Figure 1, where the plots show the distribution of firms by their main industry of operation in two snapshots taken in 2001 and 2011. The industries in the graphs are indicated by their ANZSIC major group classification code for better presentation. These classification codes and their full descriptions are listed

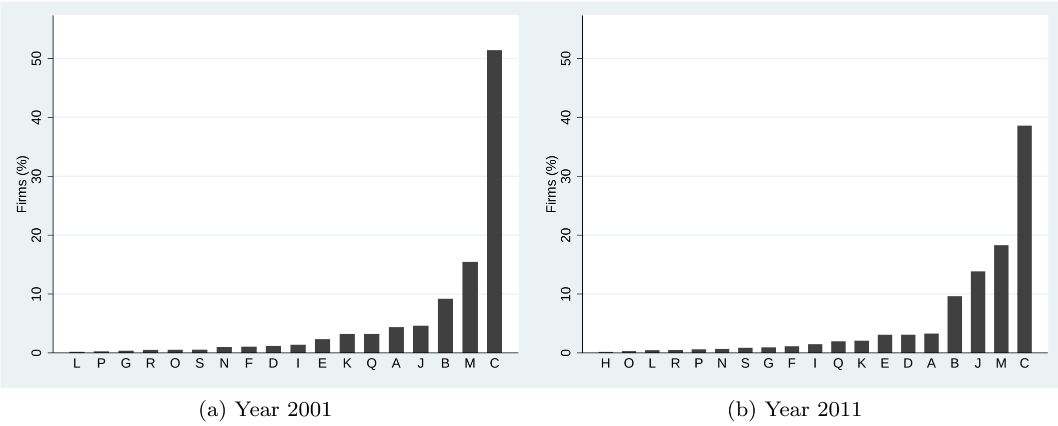



Figure 1: The distribution of firms participating in R&D tax concession program by industry in 2001 and 2011.

in Table 2.

By far, the largest group of participating firms are manufacturing firms (Class C), claiming more than half the share of all participants in the year 2001. The next largest groups are Professional, Scientific and Technical Services (Class M), Mining (Class B), and Information Media and Telecommunication (Class J). The latter group represents publishing, radio networks and television broadcasting but also software, internet, data processing, and telecommunication firms. Not surprisingly, data reveal that about 78 per cent of participating firms in this sector happen to be from the latter group specializing in online media and telecommunication. The proportion of participants from all other industries together represent only about 10% of the cohort. However, these firms operate in sectors as diverse as Rental, Hiring, and Real Estate Services (Class L), Retail Trade (Class G) to Construction (Class E).

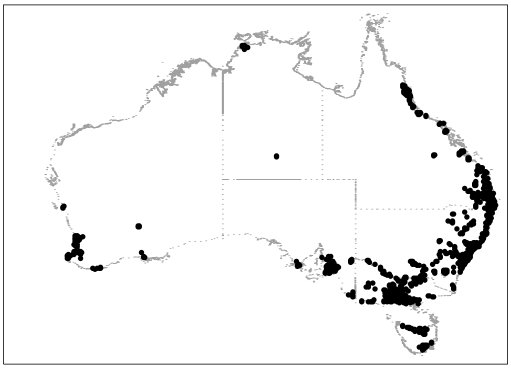
Comparing the distributions from 2001 and 2011 also reveals some shift in the way industries are represented. The top participants – manufacturing, scientific services, mining and information media – are still the front runners; nonetheless, the proportion of manufacturing firms in the program has dropped substantially during the decade, while scientific services and online media (Classes M and J) have increased their share of the participants. Moreover, there are additions of new industry groups in 2011. For instance, industries Agriculture, Forestry and Fishing (Class A) and Accommodation and Food Services (Class H)

| ANZSIC Class | ANZSIC Code From | To | Description |
|---|---|---|---|
| A | 0111 | 0521 | Agriculture, Forestry and Fishing |
| B | 0600 | 1090 | Mining |
| C | 1111 | 2599 | Manufacturing |
| D | 2611 | 2922 | Electricity, Gas, Water and Waste Services |
| E | 3011 | 3299 | Construction |
| F | 3311 | 3800 | Wholesale Trade |
| G | 3911 | 4320 | Retail Trade |
| H | 4400 | 4530 | Accommodation and Food Services |
| I | 4610 | 5309 | Transport, Postal and Warehousing |
| J | 5411 | 6020 | Information Media and Telecommunication |
| K | 6210 | 6420 | Financial and Insurance Services |
| L | 6611 | 6720 | Rental, Hiring, and Real Estate Services |
| M | 6910 | 7000 | Professional, Scientific and Technical Services |
| N | 7211 | 7320 | Administration and Support Services |
| O | 7510 | 7720 | Public Administration and Safety |
| P | 8010 | 8220 | Education and Training |
| Q | 8401 | 8790 | Health Care and Social Assistance |
| R | 8910 | 9209 | Arts and Recreation Services |
| S | 9411 | 9603 | Other Services |

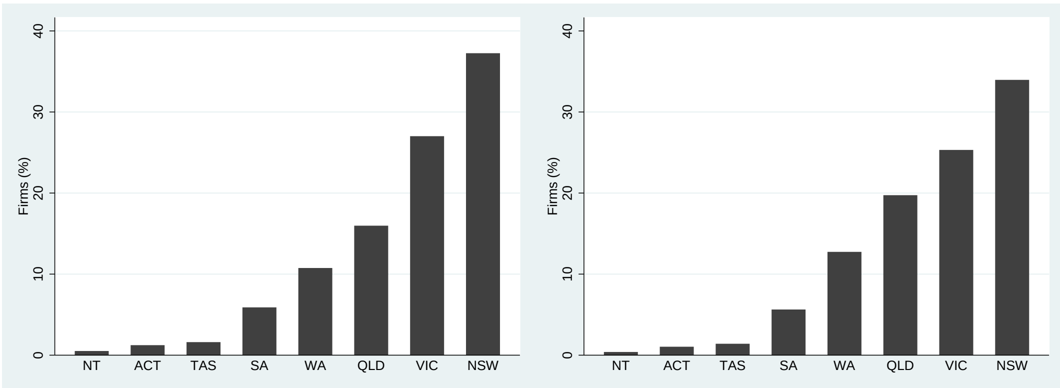
Table 2: ANZSIC industry classifications and their description.

that had no participation in 2001 are now represented but by a small number of firms in 2011. The pattern as a whole indicates an increased diversity in the range of R&D undertaken in Australia, but also parallels the paradigm shift that is taking place in most advanced industrialized countries away from manufacturing and towards services.

The last feature that we will showcase is the geographical distribution of firms. As is the case with the distribution of population in Australia, the economic and innovative activity in Australia is also mostly concentrated on the coastal areas and especially in the vicinity of metropolitan cities (Figure 2 panel (a)). Of all the states and territories in Australia, the most populated are New South Wales (NSW), Victoria (VIC), and Queensland (QLD), and these three states claim the larger shares of participants in the program (Figure 2 panels (b) and (c)). The pattern as a whole has shown very little change from 2001 to 2011, except that during the course of these years the share of New South Wales and Victoria has declined



(a) Distribution map




(b) Year 2001

(c) Year 2011

Figure 2: The geographic distribution of firms participating in R&D tax concession program. Due to the confidentiality of data, all firms with fewer than five neighbors within $\pm 1^\circ$ of coordinates are suppressed in panel (a) to protect individual identities.

and there has been some shift towards Queensland and Western Australia (WA). This shift, again, echoes a decline in manufacturing – NSW and VIC are major manufacturing hubs – in tandem with a boost in resources industries.

## 3.2 Foreign Multinationals and Sample Selection

In our data, one group of firms, namely, subsidiaries of foreign multinationals, are bound to benefit more from their international links (depending on the country of headquarter and the country of other subsidiaries). Owing to our specific focus on R&D in Australia and the increasing intricacies of multinational operation, we do not attempt to model this channel in details. The problem is confounded by the fact that a non-trivial number of firms in our sample change status from domestic to multinational or vice versa in the course of the years,

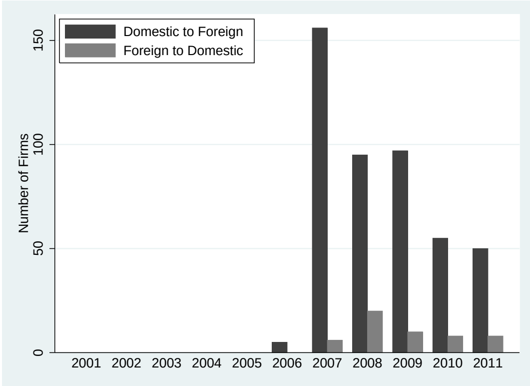



Figure 3: The number of firms that change status from domestic to foreign multinational and vice versa during each year.

so that this issue cannot be considered in the context of a fixed effect (Figure 3). The number of firms changing status to foreign multinational especially peaks in 2007 – when restrictions where lifted on foreign multinationals in claiming tax concession for their incremental R&D – but continues during the years that follow.

Part of this activity could be associated with the acquisition of Australian firms by foreign multinationals as conducting research becomes more lucrative in Australia over the ensuing years. The other part could well be foreign subsidiaries having posed as an Australian entity prior to 2007 in order to benefit from the full scope of R&D tax subsidies. We are unable to distinguish between the two cases using the information available to us, hence, we drop all multinationals from our analysis sample to make our predictions narrow and accurate and, above all, pertaining to the Australian industries. For this purpose, we define multinationals in the strictest sense by dropping all firms that report a foreign country as their headquarter for at least one year during the observed sample (9,178 observations). We still use these foreign subsidiaries as sources of knowledge spillover to domestic firms as there is evidence that domestic firms can benefit from the presence of foreign multinationals while the reverse is not necessarily true (Blomtröm & Kokko, 1998).

In a follow up investigation, we repeat our main estimation exercises by also including the foreign multinationals and report the results in Appendix A to highlight the differences between the behavior of domestic firms versus foreign subsidiaries. Comparing the results in particular suggests that foreign multinationals have less reliance on their capacity to absorb local knowledge which points to these firms putting greater importance on their international linkages.

## 4 Spillovers

The cornerstone of the study is a set of proxies that measure the size and strength of inward spillover of knowledge from various sources. We take guidance from Bloom et al. (2013) to model the spilling of knowledge between two firms $j$ and $j'$ in terms of random encounters between the R&D staff of the two firms. The number of such incidences are $RDSTAFF_{j'} \times RDSTAFF_j$, where $RDSTAFF$ is the full-time equivalent number of staff members engaged in R&D. To measure the full scale of spillover possibilities for firm $j$, we aggregate over all the external firms in our data during the same year, which, expressed in log terms gives

$$\begin{aligned} SPILL_{jt} &= \log\big(\sum_{j' \neq j} RDSTAFF_{jt} \times RDSTAFF_{j't}\big) \\ &= \log(RDSTAFF_{jt}) + \log\big(\sum_{j' \neq j} RDSTAFF_{j't}\big) \\ &= \log(RDSTAFF_{jt}) + S_{jt}. \end{aligned} \tag{1}$$

The first term, the log of R&D staff in firm $j$, can be thought of as the *absorptive capacity* of firm $j$ in turning outside knowledge into the firm-specific knowledge that can then be applied to the ongoing innovation projects of the firm. The second term, $S$, proxies for the size of outside pool of knowledge that is newly generated during the period. With an abuse of terminology, we will henceforth use the term *knowledge* to address the pool of newly generated knowledge and maintain brevity. We would like to emphasize again that index $j$ spans sample firms excluding foreign multinationals, whereas index $j'$ covers all firms, domestic or multinational, as we believe that subsidiaries of foreign firms can still be a source of knowledge spillover to domestic firms as long as they carry out research in Australia.

The aggregation in $S$ weights all firms uniformly regardless of the fact that many of those firms might be operating in industries where the line of research is far from or totally irrelevant to what the industry of firm $j$ finds applicable. To study the possible effect of taking these links into account, we form a few extra proxies that to the extent that our data allows would decouple the variety of channels through which a firm could source its outside knowledge. First, we define *horizontal* knowledge as the cumulative research staff of all firms in the same 3-digit ANZSIC subsector as that of firm $j$, or

$$H_{jt} = \log\Big(\sum_{j' \neq j} RDSTAFF_{j't}\Big), \quad \text{and } j, j' \in \text{same 3-digit ANZSIC}. \tag{2}$$

Firms included in this aggregation mostly compete in the same market as that of firm $j$. The leakage of knowledge among these firms can be a catalyst for rapid innovation owing to the ease of replication but also poses a source of tension as firms try to avoid offering free rides to their competitors. The two countervailing incentives leave the final conclusion about the direction of effect mostly ambiguous.

Second, we define *vertical* knowledge as the cumulative research staff of firms in a vertical relationship with firm $j$. The vertical relation can be with an upstream supplier resulting in forward spillover from supplier to firm $j$ or with a downstream client firm with knowledge leaking backward from client to firm $j$. To our disadvantage, we do not observe which firms are exactly in a vertical relationship with firm $j$. Instead, we use ABS Input-Output tables for year 2007 and compute the share of output from industry of firm $j'$ that is directed towards the industry of firm $j$. The Input-Output shares have very slow dynamics, and the shares tend to stay by and large the same for the range of years covered in our data.[3] In the absence of more accurate information, we make the simplifying assumption that the proportion of researchers in firm $j'$ that are relevant to firm $j$'s line of research follow the same shares as with outputs. For a more detailed characterization of vertical links, we define separate proxies for backward and forward knowledge, which are

$$V_{jt}^{FW} = \log\Big(\sum_{j' \neq j} w_{j',j} RDSTAFF_{j't}\Big), \quad \text{and } j, j' \notin \text{same 3-digit ANZSIC}, \tag{3}$$

$$V_{jt}^{BK} = \log\Big(\sum_{j' \neq j} w_{j,j'} RDSTAFF_{j't}\Big), \quad \text{and } j, j' \notin \text{same 3-digit ANZSIC}, \tag{4}$$

where $w_{j',j}$ is the share of output by the industry of firm $j'$ that is consumed by the industry

[3]There are, in fact, quality issues with the Input-Output tables published by the ABS for years prior to 2007. From 2007 onwards, the ABS overhauled its methodology which resulted in more representative entries. For this reason, we abstain from using tables from years prior to 2007.

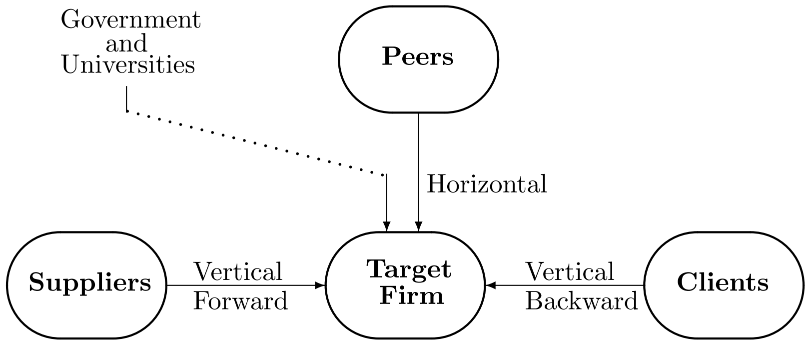



Figure 4: Modeled channels of knowledge spillover.

of firm $j$. $w_{j,j'}$ reverses the direction and looks at the share of output from the industry of firm $j$ that is consumed by the industry of firm $j'$. Following Javorcik (2004), we exclude firms that are within the same 3-digit industry from the aggregation despite some intra-industry sourcing, as their inclusion would lead to double counting and only aggrevates cross-correlations among the knowlegde variables.

Lastly, we enhance our model by not only looking at the leakage of knowledge from private firms but also by accounting for public sources of knowledge. The Australian Bureau of Statistics (ABS) publishes the amount of R&D expenditures by the state and commonwealth governments (ABS Cat.No.8109) and also by the institutes of higher education (ABS Cat.No.8111) within each Australian state and territory and on a biennial basis. Using the information, we supplement our data with the following state-level variables:

- $FEDERAL$: R&D expenditure by commonwealth government.
- $STATE$: R&D expenditure by local state governments.
- $ACADEMIA$: R&D expenditures by institutes of higher education in Australia.

The data are collected biennially, and we fill the gap years by linear interpolation. Not to be confused with the government R&D subsidies, expenditures by the commonwealth and state governments on R&D are strictly intramural spendings by agencies and institutions belonging to the corresponding government (ABS Cat.No.8109, Explanatory Notes). Figure 4 illustrates the full picture of proxies used in the modeling of knowledge spillover.

## 4.1 Geography

There is mounting evidence that the inter-firm leakage of knowledge is strongly correlated with the physical proximity of firms and happens in geographical clusters; see Chatterji et al. (2013) for a comprehensive survey. In order to engage and test the possible role of geography in spillovers, we compute the great arc distance between every two pairs of firms by plugging in the available longitude and latitude coordinates of firms into Haversine formula. In particular, if the coordinates of two firms are $(x_j, y_j)$ and $(x_{j'}, y_{j'})$, then the Haversine great arc distance between the two points is

$$d_{j,j'} = 2R \arcsin\left(\sqrt{\sin^2\left(\frac{y_j - y_{j'}}{2}\right) + \cos(y_j)\cos(y_{j'})\sin^2\left(\frac{x_j - x_{j'}}{2}\right)}\right), \tag{5}$$

in which $R$ is the average radius of the earth and is set equal to 6371.009km. We then apply the following distance-based weights

$$\mu_{j,j'} = \frac{1}{1 + \left(\frac{d_{j,j'}}{\delta}\right)^2}. \tag{6}$$

In this weighting function, $\delta$ is the radius of proximity such that firms at distance $\delta$ are weighted by 50% and firms at distance $3\delta$ or farther are weighted by less than 10% (Figure 5). Such weighting function has been extensively used in fuzzy logic in order to make the transition from one class to the other – in this case, from near to far firms – a smooth one (see, for instance, Zimmermann, 1996). The smoothness feature is especially helpful in rendering small adjustments to the distance parameter inconsequential, as opposed to a crisp boundary where changing the radius by a few kilometers could change the results when, for instance, a cluster of firms lies next to the border.

Incorporating the geographic weights into the proxies introduced earlier generates an extra set of distance-based measures of knowledge each originating from either near or far

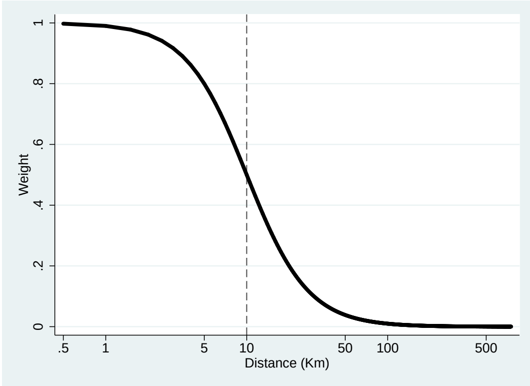



Figure 5: An illustrattion of geo-weights with $\delta$=10km.

firms. For example, in the case of horizontal knowledge, one can define

$$H_{jt} \text{ Near } = \log\Big(\sum_{j' \neq j} \mu_{j,j'} \times RDSTAFF_{j't}\Big), \tag{7}$$

$$H_{jt} \text{ Far } = \log\Big(\sum_{j' \neq j} (1 - \mu_{j,j'}) \times RDSTAFF_{j't}\Big), \tag{8}$$

where $j$ and $j'$ belong to the same 3-digit ANZSIC. We construct $V^{UP}$ Near/Far and $V^{DOWN}$ Near/Far with the same convention but using the appropriate vertical weights for the aggregation.

## 4.2 Descriptive Statistics

Our estimation entails an extensive set of covariate accounting not only for a firm's idiosyncratic characteristics but also for various external sources of knowledge. We list the full list of proxy variables defined to this point along with the description of their applications in Table 3 for easier reference.

Table 4 reports the descriptive statistics for a set of variables signifying firm size and the proxy variables for knowledge spillover. Descriptive statistics for the distance-based proxies are listed in Section 6.2 where the choice of the proximity radius is discussed first.

The first three variables in the table, namely, sales, employment and R&D expenditures, describe the scale of operation. An exploration of the descriptive statistics for these variables paints an inclusive picture where a broad spectrum of very small to very large firms are

| Variable | Proxies for: |
|---|---|
| $RDSTAFF$ | Absorptive capacity |
| $S$ | Newly generated knowledge by all external firms |
| $H$ | Newly generated knowledge from horizontally linked firms |
| $V^{FW}$ | Newly generated knowledge through forward (supplying) links |
| $V^{BK}$ | Newly generated knowledge through backward (client) links |
| $H$ Near | Newly generated knowledge from horizontally linked firms in the geographic vicinity |
| $V^{FW}$ Near | Newly generated knowledge through forward (supplying) links in the geographic vicinity |
| $V^{BK}$ Near | Newly generated knowledge through backward (client) links in the geographic vicinity |
| $H$ Far | Newly generated knowledge from horizontally linked firms in geographically far distance |
| $V^{FW}$ Far | Newly generated knowledge through forward (supplying) links in geographically far distance |
| $V^{BK}$ Far | Newly generated knowledge through backward (client) links in geographically far distance |

Table 3: The description of proxies used for the estimation of spillover effects originating from private R&D carried out by other firms.

present in our sample. The distributions are in general very skewed towards small firms which can be seen in the gross difference between the mean and median size. This skewness would follow naturally from the Pareto distribution of firm sizes (Axtell, 2001) but also from the program's emphasis on small and medium sized firms. The concession is, however, not limited to small firms, and large firms in Australia are participants as long as they are conducting eligible research.

We also notice that a few observations in our sample are not hiring any R&D staff, while spending non-zero sums on R&D. We believe that these observations are most likely paying for outsourced R&D activity rather than undertaking research internally.

The middle part of the table reports statistics on the public sources of knowledge either form universities or from government agencies. These variables only vary across states and years. As one would expect, academia has spent much more than state and federal governments combined on research given their specific focus on research-based projects.

The bottom part of the table lists statistics that pertain to private sources of knowledge

| Variable | Mean | Std.Dev. | 1st Decile | Median | 9th Decile | #obs |
|---|---|---|---|---|---|---|
| Idiosyncratic | | | | | | |
| $SALES$ (\$mil) | 82.2 | 1062.3 | 0.00 | 0.92 | 43.8 | 58,338 |
| $EMP$ | 207.5 | 4038.0 | 1.00 | 10.0 | 150.0 | 58,338 |
| $R\&D$ (\$mil) | 1.36 | 8.61 | 0.06 | 0.31 | 1.80 | 58,338 |
| $RDSTAFF$ | 7.63 | 409.8 | 0.00 | 2.00 | 9.90 | 57,977 |
| Public knowledge | | | | | | |
| $ACADEMIA$ (\$mil) | 1203.3 | 623.3 | 450.1 | 1062.3 | 2210.1 | 58,337 |
| $FEDERAL$ (\$mil) | 319.6 | 148.3 | 120.6 | 313.2 | 541.0 | 58,337 |
| $STATE$ (\$mil) | 227.7 | 75.8 | 113.6 | 256.9 | 308.7 | 58,337 |
| Private knowledge | | | | | | |
| $S$ | 10.8 | 0.50 | 10.4 | 10.9 | 11.0 | 57,205 |
| $H$ | 6.86 | 1.37 | 4.94 | 7.19 | 8.34 | 57,174 |
| $V^{FW}$ | 5.70 | 1.28 | 4.09 | 5.64 | 7.48 | 57,205 |
| $V^{BK}$ | 6.35 | 0.88 | 5.27 | 6.34 | 7.25 | 56,568 |

Table 4: Table of descriptive statistics for the set of covariates used in the modeling.

according to the list of proxies in Table 3. The aggregation of external R&D staff and the log transformation somewhat limit the range of values for these proxies, however, breaking down knowledge by vertical and horizontal links introduces more dispersion into each of these measures.

In table 5 we report the correlation coefficients between the set of key variables in our modeling specification. As the correlations show, larger firms, either in sales or employment, also spend more on R&D and hire a larger R&D staff; all those correlations are positive and rather strong. on the other hand, knowledge-based proxies do not show strong correlations with firm-specific variables. However, there are positive correlations in the order of 0.2 to 0.3 between horizontal and vertical proxies for knowledge. In other words, engagement of larger R&D staff by an industry in general coincides by the engagement of larger R&D staff by the industries that are positioned as suppliers and clients to that industry. On its face, this observation points to some degree of synergy between the R&D activities of vertically linked industries.

| Variable | $SALES$ | $EMP$ | $R\&D$ | $RDSTAFF$ | $S$ | $H$ | $V^{FW}$ |
|---|---|---|---|---|---|---|---|
| $EMP$ | 0.352 | | | | | | |
| $R\&D$ | 0.411 | 0.193 | | | | | |
| $RDSTAFF$ | 0.021 | 0.012 | 0.042 | | | | |
| $S$ | 0.026 | 0.001 | 0.016 | 0.003 | | | |
| $H$ | -0.023 | -0.025 | -0.013 | 0.002 | 0.178 | | |
| $V^{FW}$ | 0.052 | 0.022 | 0.031 | 0.005 | 0.391 | 0.300 | |
| $V^{BK}$ | 0.004 | -0.004 | -0.021 | 0.002 | 0.645 | 0.283 | 0.231 |

Table 5: Table of correlations between firm characteristics and knowledge proxies.

# 5 Econometric Methodology

The goal of this study is to investigate the factors that impact the size of R&D conducted by a firm with a focus on the role of knowledge spillover from external sources such as other firms or government bodies on the size of R&D. We are especially interested in exploring various channels through which this leakage of knowledge influences the firm's incentives. Given the panel nature of our data, we approach this problem by considering a dynamic equation in R&D expenditures. To begin with, let

$$r = \log(R\&D), \quad s = \log(SALES),$$

where $R\&D$ and $SALES$ are the annual R&D expenditure and turnover, both in nominal terms. Let $\Sigma$ represent the set of proxies defined in the previous section that measure the strength of inward spillover of knowledge from external sources such as peers, suppliers, clients, and also from not-for-profit institutions such as universities and government agencies. We model the effect of these spillover factors on the size of R&D expenditures in firm $j$ at time $t+1$ as the following linear specification

$$r_{j,t+1} = \Sigma_{jt}\alpha + b_1 r_{jt} + b_2 s_{jt} + T(r_{jt}, s_{jt}) + c_j + \tau_t + \epsilon_{jt}. \tag{9}$$

As we are dealing with R&D tax concession data, we explicitly account for the size of subsidies by the inclusion of function $T(\cdot,\cdot)$. Since we lack the information to accurately replicate the size of subsidies, we use a translog parametrization of the function for our estimation purpose, such that

$$T(r_{jt}, s_{jt}) = b_3 r_{jt} + b_4 s_{jt} + b_5 r_{jt}^2 + b_6 r_{jt} s_{jt} + b_7 s_{jt}^2. \tag{10}$$

Note that with the parametrization above $b_1$ and $b_3$ cannot be separately identified; the same applies to $b_2$ and $b_4$. We are not constrained by this unidentifiability problem in any way since we are interested in the effects we will estimate for $\Sigma$. All together, our model takes the form of the following dynamic panel representation

$$r_{j,t+1} = \rho r_{jt} + \Sigma_{jt}\alpha + X_{jt}\beta + c_j + \tau_t + \epsilon_{jt}. \tag{11}$$

The individual and time aspects of the panel are absorbed by $c_j$ and $\tau_t$. The equation above, however, is only valid if a firm continues to stay registered in the program into time $t+1$. Table 1 has already shown that there is a constant flow of firms out of the program in each year, either temporarily to reappear later or permanently as far as allowed within our window of observation. We mentioned earlier that one eligibility criteria for continuing in this program is to maintain at least \$20,000 in R&D expenditures during the financial year, and we believe one main reason for exit is that the firm's perceived future R&D expenditures fall below this threshold. We also mentioned a systematic relationship between size and exit originating from the fact that, owing to their limited resources, small firms carry out R&D in spells while larger firms often have a continuous and dedicated R&D program. This systematic relationship is illustrated in Figure 6, where we predict the average probability of exit using a Probit projection on a set of size classes and year, industry and state dummies. The illustrated relationship will constitute our approach to selection treatment that we will explain shortly.

Estimating a dynamic panel with sample selection raises two econometric issues. The first issue is the inconsistency of estimates caused by the propagation of fixed effects in the dynamic panel (Hsiao, 2003, Page 72). The systematic self-selection of firms into and out of the program adds salt to the wound by introducing selection biases. In a recent work, Semykina & Wooldridge (2013) propose a practical method to deal with both issues at the same time. They basically use the recursive nature of equation 11 to compute $r_{t+1}$ as a function of the initial condition and the history of the remaining explanatory variables.

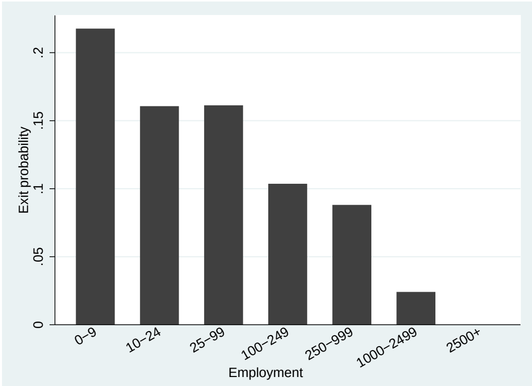



Figure 6: The relative probability of exit for different classes of employment size using the large group of 2500+ employees as the base. The sample pools all firm–years.

Owing to the nonlinear nature of the estimation, firm fixed effects are modeled as in Mundlak (1978) using a linear combination of the initial condition and the firm-level mean of continuous variables:

$$c_j = \eta + (\bar{\Sigma}_{jt}, \bar{X}_j)\xi + \gamma r_{j0}. \tag{12}$$

In the averaging of the terms in $\Sigma$, we take care to exclude the public sources since these variables are too aggregated to hold information about the idiosyncratic features of firms. Further, for the identification of panel models it is necessary that each firm be present for at least two years, therefore, we drop all firms that appear only once in the panel (5,640 observations). Time variations of R&D expenditure as a result of business cycles or other economy-wide forces are absorbed by turning $\tau_t$ into a set of year dummies.

Semykina & Wooldridge (2013) conduct the estimation in two steps. In step one, the probability that a firm continues into $t+1$ is projected onto a constant, $r_{j0}$, $\Sigma_{jt}$, and $X_{jt}$ using a Probit maximum likelihood estimation. To avoid collinearity in the second step, the log of employment is used in addition to the covariates in $X$ and $\Sigma$ as selection exclusion. In step two, nonlinear least squares is used to estimate the parameters in the following specification:

$$m_{jt} := \rho r_{0jt} + \left( \sum_{k=0}^{t} \rho^j (\Sigma_{jt-k}, X_{jt-k}) \right) \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \left( \frac{1-\rho^t}{1-\rho} \right) c_j + \phi_t \lambda_{jt} + \tau_t,$$

where $\lambda$s are the inverse Mill's ratios constructed from the estimation results of the first step.

# 6 Estimation Results

## 6.1 Baseline Estimations

In our baseline model we first look at the role of horizontal and vertical knowledge as a benchmarking practice. In addition to reporting the estimates from our main econometric approach, we also report results from OLS and truncated Tobit estimations of the same specification in order to showcase the magnitude of biases that our results would suffer from without the proper treatments. As we mentioned in Section 5, there is the combination of two biases that will be inflicted on the results: bias from the self-selection of firms into staying in or dropping out of the program, and then there is the bias from the propagation of fixed effects in the dynamic model. In comparison to OLS, truncated Tobit applies a partial treatment by specifically enforcing the lower bound of $20,000 on future R&D expenditures, as required by the program's eligibility criteria, but fails to account for the dynamic panel aspect of the problem. The full set of results is reported in columns (1) to (3) of Table 6.

Comparing the coefficients across the first three columns of results reveals the presence of significant biases, to the extent that qualitative interpretation of the results would be severely impaired. One example is the autoregressive coefficient estimated for $r$. If larger R&D expenditures indicates appetite for future R&D, then the positive correlation that will ensue between R&D and the likelihood of staying in the program would bias the autoregressive coefficient upwards, which is the case in our estimates in Table 6. Specifically, OLS and Tobit methods estimate a coefficient of 0.82 for $r_t$ whereas applying the main method generates estimates closer to 0.6. There are a few other coefficients that simply change signs when we apply the full treatment of our main methodology.

Turning attention to column (3) as our preferred set of results, we observe a positive and significant role for the absorptive capacity of a firm proxied by its number of R&D staff. This finding supports the notion that a larger R&D staff facilitates the absorption and conversion of external knowledge for the firm's specific use.

We mentioned earlier that horizontal knowledge spillover is characterized by two countervailing incentives one facilitating research among peers by generating a network of knowledge flows, the other discouraging research for the fear of free-riding. We observe that in our es-

| Variables | OLS<br>(1) | Tobit<br>(2) | SW<br>(3) | SW<br>(4) |
|---|---|---|---|---|
| $\log(RDSTAFF_t)$ | -0.183*** | -0.190*** | 0.023*** | 0.015*** |
| | (0.006) | (0.009) | (0.003) | (0.003) |
| $H_t$ | -0.025*** | -0.025*** | -0.001** | |
| | (0.006) | (0.006) | (0.000) | |
| $V_t^{FW}$ | -0.006 | -0.006 | 0.030*** | |
| | (0.006) | (0.006) | (0.003) | |
| $V_t^{BK}$ | -0.012 | -0.011 | -0.025*** | |
| | (0.009) | (0.009) | (0.003) | |
| $S_t$ | | | | 0.016*** |
| | | | | (0.002) |
| $\log(ACADEMIA_t)$ | 0.040*** | 0.037* | 0.316*** | 0.211*** |
| | (0.014) | (0.014) | (0.020) | (0.024) |
| $\log(FEDERAL_t)$ | -0.054*** | -0.055*** | -0.236*** | -0.206*** |
| | (0.010) | (0.011) | (0.015) | (0.025) |
| $\log(STATE_t)$ | -0.015* | -0.013* | -0.178*** | -0.104*** |
| | (0.008) | (0.008) | (0.023) | (0.024) |
| $r_t$ | 0.822*** | 0.821*** | 0.554*** | 0.604*** |
| | (0.005) | (0.008) | (0.009) | (0.008) |
| $s_t$ | 0.000 | 0.001 | 0.024*** | 0.023*** |
| | (0.002) | (0.004) | (0.003) | (0.003) |
| $r_t^2$ | 0.116*** | 0.112*** | 0.021*** | 0.017*** |
| | (0.002) | (0.004) | (0.003) | (0.002) |
| $r_t \times s_t$ | -0.016*** | -0.016*** | 0.017*** | 0.019*** |
| | (0.001) | (0.001) | (0.002) | (0.002) |
| $s_t^2$ | 0.004*** | 0.005*** | -0.007*** | -0.006*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Log Likelihood | -34,214.9 | -33,296.3 | -44,600.6 | -45,320.1 |
| $N$ | 38,165 | 38,165 | 38,165 | 38,566 |
| $\sigma^2$ | 0.593 | 0.349 | 0.779 | 0.784 |

Table 6: Estimated coefficients in the main model. Dependent is the log of R&D expenditure at time $t + 1$. SW refers to Semykina & Wooldridge (2013) method. Numbers in parentheses are robust standard errors. ***, **, and * indicate significance at 1%, 5% and 10%, respectively. A set of time dummies are also included but not reported.

timates, the coefficient for $H$, as the proxy for horizontal knowledge, is negative. However, we also note that despite being statistically significant, this coefficient has a very small magnitude that is near zero, as if the two forces are mostly balancing out. To show that the coefficient implies an insignificant economic impact, we find that a 10% increase in the number of R&D staff held by all other peers would force a firm to reduce its R&D expenditure by about $95 against the backdrop of $1.36 million of average R&D expenditures or $310,000 in median R&D.[4] Overall, it looks as if the two incentive mostly balance with a near zero total effect on aggregate.

Backward spillovers from clients also show a negative effect, so that a larger stock of R&D staff held by client firms acts as a disincentive. Forward spillover from suppliers, however, impacts R&D expenditures positively. Both of these latter effects show a much larger magnitude to that of the horizontal channel. For instance, a 10% increase in the stock of R&D staff by suppliers, by itself, leads to about $2,863 increase in a firm's R&D expenditures.

In column (4) we estimate an extra set of results by bunching all the horizontal and vertical channels into one component, variable $S$, to observe the average effect and also for benchmarking with the general line of works that do not make the distinctions that we are making here. The coefficient is positive and statistically significant, hence, the average effect of knowledge generated by other firms is in support of research.

Our model additionally accounts for sources of public knowledge by estimating coefficients on the log of R&D expenditures by academic institutions and government agencies in the firm's geographic state. The estimated effects in general are favorable to the role of academia as a vehicle for stimulating private R&D; the estimated coefficient is positive and statistically significant. The estimates, however, reveal a negative impact from R&D expenditures by state and federal governments on private R&D. These latter expenditures exhibit a crowding effect that dissuades private firms from carrying out R&D where government agencies are actively undertaking research projects. We notice that research activities among academic institutions have been mostly concentrated on the basic type; this type of research can be broadly applied to various applications with minimal adaptations, hence nourishes the

[4] The dollar value is computed as $e^{-0.001 \log(1.1)} - 1 \simeq -0.000095$($mil.).

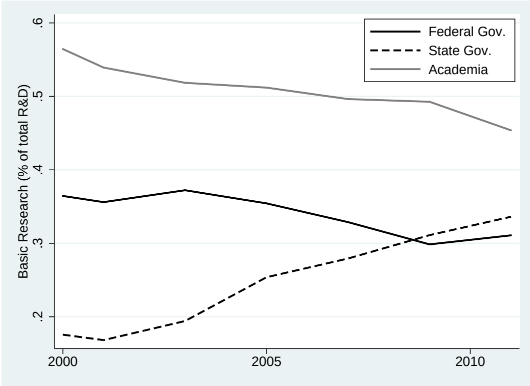



Figure 7: The proportion of expenditures on basic research by institutes of higher education and state and federal government agencies. Basic research is measured as the sum of spendings on pure and strategic basic research, and applied research is the sum of spendings on applied research and experimental developments. Annual expenditures sourced from ABS.Cat.No.8109 and ABS.Cat.No.8111.

applied type of research that is commonly undertaken among private firms. Similar evidence has been found by Jaffe (1989) regarding the inter-relationship between firms and universities in the US. On the other hand, state and federal government have been dedicating a larger proportion of their R&D expenditures to applied research (Figure 7), practically competing with research in the private sector rather than feeding it.

The remaining coefficients at the bottom part of Table 6 pertain to the autoregressive component of the model and also to the parametrization of the rebate function $T(.)$. The estimates, in particular, show some persistence in R&D expenditures at firm level but with a rapid decline in the absence of any revenue or external stimulants.[5] It should be noted that, owing to the inseparability of $T(.)$ and the autoregressive term, the coefficient for $r$ is an over-estimation of the R&D dynamics in the absence of Tax Concession program. The estimated coefficients for the quadratic terms also fortify the notion that the government tax rebate has been stimulating R&D expenditures by private companies: all the coefficients are positive and statistically significant except for the coefficient of $s^2$ that is negative. The

[5]Given the estimates from Table 6, the approximate relationship is $R\&D_{t+1} = A_t(R\&D_t)^{0.6}$, in which $A_t$ is the proper aggregation of all factors in Table 6 excluding $R\&D$ expenditure in firm $j$. Then one million dollar R&D expenditure at time $t$ will be exhausted as

$$\begin{array}{llllllll} \text{Time:} & t & & t+1 & & t+2 & & \\ R\&D & \$1,000,000 & \Rightarrow & \$3,981A_t & \Rightarrow & \$144A_t^{0.6}A_{t+1} & \Rightarrow & \dots \end{array}$$

Evidently, the main force that sustains R&D is not the current expenditures but the contribution from $A_t$, $A_{t+1}$, ....

implication of this negative coefficient is that among the participating firms, those ones that spend too little on R&D as a proportion of their revenue, that is firms with low intensity of R&D, are the firms the least affected by R&D Tax Concession program, regardless of how much the firm spends nominally. As long as the R&D intensity at time $t$ is large enough, firms are expected to raise future R&D expenditures in response to the tax concession.

## 6.2 Geography and Spillovers

We now decompose our horizontal and vertical proxies by geography for a more detailed insight into the sources of spillover. Mounting evidence from other countries already suggests that the spillover of knowledge is mostly concentrated within clusters of proximate firms and the strength of these spillovers dampens as firms get farther apart. In our case, we are following Bloom et al. (2013) to model spillovers based on inter-staff interactions, and these interactions certainly becomes infrequent and less effective as the distance between two firms increases. However, as of yet, there has been no consensus on the appropriate limit on the radius within which knowledge leakage is the strongest. In a series of works surveyed by Chatterji et al. (2013), evidence has been ranging from anything between one kilometer to hundreds of kilometers. We use an initial radius of 10km for proximity to account for the maximum chance of encounters between staff within a good portion of a metropolitan area. We then follow up by using radii of 25km and 50km for robustness check. Large Australian metropolitans (such as Sydney and Melbourne) are almost fully covered by the latter assignments.

The descriptive statistics for the near and far proxies are reported in Table 7. The two panels of the table show the statistics at the two extremes of 10km and 50km that we use as proximity radius so that we can check the full range of variations in each value. The first thing to note is that, in comparing to Table 4, the decoupling of knowledge proxies into near and far components is generating more dispersion within each proxy. Moving from the radius of 10km to 50km also has the expected outcome that the near proxies get larger and far proxies get smaller as more firms are being moved from far to near classification by the expansion of the radius.

The correlations reported in Table 8 also point to a positive relationship between proxies.

| Variable | Mean | Std.Dev. | 1st Decile | Median | 9th Decile | #obs |
|---|---|---|---|---|---|---|
| Idiosyncratic | | | | | | |
| Panel A | | | $\delta$=10km | | | |
| $H$ Near | 3.51 | 2.68 | -0.01 | 4.10 | 6.27 | 56,414 |
| $V^{FW}$ Near | 2.39 | 2.18 | -0.61 | 2.69 | 4.99 | 56,446 |
| $V^{BK}$ Near | 2.95 | 2.14 | -0.15 | 3.43 | 5.17 | 55,829 |
| $H$ Far | 6.74 | 1.38 | 4.83 | 7.03 | 8.21 | 57,172 |
| $V^{FW}$ Far | 5.61 | 1.28 | 4.05 | 5.53 | 7.38 | 57,205 |
| $V^{BK}$ Far | 6.25 | 0.88 | 5.21 | 6.27 | 7.15 | 56,568 |
| Panel B | | | $\delta$=50km | | | |
| $H$ Near | 4.68 | 2.11 | 1.89 | 5.14 | 6.91 | 56,414 |
| $V^{FW}$ Near | 3.57 | 1.78 | 1.25 | 3.73 | 5.80 | 56,446 |
| $V^{BK}$ Near | 4.14 | 1.67 | 1.97 | 4.44 | 5.89 | 55,829 |
| $H$ Far | 6.60 | 1.41 | 4.72 | 6.89 | 8.11 | 57,172 |
| $V^{FW}$ Far | 5.48 | 1.28 | 3.92 | 5.40 | 7.21 | 57,205 |
| $V^{BK}$ Far | 6.12 | 0.86 | 5.08 | 6.15 | 7.02 | 56,568 |

Table 7: Descriptive statistics for knowledge proxies decoupled by near and far distances using a proximity.

The correlations are particularly stronger within the group of near proxies and separately within far proxies. This evidence, again, reasserts the synergy between firms and their clients and suppliers in terms of research activity especially within firms that are close to each other or located within clusters, as those correlations are the strongest.

The estimated coefficients for the distance-based proxies are reported in Table 9 where the three columns correspond to the use of proximity radii of 10km, 25km, and 50km, respectively. There are a few key facts that are visible in this table and add more insight into what we found in Table 6. Most importantly, in Table 6 we found that horizontal knowledge had no remarkable impact. Now, by decoupling the proxy into near and far, we see that most of that insignificance was actually caused by the spillovers from near and far firms effectively canceling each other. The estimated coefficients in Table 9 show that R&D by peers in close proximity actually stimulates R&D expenditures with a non-trivial impact.

For backward spillover of knowledge from client firms we again find a similar pattern. Where the results in Table 6 suggested a negative effect, we observe in this table that most of that negative effect came from far clients. Increased R&D activity by client firms in close proximity indeed encourages an increase in R&D expenditure by the firm.

The results in Table 6 also suggested that suppliers are a significant source of forward

| Variable | $H$ Near | $V^{FW}$ Near | $V^{BK}$ Near | $H$ Far | $V^{FW}$ Far | |
|---|---|---|---|---|---|---|
| Panel A | | | $\delta$=10km | | | |
| $V^{FW}$ Near | 0.667 | | | | | |
| $V^{BK}$ Near | 0.653 | 0.734 | | | | |
| $H$ Far | 0.599 | 0.231 | 0.178 | | | |
| $V^{FW}$ Far | 0.181 | 0.561 | 0.082 | 0.290 | | |
| $V^{BK}$ Far | 0.201 | 0.146 | 0.419 | 0.273 | 0.234 | |
| log($RDSTAFF$) | 0.003 | 0.006 | 0.004 | 0.002 | 0.005 | 0.002 |
| Panel B | | | $\delta$=50km | | | |
| $V^{FW}$ Near | 0.568 | | | | | |
| $V^{BK}$ Near | 0.562 | 0.615 | | | | |
| $H$ Far | 0.641 | 0.213 | 0.152 | | | |
| $V^{FW}$ Far | 0.160 | 0.627 | 0.038 | 0.296 | | |
| $V^{BK}$ Far | 0.171 | 0.096 | 0.434 | 0.277 | 0.229 | |
| log($RDSTAFF$) | 0.004 | 0.007 | 0.005 | 0.001 | 0.005 | 0.001 |

Table 8: Table of correlations between distance-based proxies.

knowledge spillover; however, contrary to our expectation most of that contribution is actually sourced from far suppliers rather than from proximate suppliers. We are as yet unsure why spillover of knowledge by suppliers should be unaffected by distance. One hypothesis is that the pattern is mostly driven by one industry in which staff can easily connect and interact professionally with other staff over long distances. To test whether this is the case, we report a few re-estimations of our model in Table 10 where in each column we exclude one strong candidate industry and observe any qualitative change in results as a result of the omission.

The top row in the table indicates the excluded industry (or industries) from the analysis by its major group code. In column (1) we exclude Wholesale Retail (F) and Retail Trade (G) arguing that their increasing dependence on an internet-base business model rather than a traditional mortar-and-brick operation could be eliminating the need for face-to-face staff interactions. In column (2), our candidate is Information Media and Telecommunication (J). Most companies in this sector provide software or computer services to other businesses, which in turn could facilitate the transfer of knowledge over long distances without the need

| | (1) | (2) | (3) |
|---|---|---|---|
| $\delta$ | 10km | 50km | 100km |
| Variables | | | |
| $\log(RDSTAFF_t)$ | 0.045 | 0.007 | 0.037 |
| | (0.005) | (0.002) | (0.004) |
| $H_t$ Near | 0.026 | 0.002 | 0.033 |
| | (0.004) | (0.001) | (0.004) |
| $V_t^{FW}$ Near | -0.072 | -0.043 | -0.067 |
| | (0.005) | (0.005) | (0.006) |
| $V_t^{BK}$ Near | 0.021 | 0.009 | 0.005 |
| | (0.003) | (0.002) | (0.001) |
| $H_t$ Far | -0.024 | -0.002 | -0.021 |
| | (0.003) | (0.001) | (0.002) |
| $V_t^{FW}$ Far | 0.096 | 0.070 | 0.110 |
| | (0.007) | (0.007) | (0.009) |
| $V_t^{BK}$ Far | -0.071 | -0.053 | -0.062 |
| | (0.005) | (0.006) | (0.005) |
| Log Likelihood | -43,819.7 | -43,813.2 | -43,882.4 |
| $N$ | 37,686 | 37,686 | 37,686 |
| $\sigma^2$ | 0.775 | 0.774 | 0.776 |

Table 9: Estimated coefficients in the distance-based specification. Dependent is the log of R&D expenditures at $t + 1$. The estimation method in all columns is is that of Semykina & Wooldridge (2013). Numbers in parentheses are robust standard errors. All coefficients are statistically significant at 1% level. A set of time dummies plus additional controls are also included but not reported.

for the staff to be in the same room. The sector that is excluded in column (3) is Financial and Insurance Services (K), and our reasoning is similar to that of the retail trade: the sector is moving towards a more online-oriented operation, and several financial institutions today do not even have a physical branch. In our last test, we exclude sector Professional, Scientific and Technical Services (M) in column (4). These services hold great potentials for knowledge generation and leakage regardless of their location, and leakage from these firms can happen not on site but through other media such as research papers, reports, in conferences, and through patents.

We observe that the largest impact on the coefficients results from the omission of Scien-

| | (1) | (2) | (3) | (4) | | (5) |
|---|---|---|---|---|---|---|
| Industry Excluded | F,G | J | K | M | States Included | NSW,VIC QLD |
| Variables | | | | | | |
| $\log(RDSTAFF_t)$ | 0.015 | 0.026 | 0.018 | 0.010 | | 0.018 |
| | (0.002) | (0.003) | (0.003) | (0.003) | | (0.001) |
| $H_t$ Near | 0.028 | 0.024 | 0.021 | 0.000 | | 0.055 |
| | (0.003) | (0.003) | (0.003) | (0.000) | | (0.003) |
| $V_t^{FW}$ Near | -0.042 | -0.081 | -0.033 | -0.031 | | -0.071 |
| | (0.004) | (0.006) | (0.004) | (0.005) | | (0.004) |
| $V_t^{BK}$ Near | 0.002 | 0.046 | 0.000 | -0.002 | | -0.004 |
| | (0.001) | (0.004) | (0.000) | (0.001) | | (0.000) |
| $H_t$ Far | -0.030 | -0.004 | -0.008 | 0.014 | | -0.053 |
| | (0.002) | (0.001) | (0.001) | (0.003) | | (0.004) |
| $V_t^{FW}$ Far | 0.062 | 0.109 | 0.045 | 0.071 | | 0.095 |
| | (0.005) | (0.009) | (0.004) | (0.011) | | (0.005) |
| $V_t^{BK}$ Far | -0.023 | -0.070 | -0.036 | -0.070 | | -0.063 |
| | (0.002) | (0.007) | (0.004) | (0.011) | | (0.005) |
| Log Likelihood | -42,876.0 | -39,325.5 | -42,473.0 | -36,019.2 | | -34,243.5 |
| $N$ | 36,997 | 33,246 | 36,745 | 30,170 | | 30,164 |
| $\sigma^2$ | 0.772 | 0.790 | 0.769 | 0.799 | | 0.754 |

Table 10: Estimated coefficients in the distance-based specification when excluding specific sectors from the sample. Dependent is log of R&D expenditures at $t+1$. The estimation method is that of Semykina & Wooldridge (2013) in all columns. A set of time dummies plus additional controls are also included but not reported.

tific and Technical Services (M). Other than that, the omission of no single sector in Table 10 qualitatively changes our findings pertaining to forward spillovers. As per this evidence, we conjecture that the mechanism through which knowledge spills over from suppliers to a firm that renders distances inconsequential has to be the product or service itself and a bit of reverse engineering; a contact between the R&D staff of the two firms does not seems to be the crucial channel in this case. In the case of horizontal and backward vertical relations, there is no reception of goods, services, or instruction from other firms; hence, the only way for knowledge to be transferred from one firm to the other is through the direct interaction of staff members. Geographic proximity naturally becomes very important when personal interactions are required.

We are also aware that due to the peculiar geographic distribution of firms in Australia that mostly covers the eastern shore of Australia and then a few isolated spots along the west, north, and center of the continent, it could be that far distance is not a uniform notion across firms from different states. New South Wales, Victoria and Queensland are host to more than 80% of the participating firms which are densely distributed in a connected arc that spans most of the Australian eastern shore (Figure 2(a)). Owing to the dense cluster of firms in the locality, these firms might not feel the need to look at very remote firms as a source of knowledge. On the other hand, clusters of firms in Western Australia are the remotest from other population centers, and those firms could be reaching out to firms as far as those in the eastern shore as a source of knowledge.[6] It would be instructive to repeat the estimation by focusing attention on the three populated states and observe whether the detected patterns of spillover are affected as a result of this narrowing, which in turn implies a non-uniformity in the definition of far distance among firms depending on their geography.

We conduct this exercise by narrowing our sample to those firms that are located in New South Wales, Victoria and Queensland, and the estimated coefficients are reported in column (5) of Table 10. Most coefficients follow what one already observed in Table 9, However, there are a few interesting differences. In these results, the coefficient for the near component of horizontal spillovers is larger than what is found in Table 9. This strengthening of the coefficient simply reflects the increased opportunities for the spillover of knowledge due to the dense distribution of firms – possibly in clusters – in these states. The role of forward knowledge does not show much difference from before, but backward knowledge is now showing a negative but rather weak impact for near firms. We explain this last change by the fact that, due to abundance of sources in populated states, firms probably do not find the acquisition of knowledge from clients as useful as the knowledge they acquire from their peers and suppliers. On the other hand, firms in remote states where business population is low and competition is not that intense have to utilize every channel for knowledge spillover, including clients, in order to maintain their competitiveness.

# 7 Conclusion

A shift by government agencies towards more basic research could be rewarding.

[6]For reference, the physical distance from Perth to Sydney is about 3,900km.

We further notice that Acs et al. (2013) imply that a major part of the knowledge spillover happens not in between large firms but flows from large firms to small firms. We were interested in testing this hypothesis with our current data, but since we are using employment size as an exclusion variable in our selection equation, focusing on small firms generated collinearity and the numerical results were not reliable as a result.

# A Impact of foreign multinationals

Our main focus for this study has been the channels of knowledge spillover within Australia, and for an accurate characterization of these channels we chose to drop all firms we suspected of being a subsidiary to a foreign multinational company. Adding multinational firms back to our sample has actually some non-trivial implications given that they could be using different sources of knowledge to those that we modeled for the domestic firms. The estimation results for the full sample of domestic plus multinational firms is reported in Table 11,

The first difference we notice is that the estimated coefficient for the log of R&D staff, that is, the absorptive capacity of a firm, has turned negative in this table compared to what we had found in Table 6. This observation implies that foreign subsidiaries mostly rely on knowledge that is channeled from their headquarters or through other international links instead of relying on thier R&D staff interacting with local forces. We also notice that the impact of horizontal knowledge has become more negative than what we saw in Table 6 now that we added foreign subsidiaries. The implication is, again, that these subsidiaries have less reliance on local knowledge and are more inclined to look for knowledge from overseas.

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| Variables | (1) | (2) |
|---|---|---|
| $\log(RDSTAFF_t)$ | -0.008 | -0.021 |
| | (0.001) | (0.002) |
| $H_t$ | -0.007 | |
| | (0.001) | |
| $V_t^{FW}$ | 0.035 | |
| | (0.002) | |
| $V_t^{BK}$ | -0.004 | |
| | (0.001) | |
| $S_t$ | | 0.017 |
| | | (0.001) |
| $\log(ACADEMIA_t)$ | 0.338 | 0.355 |
| | (0.021) | (0.027) |
| $\log(FEDERAL_t)$ | -0.289 | -0.309 |
| | (0.019) | (0.024) |
| $\log(STATE_t)$ | -0.161 | -0.173 |
| | (0.023) | (0.026) |
| Log Likelihood | -54,569.0 | -55,602.7 |
| $N$ | 44,464 | 44,976 |
| $\sigma^2$ | 0.826 | 0.833 |

Table 11: Estimated coefficients in the main model when including both domestic and foreign firms in the sample. Dependent is the log of R&D expenditure at time $t+1$. Estimation method is that of Semykina & Wooldridge (2013) in all columns. Numbers in parentheses are robust standard errors. All coefficients in table are significant at 1% level. A set of time dummies are also included but not reported.

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