CENTRE FOR TRANSFORMATIVE INNOVATION

ARC Report: The Effects of University-Industry Collaboration Subsidies on Firm Performance

Alfons Palangkaraya, Paul H. Jensen, Russell Thomson and Elizabeth Webster

The effects of university-industry collaboration subsidies on firm performance

Alfons Palangkaraya*, Paul H. Jensen†, Russell Thomson* and Elizabeth Webster*

†University of Melbourne

*Centre for Transformative Innovation, Swinburne University of Technology

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Abstract

To test the efficacy of subsidised university-industry research collaboration programs on firm performance, we model data on 5000 grant applications from 2002 until 2014. The data includes firms that were successful (i.e. funded) and those that were not successful (i.e. not funded), as well as ex-ante information about the quality of the proposed project. If we compare firms whose application was rated within 10 per cent of the cut-off mark for success, the long-run effect of the subsidy (1-7 years after application) was to raise firm sales by 11.4 per cent.

1. Introduction

Governments across the OECD invest significant resources with the aim of inducing productive collaboration between universities and the private sector. University-industry collaboration is not merely a channel through which knowledge flows from universities and public research institutions but is also a mechanism to encourage public researchers to solve industry problems (Rosenberg 2010; Nelson 1990; Griliches 1998; Cohen *et al.* 2002). Considerable evidence shows that collaborating with universities is associated with increased research outputs and improved firm performance (Lööf and Broström 2006; Petruzzelli 2011; Cohen *et al.* 2002; Belderbos *et al.* 2004; Love *et al.* 2011). What is not yet known is whether productive collaboration can be induced by government subsidy or whether such subsidies tend to flow to activities which would otherwise occur. Evidence on the efficacy of subsidies aimed at stimulating private sector R&D has undergone important advances in recent years,[1] but evidence on the efficacy of government funding specifically aimed at inducing university-industry collaboration – especially on the performance of the participating firm – remains sparse.

We shed new light on the effect of collaboration grants on firm performance using confidential data on the population of applications for a $AUD300 million (USD $230m) per annum program in Australia between 2002 and 2014, linked to firm balance sheet data from company tax records. Our unique data includes both applications that were successful (i.e., funded) and those that were unsuccessful (i.e., not funded), as well as the proximity of each application to the funding quality cut-off score as judged by the independent academic experts as part of the process for awarding grants. Thereby allowing for quasi-experimental statistical evaluation methods. To our knowledge, our study is the first to estimate the effects of university-industry collaboration subsidies on firm performance using data covering on both successful and unsuccessful program applicants.

[1] See Dechezleprêtre *et al.* (2016); Howell (2017); and Santoleri *et al.* (2020).

Despite the prevalence of such programs, evidence of the impact of subsidies for university-industry collaboration is limited, especially regarding the subsidy's impact on business performance. Few in the large literature on academic engagement focus on the inducement effect of public subsidies (see Perkmann *et al.* 2013; Perkmann *et al*. 2021). Of those which do examine the inducement effect of public subsidies, the primary focus is on the effect of collaboration on universities and their researchers (see Kaiser and Kuhn 2012; Scandura 2016; and Szücs 2018).[2] A noteworthy exception is provided by Bellucci *et al.* (2019) who, based on a small sample of firms, find that firms that are awarded university-collaboration grants exhibit marginally higher employment growth, than a control group selected on observables from the population of non-participants.

The central problem in evaluating subsidies to businesses is to distinguish activity attributable to grant funding from activity that would have happened in an unobserved counterfactual. It is well recognised that comparing program participants with non-participants cannot resolve the potential bias resulting from unobserved factors that prompted the grant application in the first place (Santoleri *et al.* 2020). As a consequence, inference on program efficacy based on comparison between program participants with observationally similar *non-applicants* tends to conflate the impact of funding with the impact of collaboration. This self-selection issue is particularly important in the case of university-firm collaboration grants where the act of applying for a grant reveals that many of the initial barriers to collaboration have already been overcome – irrespective of grant success. Indeed, the very act of applying for collaboration grant confirms mutual awareness of counterparty expertise, identification of possible synergies, and that, concerns regarding competition and disclosure can be accommodated. In short, the existence of a grant application establishes a willingness to

[2] A more extensive literature on the impact of government initiated multi-firm research consortia and such consortia sometimes include university participants. See, for example, analysis of consortia in Japan (Branstetter and Sakakibara 1998; and Watanabe *et al*. 2004) and Pan-European consortia programs such as EUREKA which have the additional requirement of involving firms in multiple countries (OECD 1998; Mothe and Quelin 2000; Benfratello and Sembenelli 2002; Bayona-Sáez and García-Marco 2010; and Aguiar and Gagnepain 2017). University Science Parks are another related policy with complex multi-faceted mechanisms of impact on participating firms. See Link and Scott (2007) for a review, while Cunningham and Gök (2012) and Martin (2016) provide additional reviews on literature spanning collaboration policies and their impacts.

collaborate. Therefore, our contention is that this self-selection issue cannot readily be addressed without grant outcomes data covering, as a minimum, both successful and unsuccessful applicants.

Even comparing successful and unsuccessful applicants does not completely identify the subsidy. We would expect that better proposals will on average be awarded the subsidy and accordingly we also need to control for the quality of the proposal. In our evaluation, we have information on whether the applications were within 10 per cent of the cut-off score as assessed by the assessors of the proposals.

To date, evaluations of government grants for (single firm) intramural business R&D, has only used successful and unsuccessful applications, but has not been able to control for the quality of the proposal (Benavente *et al*. 2012; Bronzini and Iachini 2014; Bronzini and Piselli 2016; Hünermund and Czarnitzki 2019; Howell 2017; Widmann 2017; Wang *et al.* 2017; and Santoleri *et al.* 2020).[3] These approaches have the additional disadvantage of being based on small samples.[4]

In our study, we construct three control groups: i) observationally similar firms from the general population selected via the propensity score matching method; ii) applicant firms which were not successful; and iii) applicant firms whose projects which were rated ex ante by independent academic experts as being approximately similar to successful projects. These last two groups help us control for time-varying unobservable factors such as the quality of the project and willingness to collaborate.

[3] For a review of the earlier literature aimed at assessing the impact of general R&D subsidies see Zúñiga-Vicente *et al.* (2014), Dimos and Pugh (2016) and Vanino *et al.* (2019).

[4] Two recent papers provide new evidence on research outcomes (academic papers, patents and citations) based on small samples of firms awarded university-industry collaboration grants. Bruhn and McKenzie (2018) apply Regression Discontinuity Design to evaluate differences in self-reported project research outcomes to a Polish Government consortia program, collected via survey of 400 applicants (159 successful). The most relevant, in research design, to our study is Chai and Shih (2016) who apply difference-in-differences to measure research outcomes based on a sample of 204 applicants to university-industry collaboration fund in Denmark, all of whom passed a first stage evaluation but only 159 were ultimately funded.

Our main results are as follows. First, when we compare successful and unsuccessful grant applicants which were within the same rating band (10 per cent of the cut-off mark for winning the grant), we find that grantees have 12.5 per cent higher sales in the immediate period compared with firms that just missed out on a grant. The long-run effect – being defined as 1-7 years after the project began – was 11.4 per cent higher sales. This indicates that success in winning an ARC Linkage grant has an important impact on firm sales. However, the impact on other economic indicators – value-added, employment and innovation – was either smaller or statistically insignificant. Second, when we compare unsuccessful grant applicants with otherwise-similar firms that didn't apply for a Linkage grant, we find positive effects on sales and value-added. This suggests that the act of collaboration between industry and universities to prepare a grant application has benefits for the firm, possibly because the firm continues with the collaboration using alternative funding mechanisms.

Our paper makes several important contributions to the literature. First, by exploiting detailed data covering both successful and unsuccessful applications in conjunction with information about ex ante application quality, we provide the most systematic and robust evidence of the causal impact of university-industry collaboration grants to date. Over and above the merits of our administrative and firm-level data, the institutional context of our study provides an ideal setting for measuring the impact of subsidies targeting university-industry collaboration. The ARC Linkage program is not restricted to any single industry or technology,[5] and it includes a mix of small and large firms which might otherwise limit generalizability. For the purpose of evaluating the impact of funding on business performance, it is also useful that the funding is provided to the university which leads the project thereby eliminating any potential to conflate grant funding and firm balance sheet measures such as revenue.[6]

[5] With the exception of 'medical research' (e.g., human research and clinical research).

[6] Moreover, ARC Linkage grants typically include collaboration between a firm and one or more universities. In contrast, attempts to evaluate subsidies to complex multi-firm consortia, confront the additional layer of complexity in separating the impacts of induced university-firm collaboration from any impact of firm-firm collaboration along with complex consideration of how commercial competition might affect selection into the program as well as research outcomes.

Second, our results highlight a cautionary note regarding inherent difficulty distinguishing the impact of collaboration from subsidised collaboration based on an analysis of successful applicants alone. As previous studies were not able to observe unsuccessful applicants, they inferred program impact from a comparison of successful applicants with matched firms from the general population. However, we find that the performance of unsuccessful applicants is systematically different from the general population, even after matching on observable characteristics. This finding suggests that inferences on program efficacy based on comparison between program participants with observationally similar *non-applicants* are likely to conflate the impact of funding with the impact of collaboration. Thus, it implies a potential bias in previous estimates of the benefits of university-industry collaboration which follow the latter approach.[7]

Third, we focus our attention on the benefits for firms of university-industry collaboration programs across several different dimensions of firm performance – including sales, value-added, employment and intellectual property – something which has previously been largely ignored. To our knowledge, only Bellucci *et al.* (2019) measures employment outcomes in their sample of 62 Italian firms receiving university-industry collaboration grants. Our multi-indicator assessment of business performance therefore provides a far more robust conclusion about the effects of university-industry collaboration than has previously been studied.

The policy implications of our analysis are as follows. Our evidence supports a conclusion that university-industry collaboration programs enhance performance of recipient firms. We view this result necessary, but not sufficient, information for policy benefit overall. Government do not typically aim to subsidise private benefits – though the possibility of under-investment in research even where all benefits are private due to uncertainty is well recognised. More commonly, subsidies for research and innovation are justified on the basis that they generate

[7] By comparing successful applicants with unsuccessful applicants (with similar project application quality) we control for average systematic differences between applying and non-applying firms. As such, by controlling for application status we remove the most obvious differences relating to willingness to collaborate. However, it is not possible to unequivocally rule out all remaining systematic time-varying differences between treatment and control groups.

benefits to on other (third party) firms. Accordingly, we need to combine our results with information on whether the presence of more successful innovators benefits local eco-systems, supply chains and industrial agglomerations *inter alia*. Nonetheless, it is difficult to imagine benefit accruing to third parties in the absence of benefit to program participants.

2. Institutional Setting and Data

We study the population of applicants to the ARC Linkage Grant scheme between 2002 and 2014. The longstanding Linkage program provides around $AUD300 million annually (~$USD220 million) with the aim of encouraging and extending cooperative research between researchers in universities and business. The program aims to support research alliances between universities and industry to enhance commercial benefits of research. All public and private Australian universities, and a small number of other tertiary education institutes, are eligible to be an administering organisation in the scheme.

The Linkage program provides matched government funding – firms must contribute at least 25% of the total funds requested from the government – and enables university researchers to manage and coordinate a collaborative project through a team of Chief and Partner Investigators from both the universities and firms. Chief Investigators on the application must be employed at an eligible organisation (at least 0.2 FTE) and must reside predominantly in Australia during the project activity period.

Private-sector firms make cash (and/or in-kind) contributions to the project and typically contribute to the research agenda, sometimes via direct collaboration on the research. There are multiple rounds of applications each year and grants are awarded based on written proposals. Each proposal is independently assessed and scored by a small number of anonymous peer reviewers from the community of Australian scholars using a well-specified set of weighted assessment criteria (including investigator capability (25%), project quality and innovation (25%), feasibility and commitment (20%), and benefit (30%)). Peer reviewers provide feedback to applicants to which applicants are permitted to make short responses. Following this, the scored applications and the applicants' responses are then considered by a panel of experts (known as the ARC College of Experts) which then makes a final ranking of applications. Grant decisions are then finalised and announced by the government minister.

For each grant round over the period of study, we were provided confidentialised access to the data including a band of applicants including 10 per cent of applicants that were immediately above and immediately below the cut-off point for funding.

In many regards, the institutional context considered provides an ideal setting for measuring the impact of university-industry collaboration grants or subsidies. First, the program is not restricted to any single industry or technology (with the exception of 'medical research' and clinical trials), and it includes a mix of small and large firms (and public/private universities). This is important for inferring external validity. Second, unlike government supported multi-firm consortia programs in Japan and the USA that have been subject of many evaluations, most ARC Linkage grants are collaborations between just one firm and one or more universities.[8] Evaluating the impact of funding models which support complex multi-firm consortia introduce the additional complexity of separating out any effect of firm-firm collaboration along with complex consideration of how commercial competition might affect selection into the program as well as research outcomes.

For this project we linked confidential data on all firms that applied for an ARC Linkage grant for funding start years 2002 to 2014, with economic data from the population of Australian firms over the period 2001-02 to 2013-14. The economic data is from the Australian Bureau of Statistics' (ABS) Business Longitudinal Analytic Database Environment (BLADE), containing annual economic information on the full population of Australian businesses since 2001-02. This database is confidential, and the authors do not see any individual records. The ABS performed all data merging and data processing based on the Australian Business Number (ABN) of each industry partner. All summary information from the econometric analysis is scrutinised by ABS officers before being released to the authors.

The ARC Linkage application databases contain the entity name of the industry partner, but not the corresponding ABN. Of the 7,433 distinct non-university applicants, we were able to

[8] For example, multi-firm consortia that include public research institutions and universities have been studied in the context of Japan (Branstetter and Sakakibara 1998); Europe (Mothe and Quelin 2000); Squicciarini (2008) Finland. Support for university-industry 'Science Parks' are another related policy, see Link and Scott (2007) for a review of evidence on University Science Parks and firm performance.

find an Australian Business Number for 5,560 (74.8 per cent) using a combination of machine matching and manual lookup. Of the organisations missing an ABN, 50 per cent are international businesses; 17 per cent are civic organisations and 15 per cent are government agencies. Although most of the organisations with an ABN are private sector businesses, this is not exclusively the case as some government and not-for-profit organisations exist in the ABN sample. The overall grant success rate was 44.4 per cent.

Most (small and simple) businesses have only one ABN. However, many large or complex businesses have multiple ABNs typically following a parent-subsidiary relationship. The parent is called the Enterprise Group, and this corresponds to highest consolidated accounting level within Australia. Ideally, we should work with a dataset that aggregates all ARC activity and all economic data to the unit the research is designed to affect. In our dataset, we have used the management unit[9] as this is the entity used for large and complicated businesses. For the remaining units, the entity is simply the activity defined by the ABN. The term 'firm' in this paper refers to this entity.

Table 1 reveals that firms that have applied for an ARC Linkage grant are larger than those that have not applied by several orders of magnitude. Annual production[10] levels are about 30 times larger; employment 40 times; patents are average 150 times larger and so on. Successful applicants are, on all measures, about 50 per cent larger than the average applicant.

Table 1: Average characteristics of firms by ARC Linkage applicant status, 2001-02 to 2014-15

ARC Linkage applicant status	Production ($'000)	Employment (heads)	Assets ($'000)†	Investment† ($'000)	Exports ($'000)	Patent (stock)	Trade-mark (stock)
Non-applicants	854	16	3,295	219	170	0.01	0.15
All applicants	26,500	629	360,000	30,300	26,700	0.77	9.06
Successful applicants	36,900	926	569,000	51,400	39,700	1.19	12.44
TOTAL	**994**	**19**	**5,246**	**383**	**315**	**0.01**	**0.20**

Notes: † Tangible only. Total observations = 10.2 million (All applied = 5560); * rights at IP Australia only.

[9] The ABS call this the Type of Activity Unit.
[10] Production level is measured as sales revenue less non-capital purchases (i.e. inputs) in current $.

3. Statistical Method

Our aim is to estimate the impact of the ARC Linkage program on the production levels of participating firms (i.e. firms named as partners on an ARC Linkage application). Two types of 'program' participation (i.e. treatment) are possible: i) participating in the application procedure; and ii) being awarded a grant (in conjunction with the university partner).

The main challenge in an evaluation is to isolate the effect of treatment (either applying for the grant or winning the grant funds), from the tendency of applicants to be more productive, or grantees to propose better projects. That is, we need to eliminate biased selection into treatment. Veugelers and Cassiman (2005) and Segarra-Blasco and Arauzo-Carod (2008), for example, showed that the decision to conduct R&D collaboration between industry and university involves systematic selection.[11] In our case, both the firm self-selects into being an applicant, based on their readiness to benefit from extra-mural R&D, and the grant selection committee select the applicants based on the quality of the proposal.

Ideally, we would design a program as an experiment whereby the decision to apply (or tendency to win a grant) is randomly allocated. Our data are however observational and, as a second-best method, we have constructed a control group of firms, which are similar in many respects to applicants or grantees, except that they have not applied for (or won) a grant. To establish this counterfactual and eliminate selection effects, we make two adjustments. First, we employ a panel estimation method (which is a difference-in-difference estimator) to eliminate the effect of unobservable but persistent features of the firm, such as a superior work culture or better management (Heckman *et al.* 1997). Second, to eliminate the possibility that some applications embody projects with better potential we limit our sample to applications that were assessed by experts as being 10 per cent above or below the grant threshold.[12] The rationale is that these 20 per cent of applications are similar in quality, given

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[11] For the employment of this method when applied to research support see also Almus and Czarnitzki (2003); Czarnitzki and Licht (2006); Aerts and Schmidt (2008); González and Pazó (2008); Guerzoni and Raiteri (2015); Scandura (2016); and Vanino *et al*. (2019).

[12] The exact scores for each individual application project were not provided thereby precluding the possibility of using a regression discontinuity design.

the noise in the assessment scores, and therefore any effect of being a grantee will likely be due to the receipt of the funds, not the quality of the opportunity. Accordingly, any difference in firm performance post-grant can statistically be attributed to the effect of the grant *per se*.

In addition, to assess whether the application process itself influences performance, we compared applicant firms with a control group matched from the pool of non-participant firms. The matching variables are the lagged level of the performance measure being evaluated, patent status[13], year and one-digit industry of the applicant firms in the years before their first application (bearing in mind our Linkage dataset begins in 2002). Using a control group matched on observable characteristics means we are comparing like-with-like to ensure that the parallel-path assumption behind our DID estimation is not violated.[14]

Table 2 provides data on the summary statistics for sample firms, by both application status (successful, unsuccessful and non-applicant) and matching status (before and after matching) for several selected years (2004, 2007 and 2011). For convenience, we only present the matching comparison in terms of the variable 'sales' since it is our key outcome variable. In the results section, different matching models were run for different outcome variables and for each first application year period. The most important point to note about the comparison provided in Table 2 is that the matching process has effectively produced control groups that are very similar in terms of the key outcome variable, sales.

[13] Patent status is a binary variable = 1 if the firm has a patent in-force; = 0 if not.
[14] This means we do not have to extrapolate and infer, say, the program effect on a large firm from data on small firms.

Table 2: Matched sample firm average log sales before and after matching with PSM nearest neighbour

		Matching year					
		2004		2007		2011	
		Sample size	Sales (log)	Sample size	Sales (log)	Sample size	Sales (log)
Unsuccessful & Non-applicant							
Before matching	Unsuccessful	72	14.35	68	13.79	105	14.70
	Non-applicant	399,923	12.74	349,224	12.87	379,983	12.81
	t-stat mean differences		-8.36		-4.61		-11.72
After matching	Unsuccessful	61	14.71	48	14.42	87	15.17
	Non-applicant	61	14.64	48	14.19	87	15.08
	t-stat mean differences		-0.16		-0.60		-0.34
Successful & Non-applicant							
Before matching	Successful	87	14.76	63	14.57	52	14.68
	Non-applicant	399,923	12.47	349,224	12.87	379,983	12.81
	t-stat mean differences		-11.58		-8.18		-8.16
After matching	Successful	67	15.01	48	15.21	42	14.91
	Non-applicant	67	15.11	48	15.22	42	14.96
	t-stat mean differences		0.24		0.02		0.11
Successful & Unsuccessful							
Before matching	Successful	87	14.76	63	14.52	52	14.68
	Unsuccessful†	796	14.42	792	14.56	834	14.52
	t-stat mean differences		-1.33		-0.18		-0.51
After matching	Successful	66	15.13	47	15.20	42	14.91
	Unsuccessful	66	14.86	47	15.11	42	14.53
	t-stat mean differences		-0.68		-0.23		-0.92

Notes: Matching is done year by year depending on the grant application year over the sample period of 2004-2011. Presented in this table are the matching years of 2004, 2007, and 2011. Other year matching characteristics are relatively similar results. †The sample size for Unsuccessful in this matching group is larger than that in the Unsuccessful & Non-applicant matching group above is because in the latter the sample is restricted to only unsuccessful applicant which first applied in the corresponding matching year. This is to ensure that the matching to Non-applicant is not influenced by any grant application process. The same restriction is not enforced in the Successful & Unsuccessful matching since both groups are already influenced, if any, by the grant application process.

Formally, our model is defined in the following way: we define D_i as being under treatment (e.g. being an ARC Linkage grantee), where $D_i = 1$ if firm i is an ARC Linkage partner and $D_i = 0$ otherwise. Y_i^1 is the observed outcome (say, production levels) of the applicant firm *i*; and Y_i^0 as the unobserved (counterfactual) outcome of the same applicant if they had not won a grant. We denote X_i as a vector of observed characteristics of the firm that are likely to have caused production levels to rise (independently from the ARC grant). Hence, $E(Y_i^1|X_i, D_i = 1)$

is the observed average outcome of grantees conditional on X_i and $E(Y_i^0|X_i, D_i = 1)$ as the counterfactual average outcome of rejected applicants.

The impact of the ARC Linkage program is measured by the average treatment effect on the treated (ATT) denoted by τ:

$$\tau = E\left(Y_i^1|X_i, D_i = 1\right) - E\left(Y_i^0|X_i, D_i = 1\right) \qquad (1)$$

Accordingly, in equation (1), τ measures the difference between observed average outcomes after treatment and counterfactual average outcomes had the firms not received the treatment, after we control for observed potential confounding factors X_i.

The essential evaluation problem is that by definition, the counterfactual, $Y_i^0|X_i, D_i = 1$, is never observed. The best we can do is to infer the counterfactual from non-treated firms: a control group of applicants that mimic as closely as possible the grantees in the same year and in the same context. In our main evaluation, we limit the treatment group to the set of grantees that in any one year, were awarded a grant with an assessment score that was no more than 10 per cent above the grant threshold. As mentioned above, to control for the quality of the proposal, we select for our control group applicant firms that were no more than 10 per cent below the threshold. The assumption here is that because assessing projects contains a considerable degree of subjectivity, this group will be relatively homogeneous in project quality.

Difference-in-differences analysis is most easily applied when there is one program being offered at only one point in time (so, into equation (1) we add a time subscript, t = 0 before program and t = 1 after program). However, the ARC Linkage scheme is more complex than this. Firms can have overlapping ARC applications, some of which are granted, and multiple applications and grants in not only one year, but over the full study period. Thus, the existence of multi-applicant and multi-grant firms makes it hard for us to devise a clean before-and-after program time. In order to isolate the effect of the grant, we include all firms in the analysis but only consider their first application or their first grant if they are multi-application or multi-grant firms.[15]

The program effect is defined as follows:

- The before-treatment period (t = 0) is defined as the years before the ARC Linkage project began or would have begun (if funded). In other words: if the treatment is 'application', the pre-treatment period is the period before the first application; if the treatment is 'grant', the pre-treatment period is the period before the first grant.

- The after-treatment period (t = 1) is defined in two ways. For the 'immediate' effect, this is the years during which the grant is (or would have been) operative. Both the median and mode of program duration is 3 years. For the 'long-run' effect this is as up to four years after the grant finished (or would have finished).

We operationalise (1) by estimating the following panel fixed-effect regression of the same matched sample:

$$Y_{i,t} = \tau D_{i,t} + \gamma_t + \mu_i + \varepsilon_{it} \qquad (2)$$

where D_{it} is the treatment period indicator, γ_t denotes year dummy variables, μ_i is a firm fixed-effect and ε_{it} is the sum of all other unobserved time-varying determinants that are not correlated with being granted. For the immediate effect, D_{it} = 1 for the funded years (around 3 years) if the application is successful. For the long-run effect, D_{it} = 1 for all periods since the grant began.

The matching difference-in-differences estimate of the treatment effects (τ) is the difference between the change in the outcomes before and after program participation of applicant firms and that of matched non-applicant firms. Under the parallel path assumption, any imbalance between the matched program and control groups in the distribution of covariates and time-

[15] Similarly, Vanino *et al*. (2019) include all firms but only their first application. We also considered other approaches (e.g. dropping all multi-applicant and multi-grant firms) and found results similar to those presented in the body of this paper.

invariant effects is controlled for. In the main estimates, we define Y as log sales, log employment, log value added (=sales less cost of sales), number of patent applications and trade mark applications to IP Australia (which is included in the BLADE data).

4. Results

Results are presented for the following alternative comparison groups:

1. Unsuccessful applicants and firms that never applied (i.e. non-participants) matched using propensity score matching nearest neighbour (PSM1).
2. Successful applicants and firms that never applied (i.e. non-participants); also matched with PSM1.
3. Successful and unsuccessful applicants; no matching.
4. Successful and unsuccessful applicants; PSM1 matching.
5. Successful and unsuccessful applicants, whose applications are scored within the 10 per cent sample bands below and above the grant threshold; no matching
6. Successful and unsuccessful applicants whose applications are scored within the 10 per cent sample bands below and above the grant threshold; PSM1 matching.

The estimates of the average treatment effects on the treated are presented in Table 3. The immediate average treatment effect is the coefficient of a dummy variable equal to one for the years in which the linkage grant is begin paid. Table 4 shows the results for the long-run effect, the coefficients from a dummy variable which is equal to unity for all years on or after the grant being paid (inclusive).

Table 3: DID estimates of immediate average treatment effect on the treated

Comparison groups	Matching	No. of firms	Sales (log)	Value added (log)	Employment (log)	Patent (no.)	Trade mark (no.)
Unsuccessful & Non-applicant	Yes (PSM1)	905 – 940	0.129*** (0.029)	0.100*** (0.038)	0.036 (0.026)	0.015* (0.008)	0.038 (0.035)
Successful & Non-applicant	Yes (PSM1)	825 – 1087	0.132*** (0.029)	0.036 (0.031)	0.091*** (0.022)	0.006 (0.012)	-0.036 0.058
Successful & Unsuccessful	No	2150 – 2662	0.150*** (0.021)	0.054** (0.022)	0.092*** (0.014)	-0.007 (0.010)	-0.030 (0.020)
Successful & Unsuccessful	Yes (PSM1)	573 – 1058	0.091*** (0.026)	0.033 (0.028)	0.069*** (0.020)	-0.003 (0.010)	-0.006 (0.033)
Successful & Unsuccessful	Yes (10% band)	696 – 808	0.125*** (0.033)	-0.011 (0.035)	0.068*** (0.021)	-0.022 (0.020)	-0.035 (0.028)
Successful & Unsuccessful	Yes (10% band & PSM1)	191 – 337	0.041 (0.040)	0.073 (0.046)	0.073*** (0.032)	-0.033* (0.018)	-0.023 (0.039)

Note: PSM1 is propensity score matched sample based on nearest neighbour; () standard errors; Value added = sales – cost of sales; Patent and trade mark are number of applications; t-test significantly different at the *** 1% and **5% levels; 10% bands are ten per cent of samples applicants whose assessment score are closest to the either side of the threshold score. Short-run effect: average effect during the treatment year(s); Sample size varies across model specifications.

Table 4: DID estimates of long-run average treatment effect on the treated

Comparison groups	Matching	No. of firms	Sales (log)	Value added (log)	Employment (log)	Patent (no.)	Trade mark (no.)
Unsuccessful & Non-applicant	Yes (PSM1)	732 –	0.134***	0.058*	0.096***	-0.009	-0.032
		1170	(0.027)	(0.033)	(0.023)	(0.008)	(0.032)
Successful & Non-applicant	Yes (PSM1)	577 –	0.173***	0.056	0.114***	-0.007	0.091
		1087	(0.031)	(0.036)	(0.026)	(0.015)	(0.071)
Successful & Unsuccessful	No	2150 –	0.121***	0.081***	0.123***	0.006	-0.044*
		2662	(0.028)	(0.029)	(0.028)	(0.012)	(0.026)
Successful & Unsuccessful	Yes (PSM1)	573 –	0.108***	-0.001	0.032	0.011	-0.014
		1058	(0.032)	(0.034)	(0.024)	(0.013)	(0.042)
Successful & Unsuccessful	Yes (10% band)	696 –	0.114**	0.052		0.007	-0.056
		872	(0.046)	(0.048)		(0.028)	(0.038)
Successful & Unsuccessful	Yes (10% band &	191 –	0.078	0.037	0.063	-0.027	-0.037
	PSM1)	337	(0.050)	(0.056)	(0.041)	(0.024)	(0.050)

Note: PSM1 is propensity score matched sample based on nearest neighbour; () standard errors; Value added = sales – cost of sales; Patent and trade mark are number of applications; t-test significantly different at the *** 1% and **5% levels; 10% bands are ten per cent of samples applicants whose assessment score are closest to the either side of the threshold score. Long-run effect: average effect since the first treatment year (inclusive); Sample size varies across model specifications.

Consider first the effect of applying for a grant, even if unsuccessful, on firm performance – which is presented in the first two rows of Tables 3 and 4 (Unsuccessful & Non-applicant, and Successful & Non-applicant). The immediate effect of applying for a grant is 12.9 per cent higher sales and 10.0 per cent higher value added (both are statistically significant). The immediate effect on employment, patents and trademarks are either not significant statistically or large in terms of magnitude. The long-run effect is similar at 13.4 per cent higher sales and 5.8 per cent higher value added. In this case however, the effect on employment is 9.6 per cent and statistically significant. Comparing successful applicants to firms that never applied for the ARC Linkage grant, successful (funded) firms have on average 13.2 per cent higher sales and 9.1 per cent higher employment immediately and 17.3 per cent higher sales and 11.4 per cent higher employment over the long run.

The lack of effect on innovation – in terms of both patent and trademark impacts – in both the short- and long-run is not surprising. Although R&D collaboration may improve business performance, previous findings from Lhuillery and Pfister (2009) has found that a significant share of R&D collaboration failed to meet their patenting objectives. Schwartz *et al.* (2012) found university involvement in subsidised R&D collaborative projects failed to produce innovative outputs in terms of patents. Both sets of results above suggest that connecting with universities by jointly applying for the ARC Linkage grant is beneficial for the industry partners, regardless of the outcome of the grant application.

Rows 3 and 4 in Tables 3 and 4 compare the sets of Successful & Unsuccessful applicants for unmatched and matched control groups. In the immediate period, firms that received a Linkage grant have 15.0 per cent higher sales and 5.4 per cent higher value-added. This reduces by about a third to 9.1 per cent and 3.3 per cent when we matched the two groups on industry, patent status and pre-treatment outcome variable. Over the long-term, firms that received a Linkage grant have sales that were 12.1 higher and value-added that was 8.1 per cent higher. This reduces to 10.8 and -0.1 per cent after we used the matched sample.

Rows 5 and 6 in Tables 3 and 4 present the results of the most stringent test which involves using the 20 per cent sample of Successful & Unsuccessful grant applicants which were assessed as being just above and just below the granting threshold. This test has been devised to control for the quality of the proposal, but it also reduces our sample size and makes it difficult to achieve statistical significance. In the immediate period, applicants that were just-successful have sales that were 12.5 per cent higher and value-added that was 1.1 per cent lower than applicants that were near misses. The sales effect reduced to 4.1 per cent when we only included firms that had a match (on sales, patent status and industry). Over the long-term, sales on the just-successful were 11.4 per cent higher and value-added was 5.2 per cent higher. However, when we only included the matched pairs, these increments were 7.8 per cent for sales and 3.7 per cent for value-added but neither were statistically significant, which may be a consequence of the much smaller sample size.

An important finding from these estimates is that firms which apply to the Linkage program outperform observationally similar firms that do not apply for the Linkage program. There are several reasons for this. It suggests that selecting a comparison group from non-applicants does not adequately control for time-varying pre-treatment factors associated with establishing a collaborating partner, such as the arrival of a commercial opportunity, a new inspired manager or marked change in firm capabilities that lead to an ARC Linkage application (Kauko 1996, Jaffe 2002). The very act of seeking a collaborative venture – forming a relationship, scoping the idea – has an impact on the firm's production levels. Funding is critical for raising production levels and perhaps it is the case that unsuccessful ARC Linkage applicants find funding elsewhere to undertake the project. However, we do not observe the source or level of any alternative funding.

We also examine whether the research quality of the university partner has any effect on observed impact of collaboration on firm performance. To evaluate the importance of the type of university and the amount of funding, we re-estimate the Difference-in-Difference model with an interaction effect dummy variable which indicates whether the university involved belonged to the Group of Eight (Go8), which are Australia's most prominent eight research-intensive universities. We also interacted the treatment variable with the amount approved by the ARC. In general, Go8 universities have higher quality researchers and are better managed. Hence, one may expect that partnering in a research collaboration with them would provide larger benefit. On the other hand, the research done in these universities might be more theoretical or closer to the research frontier, but further away from business applicability. In that case, it might be more beneficial for firms to partner with universities from outside the Go8. The interacted effect estimates are summarised in Tables 5 and 6.

We find that the funded collaboration benefits on the industry partner to vary by the type of the partner university and the amount of funding awarded. For the former, partnering with Go8 universities is associated with lower benefit. The interaction effect of funding amount is mixed: it increases the effect on patenting, but it lowers the effect on value-added. In this regard, our result is consistent with Szücs (2018) who finds the association between collaborating with universities and research outcomes is amplified by university academic quality.

Table 5: Average treatment effect of grant by funded amount and type of university

	(1)	(2)	(3)	(4)	(5)	(6)
	Sales (log)	Sales (log)	Sales (log)	Employment (log)	Employment (log)	Employment (log)
Immediate Effect						
ATT	0.132***	0.136***	-0.747	0.091***	0.098***	0.687*
	(0.029)	(0.029)	(0.533)	(0.022)	(0.022)	(0.414)
ATT * GO8		-0.284			-0.566***	
		(0.247)			(0.192)	
ATT * log(Amount)			0.070*			-0.478
			(0.043)			(0.033)
No. of firms	825	825	825	841	841	841
Long-run Effect						
ATT	0.257***	0.260***	0.967	0.114***	0.121***	0.479
	(0.034)	(0.034)	(0.593)	(0.026)	(0.026)	(0.463)
ATT * GO8		-0.255			-0.662***	
		(0.280)			(0.218)	
ATT * log(Amount)			-0.057			-0.029
			(0.047)			(0.037)
No. of firms	825	825	825	841	841	841

Note: Comparison groups: Successful & non-applicant; Matching: PSM Nearest Neighbour; () standard errors; Value added = sales – cost of sales; Patent and trade mark are number of applications; t-test significantly different at the *** 1% and **5% levels; 10% bands are ten per cent of samples applicants whose assessment score are closest to the either side of the threshold score. Long-run effect: average effect since the first treatment year (inclusive); Sample size varies across model specifications.

Table 6: Average treatment effect of grant by funded amount and type of university

	(1)	(2)	(3)	(4)	(5)	(6)
	Value-Added (log)	Value-Added (log)	Value-Added (log)	Patent	Patent	Patent
Immediate Effect						
ATT	0.036	0.044	0.009	0.006	0.008	0.133
	(0.031)	(0.031)	(0.564)	(0.012)	(0.012)	(0.223)
ATT * GO8		-0.413*			-0.103	
		(0.219)			(0.099)	
ATT * log(Amount)			0.002			-0.010
			(0.045)			(0.018)
No. of firms	577	577	577	1087	1087	1086
Long-run Effect						
ATT	0.056	0.062*	2.278***	-0.007	-0.004	-0.451*
	(0.036)	(0.036)	(0.621)	(0.015)	(0.015)	(0.252)
ATT * GO8		-0.355			-0.242**	
		(0.249)			(0.114)	
ATT * log(Amount)			-0.178***			0.035*
			(0.050)			(0.020)
No. of firms	577	577	577	1087	1087	1086

Note: Comparison groups: Successful & Non-applicant; Matching: PSM Nearest Neighbour; () standard errors; Value added = sales – cost of sales; Patent and trade mark are number of applications; t-test significantly different at the *** 1% and **5% levels; 10% bands are ten per cent of samples applicants whose assessment score are closest to the either side of the threshold score. Long-run effect: average effect since the first treatment year (inclusive); Sample size varies across model specifications.

Finally, applying the event study approach, we examine the effect on turnover six years before and six years after the treatment year(s). To do this, we estimate

$$Y_{i,t} = \tau_j \sum_{j=-6}^{6} D_{i,t+j} + \gamma_t + \mu_i + \varepsilon_{it} \qquad (3)$$

Results are presented in Table 7. In columns (1) and (2) we consider control groups based on propensity score matching and the 10 per cent band, respectively. These results indicate that the first observable difference in sales occurs in the (3-4) years the grant is being paid. *A priori*, if the collaborative research funded under the Linkage grant is destined to end up in a product, we may have anticipated a longer lead-time for the collaboration to impact turnover. Though if the funded research provides ancillary evidence regarding the benefits or uses for existing products the effect may be immediate. We observe however that our result is consistent with a finding by Cohen *et al.* (2002) that collaborating with universities contribute as much to completing projects as it suggests new research projects. Additionally, survey data collected by Bruhn and McKenzie (2018) also find that firms report that collaboration grants have impact on commercialization within 2.5-3.5 years. Taken together, these results provide some confidence that refining the control group in this way is adequately matching on pre-treatment characteristics. It is interesting to observe that by both methods, the impact of the grant on sales tapers off rather quickly.

Table 7: The dynamic of average treatment effects on sales (log)

Comparison groups	PSM	10% band
6 years before grant	-0.104	-0.138
	(0.081)	(0.088)
5 years before grant	-0.066	-0.080
	(0.074)	(0.080)
4 years before grant	-0.110	-0.136
	(0.070)	(0.077)
3 years before grant	-0.042	0.053
	(0.067)	(0.074)
2 years before grant	0.049	0.089
	(0.066)	(0.071)
1 year before grant	0.069	0.105
	(0.065)	(0.070)
Grant years	0.126***	0.133***
	(0.058)	(0.057)
1 year after grant	0.121*	0.019
	(0.067)	(0.071)
2 years after grant	0.063	-0.079
	(0.069)	(0.074)
3 years after grant	0.117	0.066
	(0.074)	(0.079)
4 years after grant	0.071	0.007
	(0.081)	(0.088)
5 years after grant	-0.009	-0.009
	(0.087)	(0.094)
6 years after grant	0.104	-0.065
	(0.098)	(0.101)
N	815	786

Note: PSM1 is propensity score matched sample based on nearest neighbour; () standard errors; V; t-test significantly different at the *** 1% and **5% levels; 10% bands are ten per cent of samples applicants whose assessment score are closest to the either side of the threshold score. "Treat" is the treatment period (=apply year or grant years); pre-x and post-x are x year(s) before or after the treatment period; Sample size varies across model specifications.

5. Concluding Comments

The Australian Government has had collaborative research grant schemes since the 1990s, in-line with other developed economies. In 2019-20, the Australian Research Council (ARC) awarded nearly A$300m to incentivise university-industry research collaboration (ARC 2020). In this paper, we evaluate one of these collaboration schemes, the ARC Linkage Program. This program enables university researchers to manage and coordinate a collaborative project using combined university, government and industry funding. We match comprehensive, detailed data on the population of Program applicants to balance sheet information for a full census of Australian firms from 2002 to 2014 to evaluate the program's effect on business performance.

Despite the widespread adoption of government subsidies to promote university-industry collaboration in Australia and the developed world, robust causal evidence regarding their efficacy has been lacking. A barrier to a cleaner and more robust evaluation has been the willingness of the custodians of the data to allow researchers to access critical data. In the case of general subsidy programs for R&D the situation has been changing in recent years with release of these data resulting in a small but important group of quasi-experimental evaluations. However, university-industry collaboration grants have not yet been evaluated using this approach. Using comprehensive data from nearly 5000 grant applications to the Australian Research Council Linkage Program we fill this gap. Crucially our data include both successful and unsuccessful applications as well as ex ante information about project quality.

In contrast to most other studies, we have three control groups which enable us to make stronger causal inferences than previous studies. First, the general population selected via the propensity score matching method; second, applicant firms which were not successful; and third, application projects which were rated ex ante by experts as being approximately similar to the successful projects. These last two groups help us control for time-varying unobservables such as the quality of the project specified in the application and the preferences of the firm to collaborate with a university. Propensity score matching allows us to control for selection based on the observable firm characteristics of industry, patent status and pre-treatment outcome. The treatment outcome is variously: sales, value-added, employment, and patent and trademark filings.

Our main result is clear and statistically significant: when we compare successful and unsuccessful grant applicants which were within the same rating band (10 per cent of the cut-off mark for winning the grant), we find that firms receiving grants have 12.5 per cent higher sales in the immediate period compared with firms that applied for, but just missed out, on a grant. The effect on value-added was not statistically significant. The longer-run effect, being defined as 1-7 years after the project began – was 11.4 per cent higher sales. When we expanded this to the whole sample of Linkage grant applicant firms, we found that immediate sales of successful firms were 15.0 per cent higher and value-added was 5.4 per cent higher than unsuccessful firms. The long-run effects were similar and statistically significant: sales were 12.1 per cent higher and value-added was 8.1 per cent higher.

Interestingly, unsuccessful firm applicants, compared with a matched sample from the general population had both higher sales and value-added in both the immediate period and long-run which suggests that connecting with universities through a joint application process is beneficial for the industry partners, regardless of the outcome of the grant application. This sounds a strong cautionary note regarding previous studies that compare program participants (i.e. successful applicants) with observationally similar firms from the general population when assessing university-industry collaboration grants. From our perspective, these estimates of the supposed benefits of university-industry collaboration are likely to be biased. It also suggests that unsuccessful applicants may have gained funding from other sources, but we do not have access to this information.

We also find that industry benefits varied by the type of the partner university and the amount of funding awarded. For the former, partnering with Go8 (large, research-intensive) universities is somewhat surprisingly associated with lower benefit. However, this finding may occur because non-applicant firms – like big pharmaceuticals – might prefer to collaborate via larger joint ventures or R&D contracts, etc. rather than the Linkage program which grants involves smaller amounts of money and requires a formal application process that takes many months to complete. The interaction effect with the funding amount is mixed: it increases the effect on patenting, but it lowers the effect on value-added.

Our evidence supports the efficacy of grants in changing firm behaviour to enhance their performance. Yet, it would be premature on this basis to conclude such grants are welfare-enhancing. Governments should not use public money to subsidise business profits. In our study, we focus on the private returns accruing to the firm and its workers, whereas the key justification for all innovation subsidies are the existence of external benefits i.e. social returns to innovation subsidies. Further work, along the lines conducted by Azoulay *et al*. (2019), is needed to understand the extent of private benefits relative to the overall project cost and, if they are large, why firms might eschew such benefits in the absence of government subsidy.

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