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Impact of Commercialisation Australia on Business Performance

Sasan Bakhtiari
Angelina Bruno

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Abstract

Commercialisation Australia (CA) was an Australian government grant program that ran from 2009 to 2014. Its purpose was to support companies and innovators during the commercialisation phase of developing their products and ideas. Focusing on the small and young firms that were supported by the program, we find that the participating firms tended to invest in capital and Research and Development (R&D) in larger amounts than a similar comparison group. Participating firms also demonstrated better performance in that they had larger increases in their rates of turnover growth than the comparison group. There are also positive effects on exporting activity, patenting, and trademarking.

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Australian Government
Department of Industry, Innovation and Science

Office of the Chief Economist

For further information on this research paper please contact:

Sasan Bakhtiari

Industry and Firm Analysis

Department of Industry, Innovation and Science

GPO Box 9839

Canberra ACT 2601

Phone : +61 2 9397 1639

Email: sasan.bakhtiari@industry.gov.au

Key points

- **Most firms in the Commercialisation Australia (CA) program are small and young. These firms have also received the majority of CA grants.**
- **CA participants are mostly from Manufacturing and Professional, Scientific and Technical (PST) Services, and from sub-divisions associated with advanced technology.**
- **CA participants had higher R&D and capital expenditures than other similar firms in the comparison group.**
- **Participants, also outperformed other firms in that they had larger increases in turnover growth than the comparison group.**
- **Overall, there was an increase in exporting activity, and patents and trademark applications among the CA participants.**

1. Introduction

The Australian government introduced the Commercialisation Australia (CA) program in 2009. The policy objective of the CA program was to build the capacity of, and opportunities for, Australia's researchers, entrepreneurs and innovative small and medium size firms to convert ideas into successful commercial ventures.

In general, Research and Development (R&D) and innovation are two areas where it is more difficult to attract private investment. The general perception is that R&D and innovation are too risky and have high probabilities of failure. The perception of such risk keeps investors away from such ventures or makes them demand extraordinary concessions from the firm (Akerlof, 1970).

The current body of studies already provides evidence of systematic underinvestment in innovative firms, especially those firms in the advanced technology areas, (Freel 1999, 2007, Carpenter 2002, and Westhead & Storey 1997). Similarly in Australia, Bakhtiari (2017a) finds that small and young firms applying for debt or equity financing in order to innovate are more likely to be rejected.

The CA program, in particular, had a special focus on applicants that were in need of financing for the proposed project and unable to obtain the required financing through alternative sources (ANAO, 2014).

The last CA grants were offered in 2014. The program was replaced by the new Accelerating Commercialisation element of the Entrepreneurs' Programme (EP). While there are some differences, Accelerating Commercialisation has a similar policy intent to the Commercialisation Australia program.

This study focuses on the CA program and evaluates how participating firms fared relative to a comparison group. However, the methodology may be applied to the analysis of the Accelerating Commercialisation element of EP and also to other programs with similar policy intents.

We begin by exploring the composition of CA participants and present some descriptive statistics on those firms. Our focus is on the innovative and entrepreneurial features of these firms. Entrepreneurial firms, in particular, are generally associated with being young, innovative, and ready to grow. They are generally also very insecure and in urgent need of investment, but have difficulty in attracting investment. Those young firms that survive and grow, however, make an over-sized contribution to net job creation in Australia (Bakhtiari, 2017b).

The findings show that the majority of program participants are quite small and young, hence, akin to entrepreneurial firms. A few grants were also awarded to mature and large firms. We do not analyse these mature and larger firms given that they are relatively small in number and often have complex corporate structures which are not conducive to detailed analysis.

Focusing on the small young firms, we compare the dynamics of the CA participants with a comparison group of non-participating firms to measure the impact of this program on their growth. We construct the comparison group using observable characteristics including industry classification, turnover, export status, R&D-activity and firm age. Using R&D-activity to construct a comparison group is particularly useful, as R&D is a leading indicator of product innovation and commercialisation intent, which are the key characteristics of the program's target market. Our analysis shows the majority of CA firms also participated in R&D tax programs. We look at additional growth in turnover and added investments in capital and R&D as measures of program success.

We can establish that participating firms in the CA program had higher levels of capital investment and R&D expenditures immediately after the grant relative to the comparison group of similar firms. We also find that participating firms outperformed other firms in that their turnover growth increased by a larger amount.

We also look at the response of the CA participants in terms of exporting activity, patenting and trademarking.

The remainder of the paper is organised as follows: in the next section, we will provide an overview of the CA program. In Section 3, we describe the data being used for the analysis. In Section 4, we provide an overview of the program participants and highlight their features. Section 5 describes our evaluation methodology, with the results presented in Section 6. The papers is concluded in Section 7.

2. Overview of the program

The CA program was established in 2009 and started offering the first grants from July 2010. The last grants were awarded in June 2014. The program had four components, each offering grants for a certain type of activity relevant to commercialisation. These components are:

1. **Skills and Knowledge**: intended to get access to specialised advice and services. The amount of grant was capped at $50,000 with a 20 per cent matching contribution required from the recipient. Maximum length of grant is 12 months.
2. **Experienced Executives**: intended to hire an experienced executive officer. These grants offered up to $175,000 per year with a 50 per cent matching contribution required from the recipient. Maximum length of grant is two years.
3. **Proof of Concept**: intended to assist with the testing, development and evaluating the commercial viability of a business model or idea for a product. The grant amount was between $50,000 and $250,000 with a 50 per cent matching contribution required from the recipient. Maximum length of grant is 12 months
4. **Early Stage Commercialisation**: intended to carry out activities that focus on the development of a new product, process or service and their commercialisation. Grant amount was between $50,000 and $2 million with a 50 per cent matching contribution from the recipient. Maximum length of grant is two years.

Alongside the grants, the program also offered additional support to firms in the form of case managers who were private sector advisers with experience in commercialisation.

The annual turnover limit to be eligible for the CA program was initially $20 million. However, in December 2011 this threshold was increased to $50 million to increase the program's capacity to assist both small and medium sized enterprises (SMEs).[1] Exceptions to this eligibility rule were also made on a case-by-case basis. The grant was open to non-tax-exempt firms but also to individual innovators applying through a university or through other forms of industry partnership.

To satisfy the merit criteria, the applicants needed to demonstrate the viability and marketability of the idea. They also needed to demonstrate a need for funding for the project and be unable to obtain the funding from alternative sources (ANAO, 2014 Table 1.4).

A total of 689 grants were awarded to 553 firms during the life of the program. Some firms received more than one grant from different components of the CA program.

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[1] Other changes made to the programme in December 2011 included lifting the repayable grant requirement and expanding eligible expenditure guidelines for Early Stage Commercialisation to allow more generous support for the development of pilot plant and innovative manufacturing facilities.

Of the total number of grants, 215 grants were for the Skills and Knowledge component, 73 were for the Experienced Executives component, 222 were for the Proof of Concept component, and 179 were for the Early Stage Commercialisation component.

3. Linked data

The analysis undertaken in this paper is based on a linked dataset that basically identifies the CA participants in the Business Longitudinal Analysis Data Environment (BLADE) provided by the Australian Bureau of Statistics (ABS).

The BLADE serves as the source providing operational information for firms and also the source for the formation of the comparison group. The core of the BLADE is integrated administrative tax data and covers all firms registered for the GST. For more details on the composition of the data see Hansell & Rafi (2018).The unit of observations in the BLADE is a firm defined as a Type-of-Activity Unit.[2]

Information on subsidiaries or subdivisions of a firm are not available in the BLADE. Consequently, any data linked to the BLADE from outside sources has to be aggregated to the head-quarter level. Given this restriction, we obtain CA data that are aggregated to the firm level. These data are such that we only observe the total amount of grants awarded to a firm and the first and last year of program participation. Due to the aggregation, details such as the grant's component are lost. For this reason, we focus on the first year of participation for a firm and not on individual grants claimed by the firm.

The main measure of firm size in the study is turnover and employment (reported in headcounts). The ABS uses this information along with wages and other supplementary data and estimates full-time equivalent employment (FTE). We rely on this latter measure of employment as it is a better proxy for man-hours.

FTE is missing for a large number of firms in the BLADE. However, there is a strong relationship between FTE and wages in the BLADE, and this relationship is exploited where possible to impute FTE values. Specifically, FTE is assumed to have the following relationship with wages:

$$\log(FTE_{jit}) = \alpha_o + \alpha_1 \log(Wages_{jit}) + \tau_t + \iota_i + \varepsilon,$$

where the indexes refer to firm *j* belonging to industry *i* at time *t*. τ and ι indicate a series of time and industry dummies, respectively, that control for macro forces and industry-specific effects.

We then use the estimated model to predict the value for cases where FTE is missing but wages are reported. The R^2 for the fit is 0.95 which is quite high by statistical measures. It means that the imputed FTEs do not entail much noise.

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[2] The ABS defines Type-of activity Unit as "a producing unit comprising one or more legal entities, sub-entities or branches of a legal entity that can report productive and employment activities via a minimum set of data items" (ABS Cat.No.1292.0)

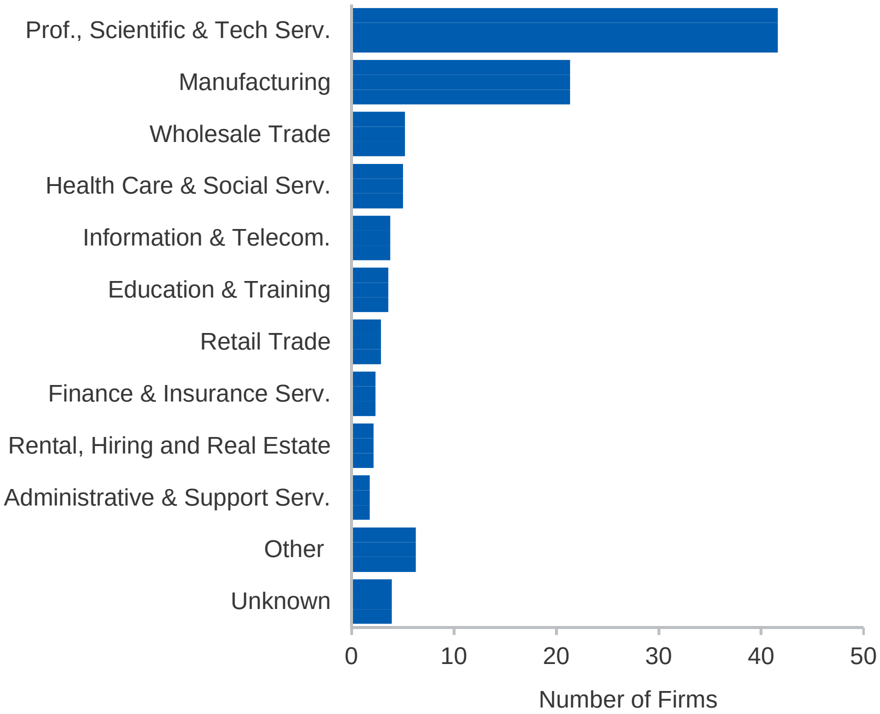
4. The recipient firms

The main aim of the CA program was to assist innovative firms and entrepreneurs to develop and commercialise new products. In this section, we will explore the features of the participating firms and establish how close they get to this perception.

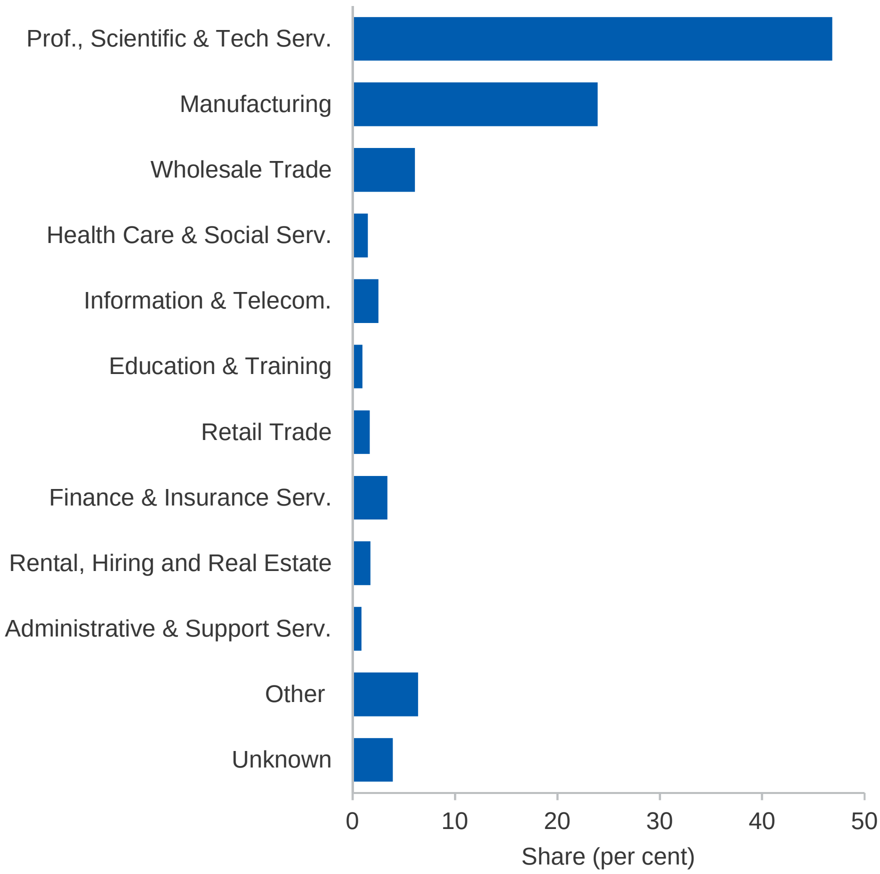
In the first instance, we look at the industrial composition of the CA participants. The composition by main Australia and New Zealand Standard Industry Classification (ANZSIC) divisions is shown in **Error! Reference source not found.**. Panel (A) in the figure shows the shares by the number of firms, whereas Panel (B) shows the share of grant amount being allotted to each industry.

Figure 4.1 The industrial composition of CA participants by major ANZSIC division.

(A) Number of firms



(B) Grant amount



Note: Group other includes all other ANZSIC divisions not shown individually in the picture.

Source: Department of Industry, Innovation and Science (2018)

Both panels confirm that the majority of the participants belong to an industry sector that is strongly associated with the advanced technology area. About 63 per cent of participating firms belong to Professional, Scientific and Technical Services, together with Manufacturing. In terms of grant amount, more than 70 per cent of all the grant funding has been allotted to these two industries.

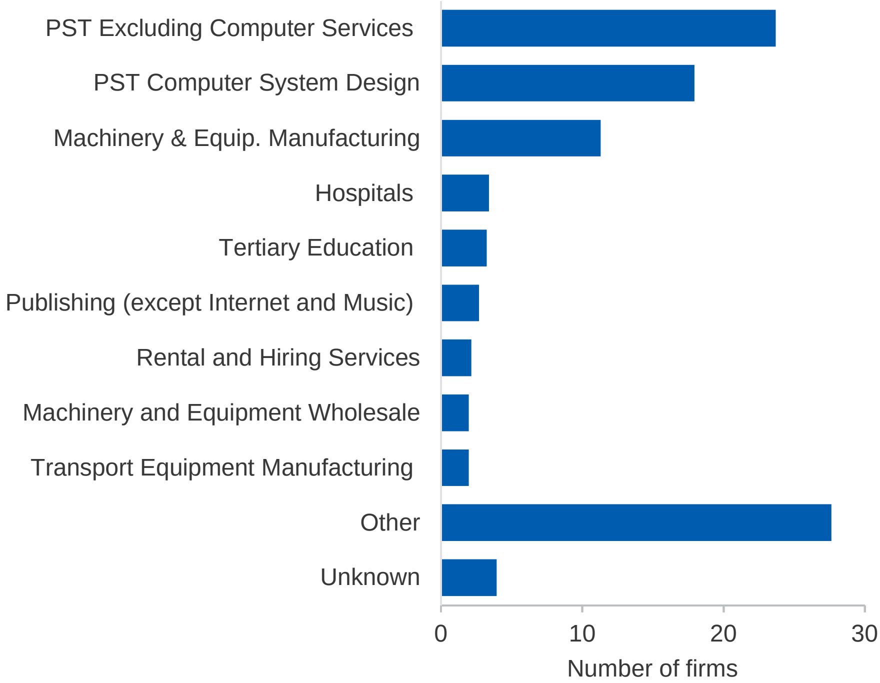
Wholesale Trade is at the third place both in terms of the number of firms and grant funding. The share of grants awarded to other industries is quite small compared to the share claimed by the three aforementioned industries.

Participants from Professional, Scientific and Technical services also received the largest grants per firm. The average grant value offered to these participants per firm is $481,371. Participants from Manufacturing are, again, at the second place with the average grant awarded having a value of $479,655. The average grant awarded to participants from all other industries is about $337,501.

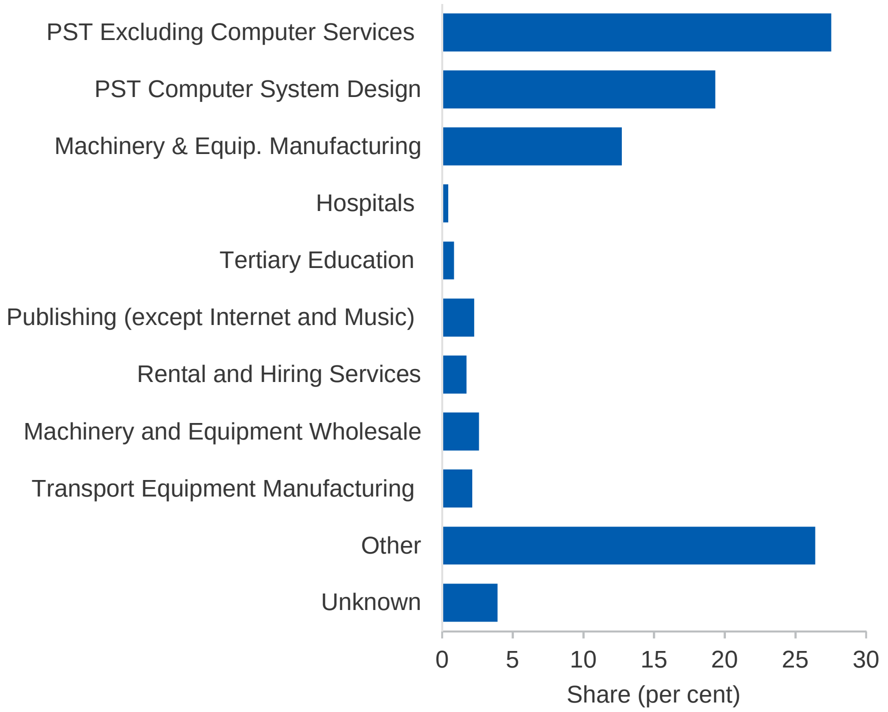
To make a more concrete case that the CA grants have been mostly awarded to advanced technology firms, we further look at a few two-digit ANZSICs that received the largest share of CA grants. The sectors with the highest population of the CA firms are identified in Figure 4.2.

Figure 4.1 The proportion of CA participants by two-digit ANZSIC

A) Number of firms



B) Grant amount



Note: PST stands for Professional, Scientific and Technical Services. Group *other* includes all other two-digit ANZSICs not shown separately in the picture.

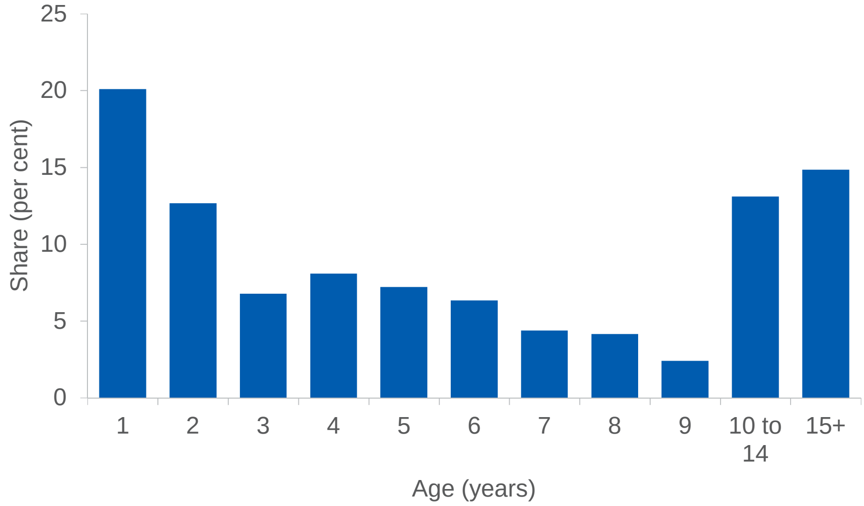
Source: Department of Industry, Innovation and Science (2018)

The two sub-sectors with the highest population of the CA participants belong to the PST Services. The first subsector, PST Excluding Computer Services, includes areas such as scientific research, architectural and engineering design, and market research among others. The other subsector concerns computer system design. Both of these sectors are associated with advanced technology and innovative activities.

The one other sub-sector with a high population of participating firms is Machinery and Equipment Manufacturing. Firms in this area are engaged in a variety of design and production activities including that of computers, electronics, scientific tools, and specialised machinery. Many of these areas are, again, associated with advanced technology and innovative activities.

We further explore how entrepreneurial the CA participants are by also looking at their age one year prior to receiving their first grant, with age one being the year of entry. The age distribution of CA participants is shown in Figure 4.3.

Figure 4.3 Distribution of CA participants by age.



Source: Department of Industry, Innovation and Science (2018)

The figure shows that 20 per cent of firms are one year old at the time their first CA grant is awarded. About 40 per cent of the CA participants are three years old or younger at the time of their first grant. More than three quarters of the CA participants are eight years old or younger at the time of their first grant. This picture is consistent with a program focused on entrepreneurs and innovative firms which generally tend to be younger. It is also noted that, about 28 per cent of the participants are more than 10 years old.

For a better clue to the characterisation of the participating firms, we investigate the size distribution of the program participants. The CA grants are offered in different years to different firms. To provide a homogeneous picture of what the size distribution of the CA participants looks like, we explore a set of descriptive statistics about the employment and turnover size of the participants one year before they receive their first grant. We then follow the same statistics in the year they receive the grant and one year after.

The statistics for FTE are listed in Table 4.1, and the statistics for turnover are listed in Table 4.2

Table 4.1 Distribution of FTE among the CA participants before, during and after assistance.

	Before	During	After
Mean	694.5	518.1	495.0
10th Pctl.	1.2	0.9	1.1
25th Pctl.	2.2	2.0	2.2
50th Pctl.	6.0	4.6	6.2
75th Pctl.	17.9	13.7	15.5
90th Pctl.	2845.6	692.7	361.4
N	250	340	361

Notes: Several firms have missing employment.

Source: Department of Industry, Innovation and Science (2018)

Table 4.2 Distribution of turnover among the CA participants before, during and after assistance.

	Before	During	After
Mean	29,793.8	23,177.4	21,866.2
10th Pctl.	0.0	11.4	8.6
25th Pctl.	4.9	59.6	80.0
50th Pctl.	174.3	249.8	355.1
75th Pctl.	1,155.6	995.7	1,277.8
90th Pctl.	8,287.3	6,086.9	7,958.9
N	453	551	552

Notes: Turnover is in thousands of current dollars.

Source: Department of Industry, Innovation and Science (2018)

The statistics for both employment and turnover corroborate that most of the participant firms are small. The ABS considers firms with fewer than 20 employees as small, and Table 4.1 shows that under this definition more than three quarters of participating firms qualify as a small firm the year before and also during and after the first year of the grant.

The Australian Taxation Office defines firms with less than $10 million in turnover as small. Table 4.2 again points out that more than 90 percent of participating firms are small the year before and also during and after the grant.

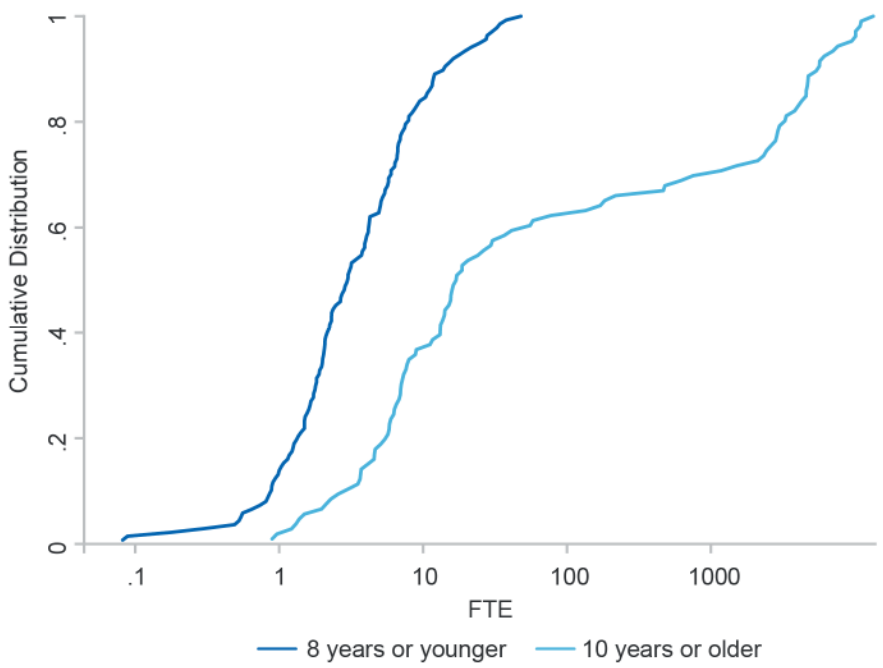
Despite most CA participants being small, the mean values in Table 4.1 and Table 4.2 hint that a few large firms also benefited from the CA program. These firms have more than 500 employees and in excess of $23 million in turnover.

We also suspect that the larger CA participants are the older ones. For this reason, we do a comparative analysis by dividing the sample of CA participants into young and old. In view of Figure 4.3, we assign firms that are eight years old or younger as *young* and firms that are 10 years or older as *old*. We leave a small age gap in between the two groups to strengthen the distinction.

We compare the relative size of the two groups using the Cumulative Distribution Function (CDF) of FTE and turnover of firms in the year before they receive the CA grants. An order of stochastic dominance between the two CDFs indicates that firms in one group are more likely to be larger than the firms in the other group.

The distribution of one group stochastically dominates the other group if its CDF lies underneath (or to the right of) the other one. In this case, the distribution of the former group is mostly to the right of the latter one (skewed towards larger values). The CDFs for FTE are shown in Figure 4.2.

Figure 4.2 The CDF of FTE for young and old participants.



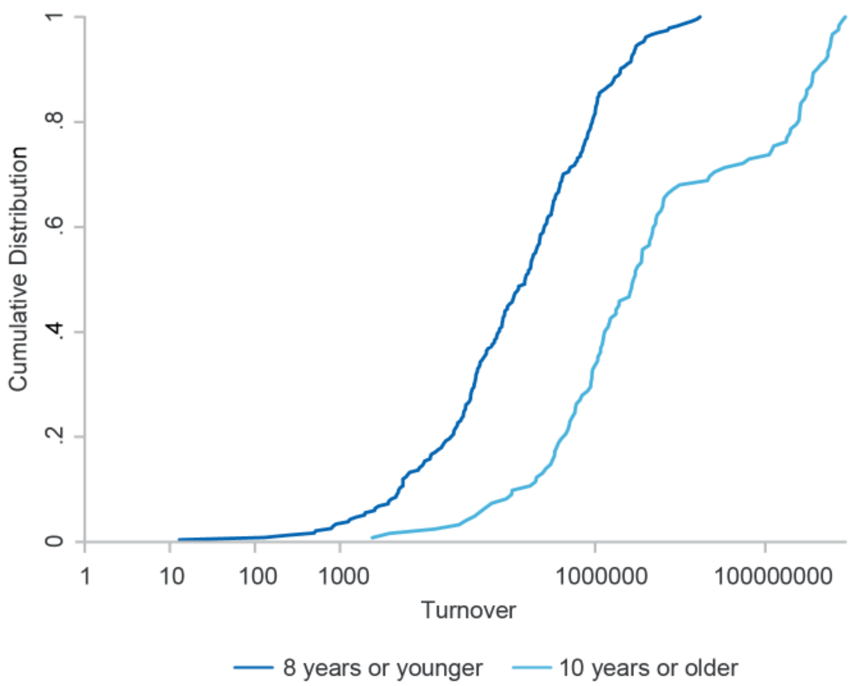
Source: Department of Industry, Innovation and Science (2018)

One observes that in this figure, the CDF for old participants stochastically dominates that of the young participants (lies below it). The gap between the two CDFs is quite wide. In other words, older participants are much larger than young participants.

Besides, there are old firms with sizes in excess of 100 or even 1000 employees in the CA program. In fact, many of the old firms in this picture are in excess of a thousand employees (that corresponds to the steep part at the end of the CDF). On the other hand, young firms in the program have fewer than 30 employees and are far smaller than the old firms in the program.

We also compare the turnover size of young and old participants in Figure 4.3. These turnovers, again, belong to the year before the first grant is received. The same picture emerges, where the CDF of turnover for old participants stochastically dominates that of the young participants. The annual turnover of young participants is mostly below $30 million, whereas many of old participants have annual turnovers in excess of $100 million.

Figure 4.3 The CDF of turnover for young and old participants.



Source: Department of Industry, Innovation and Science (2018)

With this evidence, one concludes that the CA participants can be classified into two almost mutually exclusive groups: small young firms and mature large firms. The majority of the firms in the program are of the first classification.

For the analysis presented in the paper, the mature large firms have been excluded. As mentioned in Section 3, the BLADE is at firm level and has no information on the operation of individual subsidiaries, which are the likely recipient of the grant. For this reason, we drop all CA participants with turnover above $30 million henceforth. This turnover level covers the largest participating firms. By association firms older than 8 years are also being dropped (Figure 4.3). 74 participating firms are dropped as a result.

5. Methodology

In this section we describe the methodology used to analyse the impact of the CA program on participants against a comparison group (the counterfactual) of similar firms. To do this, we use inverse propensity weighting to estimate the treatment effect for the CA participants. This approach was first introduced by Hirano et al. (2003) and has the advantage of being less computationally intensive than comparable methods such as nearest neighbour or propensity score matching, while it offers the same degree of consistency. Dealing with a large dataset, the low computational intensity of the method proves very helpful.

The idea behind the methodology is that estimating the impact of a treatment is equivalent to the case of missing data: for treated observations the counterfactual is missing, whereas for the untreated the treated observations are missing.

To implement the inverse propensity weights, one first estimates the propensities using a model such as

$$\mathrm{Prob}\left\{CA_{ji0} = 1\right\} = \Phi\left(aX_{ij0} + \tau_0 + \iota_i\right) \tag{1}$$

where *j* and *I* index individual firm and its industry. Time zero is the year before the first CA grant is awarded.

In (1), X is a series of firm-level characteristics that matter for receiving the treatment and its effect. ι is a series of industry dummies at 2–digit ANZSICs, whereas τ is a set of dummies for the year of the first grant ─ or simply the year of operation for non-participants. For X, we use the log of turnover, dummies indicating whether the firm is an exporter, undertook R&D-activity, and dummies for firm age, all one year prior to treatment. Φ is the standard normal CDF.

Let the predicted propensities from (1) be p. Then the Average Treatment Effect (ATE) is computed as (Wooldridge, 2010, Chp 21.3):

$$\mathrm{ATE} = \mathrm{E}\left[\frac{Y}{p}|CA = 1\right] - \mathrm{E}\left[\frac{Y}{1-p}|CA = 0\right], \tag{2}$$

where Y is any performance measure of interest. This statistic estimates what would have happen had the grant been given to every firm.

Alternatively, the Average Treatment effect on the Treated (ATT) is defined as (Wooldridge, 2010, Chp 21.3):

$$\mathrm{ATT} = \mathrm{E}\left[\frac{Y}{\rho}|CA = 1\right] - \mathrm{E}\left[\frac{pY}{\rho(1-p)}|CA = 0\right]. \tag{3}$$

In the ATT, ρ is the unconditional probability that a firm receives CA grants. In this case, ρ will be the number of CA firms divided by the total. This effect estimates the average effect of the program on the recipient firms only.

In what follows, we will focus on the ATT statistic as the measure of the program's effectiveness. The CA program was not meant to be available to all firms but to a selected group of firms with viable commercialisation intent. As such, the ATT statistic provides an understanding of whether the program was successful with the targeted group of firms.

In the hypothetical case that participation in the program is completely random, ATT and ATE will be the same. However, given the selected nature of participants, some selection bias is expected. In this case, a higher value for ATT statistic suggests a selection where the participants are inherently better performing (or are able to make better use of the grants) than the comparison group. A smaller ATT suggests the reverse. Results and analysis of the ATE is provided in the appendix Table A1.

Looking at the ATT and ATE, one also notices that for a proper estimation of the effects, no observation can get too close to p=0 or p=1, otherwise the estimate of impacts can go to infinity. For this reason, we make the crucial *overlapping* assumption that basically says 0<p<1 for every observation included in the analysis. This assumption simply maintains that for every CA participant there must be a similar non-participating firm and vice versa.

To make sure that the overlapping assumption holds, we apply some filtering to our data. First, we drop all 4-digit ANZSICs where no firm received a CA grant. We drop all years before the CA program was introduced. We have also already dropped all firms with turnovers above $30 million and older than 8 years old (the class of mature large firms).

We are unable to enforce the overlapping assumption across unobservable dimensions. One such dimension is the commercialisation intent. Theoretically, it would be more accurate to compare the CA firms with those firms from the counterfactual pool that intend to commercialise a product. However, this information is unavailable. To the extent that covariates in (1) account for the intent to commercialise or other unobserved characteristics, the overlapping assumption still holds.

6. Impact analysis

We apply the methodology outlined in section 5 to firms identified as participating in the CA program versus a comparison group of firms that did not receive a CA grant. For comparison, the year before a CA participant received its first CA grant is assigned *t*=0. We then look at changes in a few performance measures for both participating and non-participating firms for the years that follow. Note that the cost of program delivery, including the cost of case managers, is not accounted for in the estimates; the estimates only focus on the performance of the firms. Moreover, we did not assess the impact on employment growth given that information on wages and FTE was missing for a large number of CA participating firms in the BLADE.

6.1 Impact on turnover

The first performance measure we use is the firm's turnover as a measure of output size. Growth in turnover can signal the introduction of a new product ─ possibly developed with the support of the CA grants ─ that is contributing to the added revenue. Growth in turnover can also be caused by increasing mark-ups or increasing demand for existing products. In the absence of more detailed information on the number of products supplied by a firm and firm-level prices, we use turnover to study the impact of the CA program on output.

One caveat is that developing and successfully commercialising a new product could take many years. The development time can also be different from industry to industry, depending on the type of products and the innovation process. Given that the data is truncated at 2015, we are unable to observe the full effect of the program on firm turnover. This problem is especially evident for the later cohorts of the CA participants.

With this note of caution, we look at the change in turnover from *t*=0 (year before the grant) to *t*=2 (the second year of the grant). There are a few extreme outliers that dominate and skew the results. To avoid skewing the results, we drop all firms whose turnover growth falls in the upper 0.5 percentile or lower 0.5 percentile. As mentioned earlier, we mainly use the ATT statistic to measure the program's effect. The ATT computed for turnover growth is reported in Table 6.1. Results for ATE in this part and the remainder are reported in the appendix Table A.1.

Table 6.1 The impact of the CA program on turnover growth (dollars)

Turnover(*t*=2) - Turnover(*t*=0)	**ATT**
All Firms	206,274.9 (202.37)***
Manufacturing	43,140.6 (1,012.9)***
Prof. Scientific and Tech. Services	312,372.1 (266.8)***
Other industries	95,668.3 (8.9)***

Notes: *** denotes significance at 1 per cent. Firms in the upper and lower 0.5 percentile of turnover growth are dropped as outliers.

Source: Department of Industry, Innovation and Science (2018)

In the first row, we pool all firms satisfying our overlapping conditions stated in Section 5. On average, the CA participants are experiencing a larger increase in turnover growth compared to the comparison group. The ATT shows that turnover growth among the CA participants was around $206,000 above that of the comparison group.

Most participating firms are from either Manufacturing or Professional, Scientific, and Technical Services. These two sectors also tend to be in areas associated with advanced technology (Figure 4.1). Has their performance been different to the rest?

These two sectors are addressed separately in rows two and three of the table. Participating firms from Manufacturing appear to have faster turnover growth than the comparison group of manufacturing firms. According to the ATT measure in the table, CA participation led to an increase of almost $43,000 in the turnover growth of the treated firms above the comparison group.

In the case of Professional, Scientific and Technical Services, we find an even larger effect. According to the estimated ATT, The turnover growth for the treated firms is on average more than $312,000 above that of the comparison group.

The rest of the industries, put together, show an increase of more than $95,000 in their turnover growth compared to the comparison group. However, as mentioned before, the number of firms in these industries is relatively small.

6.2 Impact on capital expenditure

One area where the CA program may have a more immediate effect is investment in capital and R&D as the participating firms accelerate their development and commercialisation of new products. Both types of investment are leading indicators of innovation and turnover growth. Where turnover data is missing due to year truncation, a positive impact on R&D and capital expenditure raises the expectation that growth will happen.

In this section, we look at how the CA program affects capital expenditure. We look at the effect on R&D expenditures in the next section. Again, we drop the upper 0.5 percentile of capital expenditures to avoid extreme values. The ATT effect for capital expenditure is reported in Table 6.2.

Table 6.2 The impact of the CA program on capital expenditures (dollars)

CapEx (*t*=2)	**ATT**
All Firms	29,837.7 (11.6)***
Manufacturing	76,610.3 (98.4)***
Prof. Scientific and Tech. Services	32,251.3 (18.6)***
Other industries	35,102.5(0.3)***

Notes: *** denotes significance at 1 per cent. Firms in the upper 0.5 percentile are dropped as outliers.

Source: Department of Industry, Innovation and Science (2018)

The findings point to an increase in capital expenditure attributable to the program.

When pooling all participating firms together, we find an increase in capital expenditures among the CA participants relative to the comparison group. The ATT statistic, as the measure of program's influence, shows that capital expenditures among the participating firms was nearly $30,000 above that of the comparison group.

Once restricting the sample to Manufacturing, the increase in investment is even higher. Capital expenditures among manufacturing firms participating in the program is about $76,000 more than that among comparison group.

Within participants from Professional, Scientific and Technical Services, capital expenditures among the treated firms is on average more than $32,000 above that of the comparison group. It is a similar situation for participants from other industries.

Overall, it can be concluded that participating firms invested more on capital, and the grants were a source of financing for that purpose.

6.3 Impact on R&D

The development and commercialisation of a product, especially a new and innovative one, usually entails some form of R&D. For this reason, it is expected that CA participants would also invest more on R&D. We test this hypothesis by computing the ATT for the R&D expenditures by firms in t=2 (two years into the grant). As in earlier, we are dropping the upper 0.5 percentile of firms to avoid extreme values. The statistic is reported in Table 6.3.

Table 6.3 The impact of the CA program on R&D expenditures (dollars)

R&D (*t*=2)	ATT
All	418,941.3 (97.5)***
Manufacturing	82,303.3 (309.1)***
Prof. Scientific and Tech. Services	388,179.8 (205.6)***
Other industries	341,306.7 (3.4)***

Notes: *** and ** denote significance at 1 and 5 per cent, respectively. Firms in the upper 0.5 percentile are dropped as outliers.

Source: Department of Industry, Innovation and Science (2018)

As was the case with capital investments, one observes that participation in the CA program also led to an increase in R&D expenditures.

The average increase in R&D among the treated firms also appears to be larger than the increase in capital expenditures. The ATT statistic for the pooled sample of all participants shows that the treated firms spent close to $419,000 more on R&D than the comparison group. The numbers from Manufacturing and Professional, Scientific and Technical Services are also in the same line.

Given the size of ATT for R&D versus that for capital investment, it appears that the participating firms from Professional, Scientific and Technical Services were more in need of the CA grants for R&D investments and rather than other forms of capital investments (as was shown in the last section).

6.4 Exporting

Whether the CA program had any impact on the volume of exports by each firm is another topic of interest in most policy studies. However, as with the turnover study in Section 6.1, the quality of analysis for exporting firms will be subject to the time truncation of data in 2014–15. Instead, we investigate whether there has been an increase in the number of the participating firms that are also exporters.

We look at all the CA participants with non-missing value for their exports at one year before they receive their first grant (*t*=0) and then in fiscal year 2014–15 which is the last year of the data. The proportion of exporting firms in each case are reported in Table 6.4.

Table 6.4 Proportion of the CA participants exporting.

	t=0	2014–15
Proportion Exporting	28.3%	31.7%
Total Number	453	539

Notes: Only firms with non-missing report of exports are used.

Source: Department of Industry, Innovation and Science (2018)

The numbers show a three percentage point rise in the proportion of exporting firms among the CA participants. To see whether the change in the distribution of exporters is statistically significant, we form the χ^2 statistic. The χ_1^2 statistic in this case is equal to 20.1. This statistic is significant at 1 per cent level, indicating that the increase in the proportion of exporters is statistically significant and a real effect.

The effect above constitutes the extensive margin of exporting in economics terminology, that is, the ability to encourage more firms to export. There is also an intensive margin effect, which is the case when the already exporting firms increase their volume of exports.

To look at the intensive margin, we showcase the distribution of export intensity of participating firms ─ defined as value of exports over turnover ─ from the year prior to the grant to a few years after the grant. The change in the different percentiles of the distribution would be useful in highlighting any trend that took place. These percentiles are listed in Table 6.5.

Table 6.5 The distribution of export intensity for CA participants.

	Percentiles						
	10th	25th	50th	75th	90th	Count	Mean
t = 0	0.3	1.8	13.1	47.6	88.5	123	27.4
t = 2	0.5	3.9	13.6	37.2	69.3	160	24.6
t = 3	0.5	2.7	20.3	51.3	70.9	167	29.8
t = 4	0.8	5.5	25.7	57.1	89.0	124	35.9

Notes: Export intensity is export sales divided by turnover and is expressed in percentage. Time *t* = 0 is one year before treatment.

Source: Department of Industry, Innovation and Science (2018)

As the numbers in the table show, the average export intensity of a CA participant starts to increase two years after receiving the first grant, after a dip in the first year.

The reported percentile also corroborate that the whole distribution of export intensity starts to move towards higher values two years after receiving the grant. The distribution moves even further towards higher values in the third year after receiving the grant. In this sense, the intensive margin of export intensity is also responding to the CA program.

6.5 Intellectual Property

Patent and trademark activity among the CA participants potentially signals the introduction or the imminent introduction of a new product. This section explores these activities among the CA participants.

The economic literature generally contemplates a lag of one to three years from research to patenting depending on the area and the type of patent (for instance, see Kondo, 1999; Wang & Hagedoom, 2014). Most economists use an average lag of two years from research to patenting as a rule of thumb.

Table 6.6 lists the count of participating firms that applied for patent or trademarks in each year before, during and after the grant was awarded. The table also lists the number of patents and trademarks applied for. The number of patents (trademarks) are larger than or equal to the number of firms in each year as a firm may apply for more than one patent (or trademark) in a given year.

First of all, the numbers in the table show that the CA participants are quite active in applying for patents and trademarks after being awarded the grant.

Table 6.6 Count of patents and trademarks by the CA firms.

	Patent applicants	Patent count	Trademark applicants	Trademark count
t = 0	49	141	84	177
t = 1	59	166	90	200
t = 2	60	144	82	201
t = 3	67	200	63	141
t = 4	49	127	50	93
t = 5	31	93	26	59
t = 6	21	92	n/a	n/a
t = 7	13	58	n/a	n/a

Note: *t*=0 is the year before the grant.

Source: Department of Industry, Innovation and Science (2018); Intellectual Property Government Open Data (2017)

Furthermore, the number of applications for both patents and trademarks (and the number of firms that apply for them) increases over the period *t*=1 to *t*=3. The trend hits a peak in *t*=3 (third year of the grant). With an average lag of two years from research to product, one finds the pattern suggestive of new product introduction tied to the CA grants.

The numbers start to drop after year *t*=3. This drop could be caused by the firm having already registered its developed product. The drop can also be a result of time truncation. Future updates to the data would eliminate this ambiguity.

6.6 From CA to R&D tax assistance

Between 1985 and 2011, the Australian government offered the R&D Tax Concession (RDTC) program. This program gave firms carrying out R&D projects a proportion of their R&D expenditures as tax deductions. In 2011–12, the program was replaced by the R&D Tax Incentive (RDTI). A firm has to spend at least $20,000 on R&D to be eligible for either program.

Table 6.7 shows the counts of the CA participants who applied for the RDTC or RDTI from the year before the first grant was awarded and for each year after that.

Table 6.7 CA participation in R&D Tax Concession/Incentive (firm counts)

	R&D Tax Concession	R&D Tax Incentive
$t = 0$	145	129
$t = 1$	64	250
$t = 2$	13	299
$t = 3$	n/a	244
$t = 4$	n/a	141
$t = 5$	n/a	53
$t = 6$	n/a	9
$t = 7$		

Notes: The R&D Tax Concession was replaced by the R&D Tax Incentive in 2011-12. $t = 0$ is the year before the grant.

Source: Department of Industry, Innovation and Science (2018)

The notable pattern in Table 6.7 is that the number of R&D program participants jumps in the first year of the grant (t=1) and afterwards. This pattern is most likely driven by the CA program encouraging firms to invest more on R&D (Table 6.3). By doing this, the firms are more likely to cross the $20,000 threshold required by the R&D programs and be eligible for the associated tax rebates.

Again, the number of the CA participants registered for RDTC and RDTI tapers off over time. This decline in numbers could be because firms are reducing R&D expenditures as a result of the product development concluding or simply because of time truncation. Future updates to the data will determine the exact cause.

6.7 Survival Rates

As noted earlier, the majority of CA participants are small and young firms. Bakhtiari (2017b) shows that about a quarter of these firms fail and exit the market in the first three years. Consequently, one basic measure of success for the CA program can be the rate of survival among the participant firms.

Analysis shows that most CA participants do survive. Overall, 98.0 per cent of CA participants survive and can still be observed by 2014-15, which is the last year of the available data (Table 6.8).

Table 6.8 The rate of survival among the CA participants.

	Count of firms	Firms surviving up to 2014-15	Survival rate
All	552	541	98.0
Manufacturing	121	121	100.0
Prof. Scientific and Tech. Services	231	226	97.8
Other industries	200	194	97.0

Source: Department of Industry, Innovation and Science (2018)

In the previous sections, the evidence pointed to better performance by participating firms in terms of turnover growth and R&D and capital investments. In Table 6.8 one observes again that the CA participants from all groups of industries are also more likely to survive.

7. Conclusion

The CA program's main target was to support innovative firms and entrepreneurs in commercialising their ideas. We find that most firms in the program are indeed small, young and innovative. Focusing on these firms, we observe that most CA participants invested in R&D and physical capital in higher volumes than other firms. A proportion of these firms also commence exporting in the years after their first grant, while already exporting firms appear to increase their volume of exports. Participating firms in Manufacturing and Professional, Scientific and Technical Services industries experienced higher turnover growth than the comparison firms. The bulk of participating firms and especially advanced-technology firms in the program also belonged to these industries. As a result, the longer term impact on innovation and growth is expected to be substantial. There are also other positive effects in terms of survival rates and patenting/trade marking.

Our analysis faces some shortcomings mainly due to issues related to data availability. For one thing, the availability of the BLADE data for fiscal years after 2014–15 will help to build a better and longer-term picture of the program's effect. The availability of data on unsuccessful applicants could also help build a useful comparison group of firms based on firms that have the intent to commercialise. The type of grant a firm received was unavailable in our dataset. It would be useful to analyse individual components of the CA program, but it should be noted that splitting the already small sample of recipient firms by the type of grant can also undermine the law of large numbers and the quality of statistical results. Such an analysis therefore needs to be exercised with care.

Appendix A Appendix A – Average treatment effects

We also compute the ATE statistic for each of the exercises conducted in the main text and report them in Table A.1.

Table A.1 The impact of the CA program on turnover growth, capital expenditures and R&D expenditures (dollars), average treatment effects (ATEs)

	Turnover	Capex	R&D
All	322,771.0 (10,916.9)***	10,716.5 (1,364.2)***	696,788.3 (18,477.7)***
Manufacturing	71,426.4 (36,504.9)*	58,475.0 (17,468.6)***	-36,637.5 (15,595.3)***
Prof. Scientific and Tech. Services	205,812.3 (29,700.6)***	-11,297.7 (1,252.1)***	735,568.3 (53,290.7)***
Other industries	-67,317.0 (18,198.7)***	-29,598.2 (1,001.9)***	2,667.6 (12,753.8)

Notes: *** and * denote significance at 1 and 10 per cent, respectively. Firms in the upper 0.5 percentile are dropped as outliers.

Source: Department of Industry, Innovation and Science (2018)

In most cases, the ATE statistics reported in the table have larger differences from the corresponding ATTs computed in Tables 6.1 to 6.3. The difference highlights that the CA program was very selective in the firms being awarded the grants. Such level of selection is generally expected in government programs due to the scarcity of the grants and the large number of applicants.

Disclaimer

The results of these studies are based, in part, on ABR data supplied by the Registrar to the ABS under A New Tax System (Australian Business Number) Act 1999 and tax data supplied by the ATO to the ABS under the Taxation Administration Act 1953. These require that such data is only used for the purpose of carrying out functions of the ABS. No individual information collected under the Census and Statistics Act 1905 is provided back to the Registrar or ATO for administrative or regulatory purposes. Any discussion of data limitations or weaknesses is in the context of using the data for statistical purposes, and is not related to the ability of the data to support the ABR or ATO's core operational requirements. Legislative requirements to ensure privacy and secrecy of this data have been followed. Only people authorised under the Australian Bureau of Statistics Act 1975 have been allowed to view data about any particular firm in conducting these analyses. In accordance with the Census and Statistics Act 1905, results have been confidentialised to ensure that they are not likely to enable identification of a particular person or organisation.

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