The impact of R&D subsidy on innovation: a study of New Zealand firms

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Access to the anonymised data used in this study was provided by Statistics NZ in accordance with security and confidentiality provisions of the Statistics Act 1975. Only people authorised by the Statistics Act 1975 are allowed to see data about a particular person, household, business or organisation and the results in this paper have been confidentialised to protect these groups from identification. Careful consideration has been given to the privacy, security and confidentiality issues associated with using administrative and survey data in the IDI. Further detail can be found in the privacy impact assessment for the IDI available from www.stats.govt.nz.

The results are based in part on tax data supplied by Inland Revenue to Statistics NZ under the Tax Administration Act 1994. This tax data must be used only for statistical purposes, and no individual information may be published or disclosed in any other form, or provided to Inland Revenue for administrative or regulatory purposes. Any person who has had access to the unit-record data has certified that they have been shown, have read, and have understood section 81 of the Tax Administration Act 1994, which relates to secrecy. Any discussion of data limitations or weaknesses is in the context of using the IDI for statistical purposes, and is not related to the data's ability to support Inland Revenue's core operational requirements.

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Abstract

This paper examines the impact of government assistance through R&D grants on innovation output for firms in New Zealand. Using a large database that links administrative and tax data with survey data, we are able to control for large number of firm characteristics and thus minimise selection bias. We find that receipt of an R&D grant significantly increases the probability that a firm in the manufacturing and service sectors applies for a patent during 2005–2009, but no positive impact is found on the probability of applying for a trademark. Using only firms that participated in the Business Operation Survey, we find that receiving a grant almost doubles the probability that a firm introduces new goods and services to the world while its effects on process innovation and any product innovation are relatively much weaker. Moreover, there is little evidence that grant receipt has differential effects between small to medium (<50 employees) and larger firms. These findings are broadly in line with recent international evidence from Japan, Canada and Italy which found positive impacts of public R&D subsidy on patenting activity and the introduction of new products.

JEL codes

O31, O34, O38

Keywords

Industrial policy, innovation, R&D

Contents

1. Introduction

Innovation is considered an important source of economic growth (Romer, 1990). However, the outputs of innovation are strongly affected by problems of non-appropriability, non-divisibility and uncertainty, making it difficult for firms to fully internalise the returns to their investment in it. As a result, the equilibrium level of private investment in innovation (i.e., R&D investment) tends to be socially suboptimal (Arrow, 1962).

In order to improve resource allocation for innovation, many countries have policies such as tax credits or assistance grants to support private R&D activity. These policies aim to reduce the costs of the innovation to firms and hence to stimulate innovative activity. According to Eurostat, the public share in R&D activities in the business sector in 2012 was 6.7% for EU28 and 11.5% for the US.[1] In New Zealand, the corresponding share was around 8.8% in 2012 (Statistics New Zealand, 2013, Table 4.01), with direct R&D subsidy for businesses ranging from NZ$33 million to NZ$90 million per year during 2009–2013.[2]

Although there is considerable evidence on the impact of such policies, most existing studies examine whether R&D subsidies affect firms' innovation *input* (e.g. on investment in R&D, tangible assets or employment). Very few consider their impact on firms' innovation *output*. Innovation output is a more interesting outcome as it is arguably a better indicator of whether the subsidy is effective. The current paper seeks to estimate the impact of R&D subsidy on innovation output for firms in New Zealand.[3] There are no R&D tax credits in New Zealand; the main lever the government uses to lift business R&D investment is direct funding through R&D support programmes, which were considerably boosted in 2013. This study will provide useful insights into the role that government R&D support programmes play in business innovation in New Zealand.

Research of this kind must confront the issue of selection bias, which arises because government assistance is not randomly assigned: grants are made in part on the basis of characteristics such as management expertise and productivity that are observed by the granting agency but not by the econometrician. Thus, a finding of correlation between assistance receipt and innovative activity does not necessarily indicate an impact of the former on the latter. This paper will address selection bias by drawing on a rich database, New Zealand's Longitudinal

[1] The public share in R&D in all sectors in 2012 was 33% for EU28 and 31% for the US (Eurostat, 2014).
[2] Statistics New Zealand (2013, Table 4.01) reports higher figures for government R&D funding for businesses (e.g. $146 million in 2012) as these figures include indirect funding (from the national government) as well as funding from local government agencies.
[3] A recent study (Ministry of Economic Development, 2011) evaluated the impact of R&D subsidy on firms' sales, employment and productivity for New Zealand firms, but innovation output was not examined.

Business Database (LBD). Since we are able to control for a large number of firm characteristics, selection bias due to observables can be mitigated and more confidence can be had as to whether any observed association between assistance receipt and innovative activity is likely to represent a causal effect. Moreover, the paper provides an alternative window on the selection bias issue by testing for impact of R&D subsidy on an outcome that is not related to innovation as well as impact on innovation outcomes of a government assistance programme that does not provide resources for R&D. Another feature that distinguishes this study from earlier ones is that it examines several innovation outcomes, making it possible to assess how R&D subsidy impacts on different levels of innovativeness.

The paper proceeds as follows. Section 2 summarises the literature on the effects of government subsidies on firms' innovation output. Section 3 outlines programmes of direct government assistance to firms in New Zealand. Sections 4 and 5 respectively describe the data and methods. Section 6 presents summary statistics, followed by the estimation results in Section 7. Section 8 summarises and concludes.

2. Brief literature review

The primary pathway through which R&D subsidies influences firms' innovation outputs is by reducing the costs of R&D borne by the firm, thereby increasing R&D activities and hopefully innovation outputs. In addition, Humphery-Jenner et al (2014) argue that R&D subsidies in the form of grants can help improve innovation outputs by providing the recipient firm with an externally validated signal of quality, thereby encouraging collaboration and venture investment into the firm's R&D projects which could result in more innovation outputs.

Several studies have documented significant impacts of R&D subsidies on innovation outputs. Branstetter and Sakakibara (2002) find that participation in a government-sponsored research consortium increased the patenting activity of Japanese firms. For Canadian firms, Bérubé and Mohnen (2009) find that firms benefiting from R&D tax credits and R&D grants introduced more new products than their counterparts that benefited from R&D tax credits alone, while Czarnitzki et al (2011) find a positive effect of R&D tax credits on the number of new products introduced by recipient firms. Most recently, in their study of Northern Italian firms, Bronzini and Piselli (2014) find that R&D grant receipt had a significant impact on the number of patents, more markedly in the case of smaller firms.

However, such significant impacts are not always observed. For example, in their survey of evaluations of government Technology Development Funds in Argentina, Brazil, Chile and

Panama, Hall and Maffioli (2008) do not find much statistically significant impact on patents or new product sales. Cappelen et al (2012) find R&D tax credits to have no impact on patenting activity and the introduction of new products by beneficiary firms in Norway.

Sometimes mixed results are found within one study. For example, Czarnitzki et al (2007) find that in Germany, subsidies for individual research do not have a significant impact on R&D and patenting but the innovative performance could be improved by additional incentives for collaboration. The same study finds that for Finnish companies, without R&D subsidies recipients would show less R&D and patenting activity, whilst those firms not receiving subsidies would perform significantly better if they were subsidised. Czarnitzki and Licht (2006) find additionality in public R&D grants with regard to innovation input measured as R&D expenditures and innovation expenditures, as well as with regard to innovation output measured by patent applications. Input additionality has been more pronounced in Eastern Germany during the transition period than in Western Germany, while the opposite is true for innovation additionality.

In summary, there is a small body of evidence indicating that R&D subsidies increase firms' innovative output, but this finding is not universal. There is clearly scope for further work.

3. Direct government assistance to firms in New Zealand

The New Zealand government provides direct assistance to firms[4] in various forms, including training, information, advice and funding. Examples include co-funding for R&D projects, market intelligence provided by offshore offices to exporters, and training to owners and managers of small businesses. While the nature and objectives of assistance vary across programmes, they share the prime motivation of enhancing the economic performance of participants and ultimately the New Zealand economy. Most of the assistance is provided through the following programmes (de Beer et al, 2010):

- Ministry of Business, Innovation, and Employment (MBIE)
    - MBIE R&D capability building: support for building R&D capability within a firm
    - MBIE R&D project: support for R&D projects provided to firms with potential for high growth
    - MBIE capital: support for firms to raise capital
- New Zealand Trade and Enterprise (NZTE)
    - NZTE capability: for building business capability
    - NZTE growth: for firms with potential for high growth
    - NZTE international: for firms to export and increase international presence

[4] Direct assistance excludes assistance that is targeted at the sector or industry level or is provided to firms through a third party (e.g., through a university).

Eligibility for government assistance varies across programmes. There have also been changes in the application process over time. For example, NZTE had a client engagement model whereby all potential candidates for NZTE growth should have received a high-level assessment of a firm's growth potential and stage of development (Ministry of Economic Development, 2009). Firms classified as high-growth potential were eligible to receive Client Management Services (CMS, part of NZTE growth). These firms were assigned an NZTE Sector or Client Manager to help firms identify the strategies and services to address their needs. Growth Services Fund (GSF, also part of NZTE growth) was only accessible to firms that were receiving Client Management Services. A client manager invited firms to apply for this assistance after a thorough screening process and helped the firm with the application process. The rejection rate was low due to the prior screening process. By contrast, any firm is able to access Market Development Services (part of NZTE international) by paying for these services. Firms that receive CMS or GSF may receive these services at no or subsidised cost. Discussions with granting agencies indicate that applicants are not evaluated against a score card, but are rather chosen based on their characteristics and a fair degree of subjectivity from the granting agency.[5]

MBIE R&D programmes include several schemes, some of which have been discontinued or supplanted by new schemes. Nevertheless, these schemes can be classified into two categories. The first category (MBIE R&D capability building) provides assistance to build R&D capability within a firm, through information services designed to enable research organisations to respond to technological information requests at low or no cost to the requesting firm, co-funding to hire a consultant on a technical innovation project, or payments to senior undergraduate and graduate students to undertake an R&D project within the firm. The second category (MBIE R&D project) provides co-funding for R&D projects for firms with more highly developed R&D capability.[6]

While some firms are keen to use as much government R&D funding as they can, there are concerns that the application process is non-transparent, picking winners, taking firms more time than saving them money (Oxley et al, 2013) and that the grants are wasteful taxpayer subsidy for unprofitable companies (O'Neil, 2014). De Beer et al (2010) show that firms that receive any kind of government assistance on average had higher sales and were more likely to export than other firms.

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[5] We thank Eyal Apatov for providing the information based on his discussion with knowledgeable staff from the granting agencies.

[6] Further details on the two R&D programmes can be found in Ministry of Economic Development (2011). These R&D programmes were administered by the Foundation for Research, Science and Technology (FRST) until 2012, when FRST was merged into MBIE. The government consolidated several R&D promoting agencies to create Callaghan Innovation in February 2013. The period covered in this study predates the existence of Callaghan Innovation.

Appendix Table 1 shows that government direct R&D funding for businesses was $16 million on 2001, gradually increasing to $60 million in 2007 before steadily declining to $33 million in 2010. A re-assessment of R&D subsidies by the National-led government saw huge jumps in funding from 2012, with funding reaching its peak of $90 million in 2013. Appendix Table 2 shows that 89 percent of the R&D funding in 2012[7] was for R&D projects and 11 percent was for R&D capability building. The average capability building grant was $14,500 per year while the average project grant was $326,500 per year. The majority (79 percent) of project funding goes to firms aged 10 years or over. Almost half of project funding was for firms with at least 100 employees, compared with just under a third for firms with under 20 employees. The largest receiving industries of project funding were 'Machinery and Equipment Manufacturing' and 'Business Services', accounting for 42 and 37 percent of funding respectively. While receiving only 11 percent of project funding, firms with fewer than five employees attract almost half of funding for capability building grants. The latter funding is relatively more evenly distributed across age groups and industries than project funding.

4. Data

4.1. Data sources

This study uses data from the LBD, a linked longitudinal dataset that contains tax- and survey-based financial data, merchandise and services trade data, a variety of sample surveys on business practices and outcomes, and government programme participation lists (Fabling, 2009), providing comprehensive information on firms' demographic characteristics, financial data, input, output, R&D activity, innovative activity and government R&D assistance.

Three main components of the LBD will be used in this study: the Business Operations Survey (BOS) for data on business operations and innovation, administrative data on business participation in government assistance programmes (GAP), and administrative data on intellectual property (IP) rights.

BOS is a large-scale business sample survey that has been conducted annually by Statistics New Zealand since 2005. The target population for BOS is all businesses in New Zealand that have at least six employees, and have been active for at least one year. The sample design is a two-level stratification according to Australian and New Zealand Standard Industrial Classification (ANZSIC) industry and employment size groups. The first level of stratification is 36 ANZSIC groupings. Within each of the ANZSIC groups there is a further stratification by four employment

[7] The latest year for R&D grants data in our analyses is 2012.

size groups, namely 6–19 employees (small), 20–29 employees (medium 1), 30–49 employees (medium 2), and 50 or more employees (large) (Statistics New Zealand, 2014a).

Each BOS survey always includes a module A that asks general questions on business operations, plus typically two specialised modules. Module B alternates between innovation (odd years) and business use of Information and Communication Technology (even years), while module C is a contestable, sponsored annually by various government departments. The biennial Module B, designed in accordance with the Oslo manual guidelines (OECD and Eurostat, 2005), replaces the national Innovation Survey (carried out one-off in 2003) as the main survey instrument for the collection of innovation data in New Zealand. This study uses data from module A and module B of odd years (2005, 2007, 2009, 2011 and 2013).

The GAP component contains administrative data on government assistance to firms during 1995–2013 under the programmes listed in Section 3. Available data include the scheme and sub-scheme of the assistance, and (for financial assistance) the amount of funding approved and amount paid in each year.

The IP data currently available in the LBD include the number of patents, trademarks and designs applied for and registered by each business in each year during 2000–2009, as recorded by the Intellectual Property Office of New Zealand (IPONZ).

Finally, firm demographic data that are not collected in BOS are drawn from other components of the LBD, such as industry classification (from the Longitudinal Business Frame), rolling mean employment (from Linked Employer-Employee Data) and primary location (defined by authors based on monthly employment counts by plant and on geographic information of plants).

4.2. Key variables

4.2.1. Measures of innovation outputs

We use seven measures of innovation outputs

1. Any innovation: whether the firm developed or introduced any new or significantly improved goods or services, operational processes, organisational/ managerial processes, or marketing methods in the last financial year
2. Process innovation: whether the firm implemented any new or significantly improved operational processes (i.e. methods of producing or distributing goods or services) in the last two financial years
3. Product innovation: whether the firm introduced onto the market any new or significantly improved goods or services in the last two financial years

4. New product to the world: whether the firm introduced to the world new goods or services that were developed by itself or developed by itself in partnership with others in the last two financial years
5. Sales due to new products: Percentage of sales that come from new goods and services in the last financial year (zero for firms without product innovation)
6. New patent: whether the firm applied for a patent in the last financial year
7. New trademark: whether the firm applied a trademark in the last financial year

The first measure (any innovation) is available from BOS Module A; the next four measures are from BOS Module B (and thus observed in odd years only).[8] All of these five measures potentially capture innovations regardless of whether they are legally protected. However, being self-reported, the definitions of these measures are likely to reflect a fair degree of subjectivity from the survey respondents. The first three measures include any new-to-the-firm innovation and thus encompass actions that represent adoption or imitation rather than true innovation. For this reason, we also use 'new products to the world' that are 'developed by this business' or 'developed by this business in partnership with others', which should, in principle, be limited to true innovation.

The last two measures are available from the IP data (for the population in each year during 2000–2009). Being from administrative sources, the data for these measures have the merit of being based on an external, nominally objective standard. However, patents and trademarks have been criticised for both understating and overstating innovation output. On the one hand, they understate innovation output because not all innovations are formally protected through patents and trademarks or should be so given the costs involved. On the other hand, patents and trademarks overstate innovation output because many are never commercialised. Furthermore, patents are used much more frequently in some industries such as pharmaceutical and chemical industries than in others (Hall et al, 2005), making it hard to compare innovativeness across industries based on patents. The use of trademarks also varies across industries, albeit less markedly than for patents (Munari, 2013).

Patents are the dominant measures of innovation output in the literature (Griliches, 1990) while trademarks have been used to a lesser, but rising, extent (e.g. Mendonça et al, 2004; Gotsch and Hipp, 2012; Flikkema et al 2014). In recent years, many studies also adopted broader-based measures of innovation, due to the available data from innovation surveys (e.g. Mairesse and Mohnen, 2005; Kampik and Dachs, 2011; Oxley et al, 2013). Hopefully by using all of these

[8] The BOS survey includes all four types of innovation identified by the Oslo manual: product innovation, process innovation, marketing innovation and organisational innovation. We focus on product and process innovation, as being more likely to be the types of innovation that result from R&D investment.

measures in this study, we can capture different aspects of innovation and see if the results are sensitive to the type of measure.[9]

4.2.2. Measures of government assistance

The 'treatment' variable in our analysis is whether or not the firm received any MBIE R&D grant in the previous three years. The three-year time frame is to allow for the possibility that R&D investment takes up to three years to produce innovation output, and the time lag ('previous') is to allow for at least one year between when a grant is received and when innovation output is observed. In some analyses, we further distinguish two types of R&D grant: R&D capability building and R&D project, as in Ministry of Economic Development (2011).

Pooling the treatment into a three-year window makes it difficult to define the pre-treatment period that suits both treated and untreated firms. However, this has the advantage of allowing for the possibility that firms' R&D investment take different gestation periods of up to three years to produce output. Furthermore, innovation outputs are non-divisible (i.e. a firm can only 'innovate' or 'not innovate', not 'partly innovate') and innovation persistence is very low among New Zealand firms.[10] Thus, if we were instead to choose a specific gestation lag (e.g. 2 years) we would miss the innovation output from firms for which the lag from grant receipt to innovation output is different (e.g. 1 or 3 years).[11]

We also have information on whether or not the firm received government assistance other than an R&D grant in the previous five years. The NZTE Enterprise Training Programme (ETP) is excluded from this measure as this programme has a low matching rate compared with other programmes.[12] The longer time frame for this measure (five years vs. three years for R&D grant) is to capture the possibility that receiving other assistance will put a firm in the pipeline which will improve its potential to later receive an R&D grant. This variable is only used as a control variable, along with other control variables, in the analysis.

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[9] Jaumotte and Pain (2005) argue that successful innovation is not simply a matter of R&D and patenting; focusing only on those indicators tends to over-emphasise the importance of manufacturing and large firms for innovation. Using data from the third European Community Innovation Survey, Jaumotte and Pain show that smaller firms and firms in the service sector, for which investment in machinery and training and the use of informal protection methods are more important, also account for a considerable share of total innovative activities.

[10] For example, among firms that appeared in the five BOS surveys, around 7.9% report 'new product to the world' innovation each survey but only 2.4% do so for at least three surveys and 0.4% in all five surveys.

[11] Of course, the gestation period for firms' R&D investment can take more than three years. However, the treatment effects can be confounded by other factors when a wider window is used. As a robustness check, we find that using a two-year window results in very similar treatment effects to using a three-year window, while the treatment effects based on a five-year window are lower. Thus, it seems most of the innovation output from R&D investment is concentrated in the three-year window.

[12] ETP's matching rate is 35%, compared with 92% for other NZTE programmes and 77% for MBIE R&D programmes, see de Beer et al (2010). De Beer et al (2010) also exclude ETP from their analysis for the same reason.

5. Methods

The starting point for examining the effects of R&D grant receipt on outcomes is a reduced-form model:

$$Y_i = \alpha + \beta_T T_i + \boldsymbol{\beta_X X_i} + \varepsilon_i \qquad (1)$$

where i indexes firms, T is a binary variable capturing whether a firm receive an R&D grant, and $\boldsymbol{X}$ is a vector of control variables. α, β_T and $\boldsymbol{\beta_X}$ are parameters to be estimated, with β_T capturing the total direct effect of R&D grant receipt on the outcome in question, holding constant other observable factors.

As Jaffe (2002) notes, the selection problem that arises in attempting to assess the impact of policies like R&D grants is widely recognised. Specifically, R&D grant receipt is potentially correlated with other firm characteristics. Thus, while a significant positive relationship between R&D grant receipt and an outcome may indicate that R&D grant receipt is associated with a better outcome, it does not prove that R&D grant receipt *per se* leads to the improvement in outcome. Firms that receive an R&D grant may be different from other firms in many observed and unobserved characteristics, and it might be these characteristics that drive a difference in outcomes. Ignoring the potential selection bias may lead to biased estimates of the impact of R&D grant receipt on outcomes.

To mitigate the potential selection bias due to observables, this study uses the propensity score matching (PSM) method. PSM estimates the treatment effect (of R&D grant receipt) by comparing a treated firm (firm receiving an R&D grant) with an untreated firm (firm not receiving an R&D grant) that is as similar to the treated firm as possible. Specifically, the PSM process involves three steps. The first step obtains the propensity score, which is the predicted probability that a firm receives an R&D grant, given a firm's characteristics. The second step matches a treated firm with an untreated firm based on their propensity scores. Treated firms form the treatment group, while untreated firms that can be matched to at least one treated firm form the control group. In the last step, the average treatment effect on the treated (impact of R&D grant receipt) is estimated as the weighted mean difference in the outcome between the treatment group and the control group, where the weighting scheme is detailed in below.

Two methods will be used to match a firm that receives an R&D grant with a firm that does not. For both methods, an untreated firm is matched with a treated firm when the difference in propensity scores between the two is less than a specified bandwidth. The likelihood of a match can be raised by setting a larger bandwidth, but this would be at the expense of the match quality.

For both methods, treated firms always have a unity weight and unmatched firms a zero weight. The differences between the two matching methods lie in the number of untreated firms that are used in the control group and how untreated firms are weighted.

In the first method (kernel matching), a 'synthetic' counterfactual is created for each treated firm, based on the kernel-weighted average of the characteristics of *all* matched untreated firms. The closer an untreated firm is to a treated firm in terms of propensity score, the higher is the weight applied to that untreated firm in creating the 'counterfactual' case for a treated firm. The second method (calliper matching) only matches a treated firm with up to *n* nearest untreated firms (where *n* is set at 5 in this study) but weights all matched firms in each match equally.[13]

If the explanatory variables used for the estimation of the propensity score equation do a good job predicting which firms receive the treatment, then it is plausible that selection bias due to unobservables is minimised as well (since selection is mostly captured by the observables). This would then mean that the estimated effect using PSM can be interpreted as causal. While a regression-with-controls model (as in equation (1)) also addresses selection bias due to observables, a matching method such as PSM gives the researcher greater flexibility in choosing how to aggregate heterogeneous treatment effects.[14] Recent examples of empirical research on the economics of the firm that use PSM include Antonioli et al (2014), Chang et al (2013) and Wamser (2013).

6. Descriptive statistics

This study uses two main estimation samples, corresponding to the two sources for innovation data. The first sample, which takes measures of innovation from the BOS survey, is based on firms that participated in the same survey. The second sample, which takes measures of innovation from the IP data, is based on the entire population. For both estimation samples, we restrict the analyses to economically active firms in the private, for-profit sector,[15] and whose two-digit industry had at least one firm that received an R&D grant in the previous three years. The IP

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[13] Each untreated firm receives a weight of one for every treated firm it can be matched to; some untreated firms can have weights that are greater than one as they can be matched to multiple treated firms.

[14] According to Cobb-Clark and Crossley (2003), when treatment effects vary across individuals, regression imposes a particular weighting when calculating an average treatment effect, where the weight for each individual is determined by his/her observable characteristics that are used as control variables in the regressions. While these weights are designed (as Ordinary Least Squares regression is) to return an efficient estimate when treatment effects are homogeneous, there is no reason for this weighted average to correspond to any parameter of interest in a heterogeneous treatment effect context. By contrast, in a matching estimator, the weighting can be manipulated so that interesting parameters, like the average effect of the treatment on the treated, can be estimated.

[15] This is the restriction that Statistics New Zealand uses in defining the target population for the business sector (see, for example, Statistics New Zealand, 2007). Around 447,000–541,000 firms meet this definition each year during 2000–2012.

sample also excludes firms in the primary sector (including agriculture, forestry, fishing and mining industries) as very few firms in this sector apply for patents or trademarks.

Furthermore, we restrict the samples to firms employing at least one worker that were economically active four years earlier for the IP sample or that are aged at least three years[16] for the BOS sample. This is to allow for the fact that firms need to have employees in order to apply for R&D grants and carry out R&D activity,[17] that grant applications are assessed based on firms' past performance, and that R&D investment takes time to generate innovation output. As a result, our IP estimation sample contains around 298,000 observations on 97,000 firms pooled across five years (2005–2009, 2009 being the latest year for which IP data are available in the LBD), while the BOS estimation sample contains over 26,400 observations on 11,200 firms pooled across five years (2005, 2007, 2009, 2011 and 2013).[18]

Table 1 compares the treated and untreated firms from the BOS sample, for both the complete sample (columns 1 and 2) and the PSM estimation sample (columns 3 and 4). Before matching, 5.3 percent of firms received an R&D grant in the previous three years and those firms ('treated' firms) are significantly different from other firms ('untreated' firms) in terms of most variables. Specifically, while the innovation rate varies markedly across different measures of innovation, the treated firms are more innovative by every measure. By the broadest definition of innovation (any product, process, marketing or organisational practice new to the firm), over two thirds of treated firms and 44 percent of untreated firms innovated in the past year. Product innovation is relatively rarer, reported by 58 percent of treated firms and 25 percent of untreated firms. The innovation gap is starkest for 'new product to the world', with 25 percent of treated firms being innovative by this measure, compared with only 3.5 percent among untreated firms. While sales due to new products averaged 7.4 percent among treated firms, the corresponding figure is only 2.9 percent among untreated firms.

[16] Firm's age is at the time the outcomes are assessed, so the firm could be a new start-up at the time of R&D grant receipt.
[17] Almost 70 percent of economically significant enterprises have no employees (Statistics New Zealand, 2014b), about 30 percent of which are in 'Rental, hiring, & real estate services'. This suggests that non-employing firms are 'placeholders' for favourable tax treatment and are unlikely to engage in innovative activity. Indeed, no BOS firms with fewer than five employees perform 'new product to the world' innovation.
[18] Actual estimation samples might be lower due to missing data or failure to meet certain restrictions (e.g. common support condition in PSM analysis).

Table 1: Means of the BOS estimation sample by R&D grant recipiency status

	Complete sample		PSM sample	
	Treated[a] (1)	Un-treated (2)	Treated[a] (3)	Un-treated (4)
Number of observations[b]	1,194	22,785	1,017	20,124
Outcome variables				
Any innovation	0.673***	0.439	0.652***	0.577
Process innovation	0.419***	0.231	0.405***	0.347
Product innovation	0.576***	0.250	0.546***	0.445
New product to the world	0.246***	0.035	0.215***	0.124
Sales due to new products (percentage)	7.418***	2.919	7.021***	5.012
Explanatory variables				
Received non-R&D govt. assistance in previous 5 years	0.450***	0.058	0.372	0.358
Has formal IP protection	0.889***	0.597	0.876	0.868
Age (years)	33.89***	26.49	32.51	32.92
Employment (people)	178.24***	71.87	135.07	151.34
State-owned enterprise	0.013***	0.004	0.010	0.010
Belongs to a business group	0.413***	0.243	0.383	0.396
Exporter	0.722***	0.249	0.682	0.690
Has foreign ownership	0.280***	0.146	0.265	0.257
Has ownership interest overseas	0.283***	0.060	0.229	0.232
Food Beverage and Tobacco	0.122***	0.036	0.122	0.122
Textile, Wood Product, Pulp, Paper Manufacturing and Printing	0.092	0.086	0.097	0.097
Petroleum, Coal, Chemical and Associated Product Manufacturing	0.108***	0.024	0.105	0.105
Machinery and Equipment Manufacturing	0.195***	0.049	0.175	0.175
Other Manufacturing[c]	0.089***	0.061	0.087	0.087
Wholesale Trade	0.070***	0.105	0.066	0.066
Business Services	0.179	0.169	0.196	0.196
Other services	0.064***	0.377	0.068	0.068
Easy access to capital	0.353***	0.265	0.331	0.344
Difficult access to capital	0.047***	0.025	0.042	0.039
Local area has good skilled labour market	0.258	0.267	0.265	0.258
Market has monopolistic competition	0.563	0.564	0.561	0.571
Market has perfect competition	0.167***	0.219	0.172	0.173
Waikato	0.084	0.077	0.083	0.089
Wellington	0.097	0.097	0.097	0.088
Rest of North Island	0.179	0.197	0.180	0.185
Canterbury	0.161***	0.128	0.151	0.146
Rest of South Island	0.095	0.109	0.093	0.097
Year 2007	0.234*	0.212	0.229	0.229
Year 2009	0.193	0.194	0.193	0.193
Year 2011	0.138***	0.189	0.141	0.141
Year 2013	0.128***	0.178	0.131	0.131

Source: BOS 2005, 2007, 2009, 2011, 2013

Notes: [a]Treated: received R&D grant in previous 3 years. [b]Numbers of observations have been randomly rounded to base 3 to protect confidentiality. [c]Includes Non-Metallic Mineral Product Manufacturing; Metal Product Manufacturing; and Other Manufacturing. The stars indicate level of significance for t-test between treated and untreated groups. * p<0.05, ** p<0.01, *** p<0.001. Statistics in columns 3–4 are weighted by the weight obtained from propensity score matching with the kernel method and a bandwidth of 0.01. See Appendix Table 3 for definitions of explanatory variables.

Treated firms are also more likely to have received non-R&D assistance; 45 percent of treated firms received non-R&D assistance in the previous five years, compared with only 5.8 percent of untreated firms. Furthermore, treated firms are older and larger. They are more likely to be state-owned, belong to a business group, have recently requested new or additional capital (both with and without ease) while less likely to operate in a perfectly competitive market. Treated firms are also more likely to have international involvement, such as exporting, being foreign owned or holding ownership interests overseas.[19]

7. Estimation results

7.1. BOS innovation outcomes

7.1.1. Propensity score equations

First, we estimate the probability that a firm receives an R&D grant, given a firm's characteristics. The predicted probability then serves as the propensity score in the PSM estimation of the treatment effect. In theory, the characteristics used to estimate the propensity score equation should not be influenced by the treatment itself and thus should ideally be observed before treatment. However, not all firms are surveyed before treatment and since most of the characteristics we use are not likely to vary over time (e.g. industry, primary location, state ownership, year of birth), we use post-treatment characteristics in order to maximise the estimation samples.[20]

As shown in Table 2, several characteristics are associated with the likelihood of R&D grant receipt. Specifically, for the BOS sample (column 1) firms that received non-R&D assistance in the previous five years are 10 percentage points more likely to have received an R&D grant in the previous three years. Larger firms are more likely to have received an R&D grant, while firms operating in more competitive markets are less likely. Confirming what was observed in Table 1, other characteristics that are significantly associated with R&D grant receipt include belonging to a business group, exporting, foreign ownership, having ownership interests overseas, and having recently requested capital. While R&D-grant-receiving firms are older and more likely to be state-owned than other firms (Table 1), the estimation reveals that age and state ownership have no significant associations with R&D grant receipt after other factors are controlled for.[21]

The PSM approach makes the treatment group and control group more comparable. Looking back to Table 1, column 3 excludes those treated firms for which no match could be found, and column 4 includes only those untreated firms whose propensity score is close to that of a treated firm. Note that while the means of most explanatory variables are statistically different

[19] More details on innovative patterns of New Zealand firms can be found in Wakeman and Le (2015).
[20] See Table 5 for a robustness check on this choice.
[21] We initially controlled for many more variables; those that had zero, insignificant coefficients were dropped (dummies for higher-quality product than competitors, (local area has) good transport infrastructure, good Information and Communication Technology infrastructure, good water and waste infrastructure, good unskilled labour market, good local business networks, and good local body planning and regulatory process, and categories of debt to equity ratio).

between the two groups before the matching (columns 1–2), no significant differences remain after the matching (columns 3–4).

Table 2: Average marginal effects on the probability of receiving an R&D grant in the previous 3 years

		IP sample	
Explanatory variable	BOS sample (1)	For patents (2)	For trademarks (3)
Received non-R&D govt. assistance in previous 5 years	0.101***	0.131***	0.132***
	(0.010)	(0.008)	(0.008)
Has formal IP protection	0.022***		
	(0.003)		
Log age	0.001	-0.002***	-0.002***
	(0.002)	(0.000)	(0.000)
Log employment	0.013***	0.003***	0.003***
	(0.002)	(0.000)	(0.000)
State-owned enterprise	0.028	0.008	0.007
	(0.024)	(0.009)	(0.009)
Belongs to a business group	0.012***	0.009***	0.009***
	(0.004)	(0.001)	(0.001)
Exporter	0.031***	0.016***	0.016***
	(0.004)	(0.001)	(0.001)
Has foreign ownership	0.009**	-0.001	-0.001
	(0.004)	(0.001)	(0.001)
Has ownership interest overseas	0.024***		
	(0.006)		
Easy access to capital	0.010***		
	(0.003)		
Difficult access to capital	0.022**		
	(0.009)		
Local area has good skilled labour market	0.002		
	(0.003)		
Market has monopolistic competition	-0.014***		
	(0.004)		
Market has perfect competition	-0.016***		
	(0.005)		
Applied for a patent 4 years earlier		0.053***	
		(0.017)	
Applied for a trademark 4 years earlier			0.003
			(0.003)
Pseudo R-squared	0.294	0.379	0.377
Sample size	24,573	297,891	297,891

Source: Authors' estimation from various LBD sources (see text for details)
Notes: *** p<0.01, ** p<0.05, * p<0.1. Average marginal effects are calculated from estimated probit coefficients. Standard errors (in parentheses) are adjusted to allow for 'clustering' due to multiple observations (in different years) of the same firm. Industry-year and location dummies are included in the regression but not reported here. Numbers of observations have been randomly rounded to base 3 to protect confidentiality.

7.1.2. Average treatment effect on the treated

The PSM approach assumes that, conditional on the treatment and control group being sufficiently similar on observed and unobserved characteristics after the PSM weighting, the difference in outcome between a treated firm and a control firm is attributed to the effect of treatment (R&D grant receipt). The average treatment effects on the treated, i.e. the average difference in outcome between the treatment group and the control group across all treated firms, are presented in Table 3. For each outcome, there are four estimates. The first two estimates are based on the kernel method (see columns 1 and 2) and the last two estimates on the calliper method (columns 3 and 4). Two alternative bandwidths are used for each method: 0.01 and 0.001. A bandwidth can be thought of as a 'tolerable difference'. The higher the chosen bandwidth is, the more likely it is to find an untreated firm that can be matched to a treated firm, yet the less likely it is that they are a good match.

Table 3: Effects of R&D grant receipt on BOS innovation outcomes

Outcome		Kernel, bandwidth 0.01 (1)	Kernel, bandwidth 0.001 (2)	Calliper, bandwidth 0.01 (3)	Calliper, bandwidth 0.001(4)
Any innovation	Mean of control	0.577	0.512	0.579	0.509
	Treatment effect	0.075***	0.093***	0.073***	0.096***
	Standard error	(0.0211)	(0.0316)	(0.0188)	(0.0322)
	Relative effect	13%	18%	13%	19%
Process innovation	Mean of control	0.347	0.298	0.353	0.299
	Treatment effect	0.053**	0.051*	0.049**	0.049
	Standard error	(0.0221)	(0.0266)	(0.0244)	(0.0316)
	Relative effect	15%	17%	14%	
Product innovation	Mean of control	0.445	0.373	0.448	0.375
	Treatment effect	0.100***	0.086***	0.098***	0.083***
	Standard error	(0.0174)	(0.0302)	(0.0213)	(0.0285)
	Relative effect	22%	23%	22%	22%
New product to the world	Mean of control	0.124	0.077	0.125	0.081
	Treatment effect	0.094***	0.087***	0.093***	0.084***
	Standard error	(0.0176)	(0.0197)	(0.0157)	(0.0218)
	Relative effect	76%	112%	75%	104%
Sales due to new products (%)	Mean of control	5.012	4.125	4.990	4.173
	Treatment effect	1.964***	1.822***	2.018***	1.772***
	Standard error	(0.416)	(0.610)	(0.521)	(0.591)
	Relative effect	39%	44%	40%	42%
Number of untreated obs.		22,782	22,782	22,782	22,782
Number of control obs.		20,121	7,641	3,003	1,587
Number of treated obs.		1,017	564	1,017	564

Source: Authors' estimation from BOS 2005, 2007, 2009, 2011, 2013

Notes: *** p<0.01, ** p<0.05, * p<0.1

Numbers of observations have been randomly rounded to base 3 to protect confidentiality. Treatment effects are estimated using the propensity score matching approach. Standard errors are bootstrapped with 100 replications. Relative effect is the ratio of (significant) treatment effect to mean of control group.

To improve the quality of matching, we only match treated firms with control firms within the same industry category (as listed in Table 1) and year. This is to prevent matching firms across very different industries or matching a firm with itself in a different year. The matching sample is also required to meet the 'common support' condition, which is that no characteristic can perfectly predict treatment status (i.e. if a treated observation has a certain characteristic, there must be at least one control observation with that characteristic in the sample, and vice versa). The standard errors of all point estimates are bootstrapped with 100 replications.[22]

Several results can be highlighted from Table 3. First, all of estimated effects are smaller than the unconditional gaps. While the unconditional gap in percentage of sales due to new products between firms that received an R&D grant and firms that did not is 4.5 percentage points (Table 1, columns 1–2), the effect of R&D grant receipt estimated by the PSM approach is only 1.8–2 percentage points (Table 3).

Second, for each bandwidth, the kernel method (Table 3, columns 1 and 2) produces similar estimates to the calliper method (columns 3 and 4). For example, the kernel method with a bandwidth of 0.01 suggests that R&D grant receipt increases the probability of product innovation by 10 percentage points, which is almost identical to the estimated produced by the calliper method with the same bandwidth (9.8 percentage points).

Third, while lowering the bandwidth always reduces the number of matches[23] and thus increases standard errors, it raises relative effects. For example, the kernel method with a bandwidth of 0.01 (column 1) suggests that R&D grant receipt increases the probability of process innovation by 15 *percent* (treatment effect of 5.3 *percentage points*, relative to the innovation rate in the control group of 35 percent), while the same method with a bandwidth of 0.001 (column 2) suggests the increase is 17 *percent*.

Fourth, in relative terms, larger effects are observed for more novel innovation. For example, based on the kernel method with a bandwidth of 0.01, R&D grant receipt almost doubles the probability of 'new product to the world' innovation (treatment effect of 9.4 percentage points, relative to innovation rate in the control group of 12.4 percent), while it only increases the probability of any product innovation by 22 percent and only increases the probability of any innovation by 13 percent. Our interpretation is that more novel innovation tends to require more financial resources, so the aid of an R&D grant is more likely to have considerable impact on this more novel innovation output. By contrast, lower-level innovation like 'any innovation' is much easier to achieve, so an R&D grant tends to play a less important role in determining whether some innovation will result. Furthermore, R&D grants might have spillover effects, in that non-recipients can benefit by imitating more novel innovations created by grant recipients.

Since the kernel method and calliper method produce similar results, for the rest of the

[22] Bootstrapping is an approach for inferring an (unknown) population parameter based on statistics of random resamples. Since the observations that are (randomly) drawn change from one resample to another, bootstrapped standard errors change each time the model is (re)run.

[23] The size of the treatment group decreases with the bandwith, as some treated observations cannot find an untreated observation to match to when the bandwidth is smaller (i.e., the matching rule is stricter).

study we will concentrate on the kernel method as this method has the advantage of using a larger control group. We will use the 0.01 bandwidth as it also uses larger control and treatment groups and tends to produce more conservative estimates of R&D grant receipt than the 0.001 bandwidth.

Table 4 presents estimated effects of R&D grant receipt on innovation outcomes by type of grant, firm size and time period.[24] A few patterns stand out from this table. First, R&D project grants have much larger effects on all innovation outcomes than R&D capability building grants. For example, while the rate of product innovation for the control group is similar for both capability building grants (42 percent, column 1) and project grants (44 percent, column 2), project grants are estimated to raise the probability of product innovation by 17 percentage points, while the effect of the capability building grants is only 5 percentage points.[25] While project grants are estimated to increase the share of sales due to new products by 4.3 percentage points, no significant effect is observed for capability building grants. This result is perhaps not surprising given the nature of the grants. As mentioned in Section 3, R&D capability building grants, which averaged $14,500 per year in 2012, provide assistance to build R&D capability within a firm, through information service designed to enable research organisations to respond to technological information requests at low or no cost to the requesting firm, co-funding to hire a consultant on a technical innovation project, or payments to senior undergraduate and graduate students to undertake a R&D project within a firm. Such assistance is unlikely to improve innovation outputs. Innovation outputs are more likely to be affected by project grants, which provide considerable co-funding (averaging $326,500 per year in 2012) for R&D projects for firms with more highly developed R&D capability. This result is indirect evidence that government assistance with limited funding is not effective in boosting innovative activity.[26]

Second, the estimated effect of R&D grant receipt is broadly similar between small to medium firms (with fewer than 50 employees) and larger firms (with at least 50 employees).[27] For example, R&D grant receipt is estimated to increases the probability of product innovation by 10 percentage points for small to medium firms (column 3), largely in line with the estimated effect

[24] The propensity score equation is re-estimated separately for each sub-sample. Almost identical results are obtained when we use the propensity score estimated for the pooled sample.
[25] Firms that received both types of grants are excluded from analyses by type of grant.
[26] To check for the possibility that the weak results due to capability building grants is because not enough time lag is allowed after grant receipt, we estimate the impact of capability grants received 2–4 years (and alternatively 3–5 years) before innovation outcomes are observed. At first, some significant, albeit small, effects are found for 'new product to the world' innovation and sales due to new products. However, these effects decrease markedly and lose statistical significance when we exclude firms that received a project grant. Thus, it seems that capability building grants can only boost innovative activity when (subsequently) accompanied by a project grant.
[27] Confirming this, in regressions on innovation outcomes where R&D grant receipt is interacted with a dummy for firm size, the interaction term is insignificant, suggesting that R&D receipt has no differential effects on innovation outcomes with respect to firm size.

on larger firms (9.2 percentage points, column 4).

Table 4: Effects of R&D grant receipt on BOS innovation outcomes by sub-samples

Outcome		Capability building grant (1)	Project grant (2)	Small to medium firms (3)	Larger firms (4)	2005–2007 (5)	2009–2013 (6)
Any innovation	Mean of control	0.562	0.557	0.571	0.587	0.566	0.579
	Treatment effect	0.057*	0.095***	0.068*	0.079**	0.072***	0.093***
	Standard error	(0.0305)	(0.0359)	(0.0348)	(0.0320)	(0.0278)	(0.0284)
	Relative effect	10%	17%	12%	13%	13%	16%
Process innovation	Mean of control	0.328	0.339	0.311	0.354	0.346	0.334
	Treatment effect	0.046*	0.086**	0.051*	0.086**	0.007	0.122***
	Standard error	(0.0261)	(0.0377)	(0.0271)	(0.0351)	(0.0286)	(0.0313)
	Relative effect	14%	25%	16%	24%		37%
Product innovation	Mean of control	0.420	0.442	0.427	0.443	0.437	0.428
	Treatment effect	0.050**	0.174***	0.104***	0.092***	0.083***	0.143***
	Standard error	(0.0244)	(0.0354)	(0.0315)	(0.0311)	(0.0256)	(0.0272)
	Relative effect	12%	39%	24%	21%	19%	33%
New product to the world	Mean of control	0.105	0.118	0.126	0.104	0.113	0.125
	Treatment effect	0.033*	0.158***	0.090***	0.086***	0.098***	0.120***
	Standard error	(0.0186)	(0.0249)	(0.0252)	(0.0232)	(0.0236)	(0.0250)
	Relative effect	31%	134%	71%	83%	86%	96%
Sales due to new products (%)	Mean of control	4.447	5.322	5.577	4.147	5.196	4.692
	Treatment effect	0.206	4.324***	2.762***	1.251**	1.901***	2.691***
	Standard error	(0.446)	(1.057)	(0.736)	(0.525)	(0.590)	(0.719)
	Relative effect		81%	50%	30%	37%	57%
Number of untreated obs.		22,596	20,817	16,203	6,579	9,987	12,798
Number of control obs.		19,425	17,064	13,041	4,818	9,213	10,764
Number of treated obs.		537	300	420	501	555	453

Source: Authors' estimation from BOS 2005, 2007, 2009, 2011, 2013
Notes: *** p<0.01, ** p<0.05, * p<0.1
Numbers of observations have been randomly rounded to base 3 to protect confidentiality. Treatment effects are estimated using the propensity score matching approach with the kernel method and a bandwidth of 0.01. Standard errors are bootstrapped with 100 replications. Relative effect is the ratio of (significant) treatment effect to mean of control group.

Third, the estimated effect of R&D grant receipt on all innovation measures is somewhat higher for 2009–2013 than for 2005–2007.[28] For example, an estimated increase by 9.8 percentage points (86 percent in relative terms) in the probability of 'new product to the world' innovation can be attributed to the effect of R&D grant receipt during 2005–2007 (column 5), compared to an estimated effect of 12 percentage points (96 percent in relative terms) during 2009–2013 (column 6). The most noticeable difference is that R&D grant receipt is estimated to raise the probability of process innovation by 12 percentage points during 2009–2013 while no effect is seen during 2005–2007. Stronger effects for the later period could be because the number of funded firms was lower while the average grant size was much higher in 2009–2013 than in 2005–2007 (see Appendix Table 1).

7.1.3. Robustness checks

We next conduct some robustness checks on the results presented in Tables 3–4. The first

[28] The breakpoint is chosen so that 2005–2007 roughly represents the pre-Global Financial Crisis period.

check is on the timing of the characteristics used to match treated to untreated firms. Theoretically, characteristics observed post-treatment may be affected by the treatment, so matching on those characteristics may underestimate the effect of the treatment on the outcome. In order to have firms that have both pre- and post-treatment characteristics, we restrict the analysis to firms that were in the 2009, 2011 and 2013 surveys that were also surveyed four years earlier. Based on this sample, we first estimate the treatments effect based on post-treatment characteristics (Table 5, column 1). We then repeat the analysis using pre-treatment characteristics (column 2). For example, to analyse outcomes observed in 2009 we use characteristics observed in 2005, a period that predates any treatment received by the treated firms in 2009. Comparing columns 1 and 2 suggests that matching based on post-treatment characteristics understates the treatment effects on all outcomes, in both absolute and relative terms. For example, matching based on post-treatment characteristics suggests that receiving an R&D in the previous three years raises the probability of 'new product to the world' by 40 percent in relative terms (column 1). When pre-treatment characteristics are used for matching, the corresponding effect is 125 percent (column 2).

Table 5: Robustness checks on effects of R&D grant receipt on BOS innovation outcomes

Outcome		(1)	(2)	(3)	(4)	(5)
Any innovation	Mean of control	0.554	0.497	0.520	0.562	0.547
	Treatment effect	0.082*	0.152***	0.129***	0.087**	0.070***
	Standard error	(0.0446)	(0.0355)	(0.0417)	(0.0414)	(0.0225)
	Relative effect	15%	31%	25%	15%	13%
Process innovation	Mean of control	0.303	0.308	0.326	0.326	0.327
	Treatment effect	0.117***	0.131***	0.095**	0.113***	0.066***
	Standard error	(0.0390)	(0.0378)	(0.0420)	(0.0437)	(0.0233)
	Relative effect	39%	43%	29%	35%	20%
Product innovation	Mean of control	0.426	0.379	0.374	0.446	0.393
	Treatment effect	0.111***	0.172***	0.086**	0.084**	0.116***
	Standard error	(0.0372)	(0.0377)	(0.0371)	(0.0391)	(0.0255)
	Relative effect	26%	45%	23%	19%	30%
New product to the world	Mean of control	0.144	0.095	0.091	0.103	0.095
	Treatment effect	0.057*	0.119***	0.090***	0.110***	0.076***
	Standard error	(0.0305)	(0.0260)	(0.0311)	(0.0329)	(0.0171)
	Relative effect	40%	125%	98%	107%	80%
Sales due to new products (%)	Mean of control	4.097	3.996	3.472	3.930	4.472
	Treatment effect	1.459*	1.810**	1.787**	2.098***	1.934***
	Standard error	(0.837)	(0.789)	(0.829)	(0.678)	(0.577)
	Relative effect	36%	45%	51%	53%	43%
Number of untreated obs.		7,725	7,692	7,518	7,533	22,596
Number of control obs.		5,577	5,424	5,109	4,608	20,346
Number of treated obs.		303	309	291	276	693

Source: Authors' estimation from BOS 2005, 2007, 2009, 2011, 2013
Notes: See notes to Table 4. See text for details on specification for each column.

Next, we re-estimate the specification in column 2 by additionally controlling for past outcome in the propensity score equation. This should further reduce selection bias as innovation outcome observed pre-treatment acts as proxy for firm's unobserved innovativeness. The result (column 3) suggests that controlling for past outcome tends to reduce the estimated treatment effects slightly. Similar effects are obtained when the PSM equation controls for past R&D activity instead of past outcome (column 4).

About a third of firms that received an R&D grant in the previous three years also received one in the current year. For these firms, the outcomes are thus being assessed during an on-going treatment rather than post-treatment. When these firms are excluded, the estimated treatment effects (column 5) are broadly similar to those in Table 3 (column 1), suggesting that the latter results are not driven by firms that still undergo a multi-year treatment.

Accordingly, the results presented in Tables 3–4 understate treatment effects by matching based on post- rather than pre-treatment characteristics, while overstating the effects by not controlling for firm's unobserved innovativeness. On balance, the results from columns 1–3 of Table 5 appear to suggest that the treatment effects presented in Tables 3–4 tend to be on the conservative side.

7.2. IP innovation outcomes

As shown in Table 6,[29] the results for the effect of R&D grant receipt on the probability of receiving a patent are qualitatively similar to those for the BOS innovation measures, but they are not as statistically significant. In particular, across the estimation sample, 1.4 percent of firms applied for a patent during 2005–2009 (column 1). R&D grant receipt is estimated to almost double the probability of applying for a patent. This effect is similar between project grants and capability building grants (columns 2–3).[30] This result contrasts the finding in Table 4 that project grants have much stronger effects than capability building grants.[31]

Disaggregated by firm size, R&D grant receipt is estimated to increase the probability of applying for a patent by 0.5 percentage point for small to medium firms, or 55 percent in relative terms. The corresponding effect on larger firms is 2.2 percentage points, or 65 percent in relative terms. However, these effects are not significant (small to medium firms) or only weakly significant (larger firms). This could be because the estimates by firm size are based on smaller samples than those based on the full sample (columns 1–3) and hence are less precisely estimated (i.e. higher standard errors, thus less likely to be statistically significant). Nevertheless, this result reinforces

[29] Table 2 (columns 2–3) contains the average marginal effects on the probability of receiving an R&D grant for the IP sample. Despite having fewer explanatory variables than for the BOS sample (due to the lack of variables that are only available through the BOS survey), the propensity score regressions for the IP sample have higher goodness of fit (R-squared of 38%) than for the BOS sample (29%).
[30] The means of the control group in columns 2 and 3 are lower than in column 1, as firms that received both types of grant are excluded from analysis by grant type.
[31] Almost identical results prevail for 'obtaining a patent' and 'obtaining a trademark'. A patent/ trademark needs to be applied for before it is registered.

the finding in Table 4 that the estimated effect of R&D grant receipt is broadly similar between the two groups of firms.

Table 6: Effects of R&D grant receipt on IP innovation outcomes

Outcome		All firms (1)	Capability building grant (2)	Project grant (3)	Small to medium firms (4)	Larger firms (5)
New patent	Mean of control	0.014	0.010	0.010	0.009	0.033
	Treatment effect	0.011***	0.010***	0.012***	0.005	0.022*
	Standard error	(0.0035)	(0.0038)	(0.0043)	(0.0031)	(0.0125)
	Relative effect	74%	105%	117%	55%	65%
New trademark	Mean of control	0.091	0.085	0.083	0.062	0.159
	Treatment effect	-0.001	0.004	-0.004	-0.001	0.017
	Standard error	(0.0060)	(0.0078)	(0.0098)	(0.0071)	(0.0200)
	Relative effect					
Number of untreated obs.		293,340	291,294	291,270	283,152	10,185
Number of control obs.		292,455	290,313	290,136	282,384	9,165
Number of treated obs.		4,137	1,893	1,512	3,156	783

Source: Authors' estimation from various LBD sources (see text for details), 2005–2009
Notes: See notes to Table 4.

Interestingly, the estimated effect of R&D grant receipt on the probability of applying for a trademark is near zero and statistically insignificant across specifications. Indeed, we would expect trademarks to be less affected by any R&D-related instrument than patents. Patenting depends on the firm's ability to discover an invention that represents an advance over the existing knowledge, typically based on scientific and technical knowledge that is increased by R&D. In contrast, trademarks represent a branding strategy that may or may not be connected to a technical invention (Camisón and Monfort-Mir, 2012; Gotsch and Hipp, 2012). Nevertheless, given that the importance of trademarks relative to patents is significantly higher in New Zealand than in other OECD countries (Jaffe, 2013), the lack of a link between R&D and trademark activity merits further study.

7.3. Testing for placebo effects

The PSM matching method is designed to minimise the effect of selection bias on the estimates of the effect of grant receipt. The fact that the magnitude of the estimated effect is robust to variations in the method and the bandwidth (Table 3) suggests that it is doing its job, but there is ultimately no way to confirm whether selection bias is still present. As an alternative window on the extent to which the observed effects might be driven by selection bias as opposed to real causation, we perform two placebo tests, re-estimating the model using first an outcome and then a treatment variable that we do not expect, a priori, to be related to technological innovation. If the model worked just as well with these 'placebo' variables, it would suggest that the estimated treatment effect is more likely to be due to selection bias; that is, the treated firms are simply better in some unobservable way than the untreated firms. Conversely, if these models do not find a significant treatment effect, that provides some indirect evidence that our results are not greatly affected by selection bias.

First, we consider the effect of R&D grant receipt on employee satisfaction, an outcome that is not likely related to a firm's innovativeness, though it might be related to more general aspects of firm quality that would influence selection. BOS has a question on how a firm compares to its major competitors on employee satisfaction, with values of 1, 2, 3 respectively indicating 'lower than', 'on a par with' and 'higher than' competitors.[32] As Table 7 (column 1) shows, the mean employee satisfaction score in the control group is 2.5, suggesting that the typical BOS firm believes that it outperforms its major competitors on employee satisfaction. The PSM approach finds no statistically significant effect of R&D grant receipt on employee satisfaction score. If firms received R&D grants because of unobservable superiority not captured by the PSM method, we would expect these selected firms to also show higher employee satisfaction. This suggests (though of course does not prove) that the PSM method is adequately capturing the firm attributes that lead to selection, so that the observed treatment effect on firm innovation is real rather than just a selection effect.

Second, we examine the impact on innovation outcomes of receipt of ETP assistance. ETP was a programme aimed at upskilling the owners and operators of small to medium enterprises (those employing up to 50 full-time equivalent employees) to help them develop and grow their businesses. It was not designed to influence innovativeness *per se*, and it provided no resources for R&D.[33] In order to compare a result for ETP receipt with our findings, we first re-estimate the impact of R&D grant receipt on the BOS sample covering firms with fewer than 50 employees for the same time period as the ETP data (2005, 2007 and 2009 only). As Table 7 (column 2) shows, the effects of R&D grant receipt on innovation outcomes for this sample are similar to those for the sample of small to medium firms in all five years (Table 4, column 3).

In column 3 (Table 7), we estimate the 'placebo' model in which the treatment variable is 'received ETP assistance in the previous three years'. Comparing the results in columns 2 and 3, we find that both R&D grants and ETP have similar effects on the probability that a firm carries out any type of innovation and neither type of assistance has any effect on process innovation. The effect of ETP receipt on the probability of any product innovation (raising by 3.7 percentage points, column 3) is only a third that of R&D grant receipt (12 percentage points, column 2). While

[32] Firms answering 'don't know' to this question are excluded from this analysis.
[33] ETP is delivered by specialist training providers via workshops, seminars or courses (group training) with the option of receiving follow-up coaching. General subjects include business planning, marketing, finance, business systems, managing resources and exporting. Specialist training includes Maori trustee training, investment ready training and, in the case of Pacific Islanders, pre-business training. The programme ceased to operate from 1 July 2010.

R&D grant receipt is estimated to raise the probability of 'new product to the world' innovation by 8.7 percentage points, no effect is found for ETP receipt. The effect of ETP receipt on sales due to new products is smaller (0.7 percentage point, column 3) than that of R&D grant receipt (1.6 percentage points, column 2) and neither estimate is significant. Interestingly, significant effects on organisational and marketing innovation are found for ETP receipt but not for R&D grant receipt. The estimated effects of ETP receipt on innovation outcomes are robust to the exclusion of firms that received an R&D grant in the previous three years (column 4).

Table 7: Placebo effects of R&D grant receipt on BOS innovation outcomes

Outcome		(1)[a]	(2)[a,c]	(3)[b,c]	(4)[b,c,d]
Employee satisfaction score	Mean of control	2.451			
	Treatment effect	-0.042			
	Standard error	(0.029)			
	Relative effect				
Any innovation	Mean of control		0.527	0.465	0.437
	Treatment effect		0.078**	0.094***	0.102***
	Standard error		(0.0381)	(0.0203)	(0.0246)
	Relative effect		15%	20%	23%
Process innovation	Mean of control		0.281	0.248	0.221
	Treatment effect		0.038	0.025	0.033
	Standard error		(0.0380)	(0.0202)	(0.0209)
	Relative effect				
Product innovation	Mean of control		0.390	0.306	0.266
	Treatment effect		0.116***	0.037*	0.046**
	Standard error		(0.0355)	(0.0210)	(0.0213)
	Relative effect		30%	12%	17%
New product to the world	Mean of control		0.109	0.072	0.040
	Treatment effect		0.087***	0.004	0.013
	Standard error		(0.0277)	(0.0119)	(0.0110)
	Relative effect		80%		
Sales due to new products (%)	Mean of control		6.142	4.343	3.670
	Treatment effect		1.587	0.702	0.700
	Standard error		(1.096)	(0.503)	(0.495)
	Relative effect				
Organisational innovation	Mean of control		0.338	0.286	0.258
	Treatment effect		-0.028	0.050**	0.066***
	Standard error		(0.0347)	(0.0197)	(0.0199)
	Relative effect			18%	26%
Marketing innovation	Mean of control		0.334	0.253	0.236
	Treatment effect		-0.024	0.064***	0.062***
	Standard error		(0.0326)	(0.0179)	(0.0184)
	Relative effect			25%	26%
Number of untreated obs.		19,527	9,888	9,462	9,195
Number of control obs.		16,506	7,737	8,706	8,406
Number of treated obs.		783	282	714	624

Source: Authors' estimation from BOS 2005, 2007, 2009, 2011, 2013
Notes: See notes to Table 4.
[a]Treatment: R&D grant receipt, [b]Treatment: ETP receipt, [c]Estimation sample only covers firms with fewer than 50 employees in 2005, 2007 and 2009, [d]Estimation sample further excludes firms that received an R&D grant in previous 3 years

Since ETP is not designed to influence a firm's technological innovativeness, the cleanest result would have been to find no effect of ETP on our innovation measures. What we found instead is that ETP assistance is associated with some increase in innovation. However, compared to the effect of an R&D grant, the ETP innovation effects are smaller, are absent in the most novel innovation outcomes ('new product to the world' and sales due to new products), and are tilted towards organisational and marketing innovation rather than the technological innovation we expect to be driven by R&D. Combined with the above results for the employee satisfaction measure, this suggests that part of the estimated effects of R&D grant receipt presented in Tables 3–5 might be due to selection on unobservables, but that selection bias is likely to be small, particularly for the most important and most novel innovation measures.[34]

8. Summary and conclusions

This study has used data from the LBD to examine the impact of R&D grant receipt on innovation outcomes for New Zealand firms. Using the PSM approach, the study shows, as expected, that a portion of the overall superior innovation performance of grant-receiving firms likely represents a selection effect, but that innovation performance of grant-receiving firms on most innovation measures exceeds that of propensity-matched firms, suggesting that there is a causal effect of grant receipt.

In particular, based on the BOS sample, we find that receiving an R&D grant almost doubles the probability that a firm introduces new goods and services to the world while its effects on process innovation and any product innovation are relatively much weaker. Moreover, R&D project grants have much larger effects on BOS-based measures of innovation outcomes than R&D capability building grants, which is to be expected, given the nature of each type of grant. There is no evidence that the effects of R&D grant receipt on these measures of innovation differ significantly between small to medium (<50 employees) and larger firms. Furthermore, we find that receipt of an R&D grant significantly increases the probability that a firm in the manufacturing and service sectors applies for a patent during 2005–2009, but no positive impact is found on the probability of applying for a trademark. These findings are broadly in line with recent international evidence from Japan, Canada and Italy (reviewed in Section 2) which found positive impacts of public R&D subsidy on patenting activity and the introduction of new products.

The results are subject to the limitations in the PSM approach. This approach rests crucially

[34] An evaluation method that can arguably deal with unobserved heterogeneity is difference-in-differences on a matched sample, such as that suggested by Blundell and Dias (2000) and adopted by Ministry of Economic Development (2011). However, this method is not suited for binary innovation outcomes, as these outcomes are non-divisible and as innovation persistence is very low among New Zealand firms. Furthermore, this method requires longitudinal data, which markedly reduces the estimation samples, especially when BOS data are used. Using this method on our only non-binary outcome (sales due to new products), we find that R&D grant receipt increases sales due to new products by 0.9 percentage point (significant only at the 1% level), compared with an effect of 2 percentage points estimated by the PSM method (Table 3). Despite its merits, the difference-in-differences method can underestimate the treatment effect by exacerbating measurement error.

on the assumption that—conditional on observables as captured by the propensity score—the assignment to treatment (i.e., receiving an R&D grant) or not is purely random. This assumption is not directly testable. We use a large number of explanatory variables to predict the probability of R&D grant receipt, which helps minimise selection bias due to unobservables (since selection on unobservables tends to be strongly linked to selection on observables). Another advantage of our data is that they come from a variety of survey and administrative sources (e.g. R&D grant receipt is from MBIE records, firm size is from tax records, patent and trademark applications are from IPONZ records, measures of innovation à la the Oslo manual are from the BOS survey, etc.), thus associations between variables are less likely to reflect respondent bias and more likely to reflect a meaningful statistical relationship and possibly causation. The robustness of the results to various formulations, combined with the results for the 'placebo' tests suggests that there is probably a true causal effect, particularly for the narrowest innovation measure (new product to the world), but selection bias likely remains part of the picture.

The results provide some evidence for the public policy value of R&D project grants, but it is important to keep in mind that innovation is an intermediate outcome of technology policy; the goal of the policy is increased productivity and sales of improved products. A previous LBD study (Ministry of Economic Development, 2011) examined whether the R&D grant programme increased receiving firms' sales, employment and productivity. That study found some evidence of impact for capability-building grants, but no evidence of impact for R&D project grants; the positive impact was limited to small firms (mean employment of about 6 or less), with no evidence of impact for larger firms. This contrasts with our finding of much stronger innovation impacts for the R&D project grants, and no significant difference in impact across firm size categories. How could it be that R&D project grants increase firm innovation but do not improve firms economic performance? Logically, there are several possibilities.

1. Project grants foster innovation and innovation fosters improved economic performance on average, but the link is so highly variable that in a small sample such as this the effect cannot be detected.
2. Project grants foster innovation and innovation fosters improved economic performance, but the lag between innovation and improved performance is so long and/or so variable that this effect cannot be detected. (The Ministry of Economic Development study considers performance outcomes up to four years after a firm first receives assistance.)
3. Project grants may foster innovation and improved economic performance, but imitations may follow innovations so quickly that the returns accrued to original innovators are not significantly higher than to imitators. This non-appropriability issue is part of the reasons why firms under-invest in R&D, and hence government subsidy is required to improve resource allocation for innovation.

4. Project grants foster innovation and true technological innovation fosters improved economic performance, but the innovation measures we are using are such poor proxies for true innovation that the link cannot be detected.
5. Project grants foster innovation, but innovation is not a sufficiently important determinant of economic performance to make an increase in innovation due to a project grant show up in economic performance relative to that of firms that did not get a grant (and presumably used other means to improve economic performance).
6. Project grants have no effect on *true* innovation (and hence no effect on economic performance), but employees of firms that have gotten grants consciously or unconsciously rationalise having gotten a grant by saying that they are innovating even if they are not.

Distinguishing among these possible explanations is important. Under explanations 1–3, the grants' success in fostering innovation implies eventual success with respect to the policy goal of improving economic performance. Explanations 5 and 6 imply that R&D project grants are not effective public policy. Explanation 4 leaves the question unresolved. Some additional insight on these issues would be provided by an analysis that looked more broadly at the relationship between innovation and economic performance for firms in the BOS data, regardless of whether or not they received government R&D support. As Callaghan Innovation ramps up its R&D support programmes, and more time passes for the firms who have already received grant support, some of the uncertainty generated by small, short samples will also be mitigated.

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Appendix

Appendix Table 1: Government direct R&D funding for businesses by year

Year	Total funding ($m)	Capability building grants: Number of funded firms	Capability building grants: Average grant amount ($)	Project grants: Number of funded firms	Project grants: Average grant amount ($)
2001	15.6	1,203	3,900	333	32,900
2002	28.0	981	5,000	603	38,300
2003	32.2	930	5,900	738	36,300
2004	36.5	777	7,700	708	43,200
2005	39.3	582	11,100	558	58,900
2006	46.8	603	14,400	483	79,000
2007	60.3	639	18,600	507	95,900
2008	48.3	489	18,300	402	97,700
2009	38.5	345	16,500	273	119,900
2010	32.9	228	36,100	153	161,800
2011	37.6	378	18,700	168	182,100
2012	72.0	552	14,500	195	326,500
2013	89.7	510	16,200	366	223,000

Source: Longitudinal Business Database

Note: Numbers of observations have been randomly rounded to base 3 to protect confidentiality. Dollar values are in current prices. Annual inflation averaged 2.5 percent during 2001–2013.

Appendix Table 2: Government direct R&D funding for businesses, 2012

	Capability building grants: Share in total funding	Capability building grants: Average grant amount ($)	Project grants: Share in total funding	Project grants: Average grant amount ($)
By grant type	0.11	14,500	0.89	326,500
By age				
<5 years	0.22	12,900	0.09	125,400
5-9 years	0.25	15,500	0.11	158,100
10-19 years	0.28	15,900	0.34	367,500
>=20 years	0.24	16,700	0.45	652,600
By firm size				
<5 employees	0.44	13,100	0.11	94,800
5-19 employees	0.19	16,600	0.19	323,200
20-49 employees	0.11	13,900	0.08	163,700
50-99 employees	0.07	17,600	0.13	391,000
>=100 employees	0.18	21,500	0.49	953,500
By industry				
Agriculture, Forestry, Fishing and Mining	0.02	9,200	[a]	[a]
Food, Beverage and Tobacco	0.10	19,200	[a]	69,800
Textile, Wood Product, Pulp, Paper Manuf. & Printing	0.02	8,600	0.00	40,400
Petroleum, Coal, Chemical & Associated Prod. Manufacturing	0.10	23,800	0.01	119,000
Machinery and Equipment Manufacturing	0.11	13,000	0.42	536,100
Other Manufacturing	0.07	16,700	0.01	100,000
Wholesale Trade	0.11	13,700	0.08	334,500
Business Services	0.30	13,500	0.37	268,200
Other services	0.18	19,500	0.10	289,000

Source: Longitudinal Business Database

Note: Total funding in 2012 was $72 million. [a]Suppressed to protect confidentiality.

Appendix Table 3: Definitions of selected explanatory variables

Variable	**Definition**
Received non-R&D govt. assistance in previous 5 years	1 if firm received government assistance other than an R&D grant in the previous five years
Has formal IP protection	1 if firm uses some form of formal intellectual property protection (e.g. patents, trademarks, copyrights)
Age	Number of years since firm was formed
Employment	Rolling mean employment, which is a 12-month rolling average of the monthly employment count figure obtained from taxation data
State-owned enterprise	1 if firm is state owned
Belongs to a business group	1 if firm belongs to a business group
Exporter	1 if proportion of firm' sales that came from exports is positive
Has foreign ownership	1 if any individual or business located overseas holds an ownership interest or shareholding in firm
Has ownership interest overseas	1 if firm holds any ownership interest or shareholding in an overseas located business
Access to capital (reference: did not request capital) [a]	
Easy access to capital	1 if firm requested new or additional debt or equity finance over the last financial year and was not classified as 'Difficult access to capital'
Difficult access to capital	1 if firm requested new or additional debt or equity finance over the last financial year and at least one type of funds were 'available, but not on acceptable terms' or 'not available'
Local area has good skilled labour market [a]	1 if firm considers local area in which it operates has good skilled labour market
Competition level (reference: 0–2 competitors)[a]	
Market has monopolistic competition	1 if firm has many competitors, several dominant
Market has perfect competition	1 if firm has many competitors, none dominant
Primary location (reference: Auckland)	Defined as the region that has the highest share of the firm's total employment
Waikato	
Wellington	
Rest of North Island	
Canterbury	
Rest of South Island	

Notes: Dummy variables equal 0 if otherwise defined. [a]Based on respondent's subjective view of the local area or market in which firm operates.

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