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Abstract

We quantify how competitive funding programs that promote university-industry (U-I) research partnerships affect firm performance. To do this, we estimate staggered difference-in-difference models using data from more than 5,000 funded and unfunded Australian Research Council Linkage Project grant applications from 2002 until 2015. Our results show grant funding led to a 12 percent increase in employment over a five-year period with both employment and turnover trending upward relative to untreated firms over our five-year post-treatment window.

JEL classification: O31, O32, O34

Keywords: University-industry research collaboration

1. Introduction

University-Industry (U-I) collaboration has become central to the 21st Century innovation system. High performing corporate labs, like Bell, IBM, and DuPont, that dominated the halcyon 'golden age' of industrial scientific research have given way to a 'new industrial ecology' characterized by a division of innovative labour between universities, tech start-ups and large corporates (Coombs and Georghiou 2002). This shift lies behind breakthroughs including the development of the world's first mRNA vaccine. Pioneering researchers from public institutions, including University of Pennsylvania, partnered with BioNTech and Moderna to bring a COVID-19 vaccine to market with breathtaking speed. The drivers of this new ecology – ranging from market pressures to evolving technological landscapes – are complex (Rosenberg and Nelson 1994, Arora et al. 2018; Arora et al. 2022). But one thing is clear: successful U-I collaboration can accelerate the impact of science.[1] In this paper, we examine whether government grants can accelerate U-I collaboration. Specifically, whether such funding has a significant effect on recipient firms' employment, turnover or patent applications.

Acknowledging the scope for market failure in markets for early-stage technology, governments across the OECD engage a library of policy interventions.[2] Given the growing evidence on how collaboration drives innovation success and how clusters thrive when participants exchange and build on each other's findings, U-I support programs warrant special attention (Guzman et al. 2024). It is not just a subset of R&D support schemes. This is especially pertinent for many countries (including Australia) which are perceived to have strong scientific capabilities but poor commercialisation capabilities. Subsidising U-I innovation collaboration is one policy intervention that have been used widely to address this

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[1] For evidence that U-I collaboration is associated with increased research outputs and improved firm performance – see Lööf and Broström 2006; Petruzzelli 2011; Cohen et al. 2002; Belderbos et al. 2004; Love et al. 2011. More recently, scholars have focused on trying to understand whether this effect is causal: see Belluci et al. 2019; Bruhn and McKenzie 2019; Kaiser and Kuhn 2012; Crescenzi et al. 2018; and Chai and Shi 2016. See also Estrada et al 2016, Steinmo and Rasmussen 2018 for an examination of their success factors.

[2] There are other ways in which knowledge from universities is transmitted to industry including contract research, training of PhD students who go to industry, exchange of research personnel, reading scientific literature, etc. While survey evidence suggests collaborative research grants are not the most important channel of diffusion (see Cohen, Nelson and Walsh 2002), they have likely become more important in recent years as corporate R&D labs have scaled back (Arora et al. 2023).

issue. We shed new light on this policy using comprehensive data on both funded and unfunded applicants for the Australian Research Council (ARC) Linkage scheme – a US$220 million per annum program designed to bridge the gap between science and business.

Evidence of the impact of subsidies for U-I collaboration remains sparse relative to the empirical literature on the impact of subsidies for innovation more broadly.[3] Nevertheless, the more recent U-I literature use data on both funded and unfunded project applicants to provide a compelling causal design, predominantly focused on research outcomes such as academic papers and patents.[4] Analysis of the effect of U-I collaboration grants on *firms' economic performance* using quasi-experimental methods based on comparison of funded and unfunded applicants are particularly rare. We are aware of three such studies and these rely on small samples due to the focus of many U-I support schemes on specific industries or regions. Chai and Shih (2016), analyse data on 101 Danish National Advanced Technology Foundation grants and find a positive effect of funding on patents but only for young firms and large projects. Bruhn and McKenzie (2018) provide evidence on the impact of Poland's In-Tech consortia scheme on patenting as well as survey-based (self-reported) commercialisation outcomes using regression discontinuity design (RDD) estimated on 301 unfunded and 158 funded[5] applications. The usual caveats to external validity of RDD apply to this result, as does its setting in a developing nation – noting that the patenting threshold in Poland is quite different from the European Patent Office. Also using RDD, Crescenzi et al. (2018) are less sanguine about the efficacy of an Italian government scheme, targeted at selected technologies in less-developed Italian regions. They find limited evidence of a positive impact on value-added, investments and employment. As the results from these

[3] The impact of government support for business R&D via grants and tax incentives on business performance (i.e., not for collaboration per se) has been subject to more analysis many of which use compelling causal design using data on funded and unfunded applications. (see recent contributions by: Bronzini and Iachini 2014; Bronzini and Piselli 2016; Hünermund and Czarnitzki 2019; Howell 2017; Widmann 2017; Wang et al. 2017; and Santoleri et al. 2022; Thomson 2017; Thomson et al. 2024; Zhao and Ziedonis 2020). 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] Other contributions based on comparison of grant recipients with observably similar firms who did not apply (e.g., Kaiser and Kuhn 2012; Belluci et al. 2019). Results are similar, though as discussed in this paper, they are difficult to interpret due to intrinsic differences between applying and non-applying firms.

[5] However, 14 projects funded were ranked below the funding cutoff and were funded after appeal.

three studies vary, there is a need to better understand whether U-I collaborative funding benefits firm performance.

In this paper we examine a major industry- and region-neutral U-I research collaboration grant scheme that has funded more than US$2 billion in research over more than a decade. The scheme is for applied, not basic, research and typically involves one firm rather than a consortium. We have a much larger usable sample of grant applications (over 5,000 in total) including funded and unfunded firms than the extant literature. This is important because one over-arching conclusion from the literature is that the effects of subsidies are very heterogenous. Our larger sample and implementation of recently developed heterogeneity robust difference-in-differences estimation methods will give us more precise and robust estimates of the causal effects of U-I collaboration subsidies and allow deeper exploration of the role of a particular conditioning factor in program success, namely firm size. Moreover, we fill a crucial gap in the existing literature which has so far primarily evaluated *targeted* U-I innovation collaboration programs which focus on SMEs, advanced technologies, less-developed regions, etc. Our results are not subject to this sort of selection bias and therefore provide more generalised estimates of innovation subsidy effects.

Using a staggered difference-in-differences estimation approach developed by Wooldridge (2021, 2023), with confirmation from a similar imputation approach developed by Borusyak et al. (2024), we estimate the causal impact of ARC Linkage funding on firm turnover, employment and patenting. We implement this state-of-the-art approach to account for the staggered treatment setting and the potential presence of treatment heterogeneity. To further ensure that two identifying assumptions of difference-in-differences models, namely parallel trends and no anticipation, the control group in our analysis comprises of observationally similar *applicants* that were unfunded. This is to account for unobserved factors that prompted the grant application in the first place (Santoleri et al. 2020). All applicants have overcome the (unobserved) barriers to collaboration such as mutual awareness of counterparty expertise, identification of possible synergies, and concerns regarding competition and disclosure.

We find ARC linkage funding associated with a significant impact on firms' employment. The strongest result indicates increased growth of 12 percent in employment in funded firms relative to matched control group of applicants who were not funded. Evidence regarding the impact of the grant on turnover is more subtle. In the case of large firms, we find turnover increases over time in the years following grant award in a weakly significant trend. We also look for systematic differences in the performance of non-funded applicants as compared to a matched control group of non-applicant firms, in the context of recent evidence on the impact of the grant application process in forming collaborative partnerships. Here we find scant evidence that the process of application affects firm performance. Rather, we find pervasive differences in pre-sample trends between applicants and non-applicants that is not ameliorated via matching on predetermined covariates. We interpret this as evidence of selection into treatment – i.e., those who apply have a reason for doing so. We argue that this latter finding highlights that care should be applied in interpreting differences between applicants and non-applicants as causal and indeed add to the evidence of intrinsic limitations of any program evaluation in the absence of data on non-funded applicants.

2. How does government support for U-I engagement affect firm performance?

University-Industry collaboration and engagement takes several forms. One universal feature is knowledge sharing; value is created through synergies between collaborating partners realized via the two-way exchange of technical and scientific knowledge and firms' identification of well-defined commercial problems (i.e., applications for knowledge, where value is created both through the firm's contribution to defining a commercially relevant problem and through exchange of scientific and technical knowledge (Stokes 2011; Cohen et al. 2002). In the case of the ARC Linkage scheme, firms contribute resources to research projects, and, in exchange the corporate partner is able to contribute to project goal setting and receive an agreed share of rights over knowledge assets created. In the ARC Linkage scheme, firms contribute resources to research projects and, in exchange, receive both input into project goals and agreed rights over created knowledge assets. This engagement can also include sharing of data, equipment, technical skills, or direct collaboration on research problems.

The formation of innovation collaborations is a non-random process which relies on finding partners who share common interests or are working on common problems. Firms are interested in finding university partners who can help them solve an industrial problem and universities are interested in finding business partners who might develop their technology.[6] Much of this matching depends on accessing the right person and this can vary by firm size. Goel *et al.* (2017), reports that university scientists find it is easier to initiate collaborative discussions with SMEs as the Chief Executive Officer is more accessible than in large firms. However, one could argue that finding a match in large organisations is easier because of their size and diversity.

Government subsidies for U-I innovation collaboration can potentially lead to *success in finding* a collaboration partner, conducting the collaborative research or both. For example, they might induce more (or higher quality) industry partners into the collaboration pool as suggested by the behavioural additionality literature (see Chapman et al., 2018; Bianchi et al. 2019).[7] Information ambiguities that hinder efficient matching as preferences are hard to observe and parties may be unwilling to disclose sensitive technical (or commercial) information in the absence of trust. The prospect of funding may allay a range of transaction costs and contracting hazards (uncertain information, disclosure, etc).[8] The enticement of funding can encourage the genesis or accumulation of relational capital within an organisation; it can elevate partnership as a priority for the firm; and it can tilt work culture towards favouring collegiate relationships with external parties. Recent research has gone so far as to suggest that the application process itself has a larger impact on firm performance than the funding received (Jaffe et al 2017; Ayoubi et al., 2019). Identifying a comparable control group of non-applicant firms is the principal challenge to empirically examining this question. We revisit this question in our empirical analysis below.

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[6] As such, U-I 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).

[7] Although there may be some firms in our data who react to the signal provided by the existence of the innovation collaboration grant – and therefore modify their behaviour and search for a university partner but don't submit a grant – we don't observe this decision.

[8] See Coase 1937; Williamson 1979; Grossman and Hart (1986); Holmstrom-Milgrom (1991; 1994).

Government funding can improve participant *firm performance* through two channels. First, funding can be decisive in whether a research project is undertaken at all, lowering the required hurdle rate, or signalling quality to focus scarce managerial attention. (Lerner 2000). Second, even for projects that might proceed without funding, the grant can deepen university-industry collaboration to enhance research productivity and impact. The potential benefits to firms of research engagement with universities are well established. Companies engage in collaboration with universities to access specialised knowledge of experts as well as proprietary data and intellectual property (Rosenberg and Nelson 1994; Etzkowitz and Leydesdorff 1997; Cohen et al 2002; D'Este, Guy, and Iammarino 2013). ARC funding supports engagement, collaborative research or partnership in research which focuses the attention of university researchers on problems of commercial relevance to the corporate partner. Such sustained engagement can facilitate tacit knowledge transfer (Zucker, Darby, and Armstrong 2002). Universities provide access to specialised scientific and engineering equipment that requires significant capital investment. Access can augment companies' research capabilities and reduces costs, ultimately increasing the return on firms' research spending. Varma (2000) and others suggesting university labs as a potential "virtual lab" for industry (Varma 2000). Engagement facilitated via the ARC Linkage program also creates a potential pipeline for recruiting skilled graduates (see e.g., Lam 2007).

Overall, the evidence appears to suggest that larger firms are both more likely to enter a university research collaboration and to derive greater benefit from such engagements (Fontana et al. 2006; Yu and Lee 2016; Sutrisna et al. 2021). The latter is because if the project proceeds, there can be unplanned knowledge exchange [spillovers] and therefore the genesis of additional projects within the firm (Mowery 1983; Veugelers and Cassiman, 2005). The extent of benefit from external knowledge is contingent on the firm's ability to integrate and utilise it (absorptive capacity). Large firms may be able to outperform smaller firms collaborating with universities because of their sophisticated complementary capabilities – including marketing skills and distribution channels (referred to as 'commercialisation capabilities' by Arora et al. 2023). Small firms may lack absorptive capacity to benefit from external knowledge (Cohen and Levinthal 1990; Bougrain and Haudeville 2002; Muscio 2007; Almeida et al. 2011).

It is important to be clear about expected observable outcomes of successful U-I engagement. New product innovations directly impact sales revenue as by introducing new revenue streams. By the same argument, product innovation is anticipated to have a positive effect on employment (van Reenen 1997; Calvina and Virgillito 2017). Process innovation is generally held to reduce costs and allowing firms to offer more competitive pricing; and new products are often associated with additional price reductions of superseded product lines. Accordingly, labour saving process innovation can lead to increased labour demand (employment) at the firm level as the innovating firm captures market share.

The impact of successful U-I engagement is expected to manifest in different dimensions of firm performance over time. Successful R&D leads ultimately to commercially applicable technology manifest as new products or improved processes. A firm preparing for growth is expected to increase employment as it scales up to capitalise on the innovation. Finally, as new products or more efficient processes reach the market, real sales growth will follow, reflecting the firm's ability to capture market share and expand output.

Reflecting the above discussion, we assess the impact of ARC Linkage grants on firm performance over time, by examining three key indicators: patenting, employment, and turnover. These metrics capture distinct aspects of innovation-driven growth. Patenting is extensively used indicator of inventive activity, though is subject to well-known limitations around subject matter and strategic behaviour. Not all inventions relate to patentable subject matter, and that firms often prefer trade secrecy in the case of process innovations (Klein 2020). Research suggests university engagement is not typically focused on patents (Agrawal and Henderson 2002; D'Este and Patel 2007). Employment growth reflects increased labour demand following both product and process innovations and avoids concerns regarding changes in prices often endogenous to the innovation process. Turnover growth summarises the firm's ability to translate innovations into increased market share or new revenue streams. By analysing these indicators longitudinally, we aim to capture the dynamic impact of improved innovation performance resulting from more or more effective R&D.

3. Institutional Setting and Data

We study the population of applicants to the ARC Linkage Grant scheme between 2002 and 2014.[9] The longstanding Linkage program provides around AU$300 million annually (~US$220 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. [10]

The Linkage program provides matched government funding – firms must contribute at least 25 per cent of the total funds requested from the government in cash – 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. There are multiple rounds of applications each year and grants are awarded based on written proposals which are assessed by a committee of scientific experts appointed by the ARC. Grant decisions are finalised and announced by the government minister.

The specific form of U-I engagement varies between projects. In all cases, private-sector firms are required to make financial contributions (cash and in-kind) contributions. In exchange for their financial contribution, firms receive some pre-agreed usage or other proprietary rights over knowledge assets created by the research. In some cases, company employed scientists and engineers are directly involved in collaborative research, whereas in

[9] The ARC is Australia's peak research funding agency. It is an independent Commonwealth Government agency which allocates funds to Australian universities through competitive programs to the tune of ~A$900m p.a. It funds any research outside of medical and clinical areas (which is funded separately) through basic research grants, individual early-career and mid-career grants for outstanding researchers and large, multi-institutional grants.

[10] A study by Nugent et al. (2022) comparing outcomes of Australian Research Council (ARC) Discovery (basic research) with ARC Linkage (applied research) funded projects demonstrated a small (and short-lived) positive effect on patenting associated with ARC Linkage grants compared to basic ARC Discovery research grants, supporting the notion that ARC Linkage Grants are more applied in nature.

other cases firms' contribution may focus on setting, monitoring project direction, goals and scope over the duration of the project.

In many respects, the institutional context considered here provides an ideal setting for measuring the impact of U-I collaboration grants on firm performance. First, the program is not restricted to any single industry or technology (it excludes '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.[11] 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 2015, with economic data from the population of Australian firms over the period 2001-02 to 2014-15. 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 company identifiers. 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, 5,560 (74.8 per cent) were matched to their unique Australian Business Number (ABN) using a combination of machine matching and manual lookup. Of the organisations missing an ABN,

[11] 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.

50 per cent are international businesses; 17 per cent are civil society organisations and 15 per cent are government agencies, which are not relevant to the analysis.[12]

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[13] levels are about 30 times larger; employment 40 times; patents are average 150 times larger and so on. Funded applicants are, on all measures, about 50 per cent larger than the average applicant. This is not surprising and merely highlights the importance of identifying a suitable control group for treated firms. The confidential unit-record data used for this study incudes tax return data from all firms in Australia. Even after filtering for firms with at least one employee and non-zero assets the total population includes micro-enterprises such as contractors and family run retail or service businesses.

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)	Trademark (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
Funded 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.

4. Empirical model

Our aim is to estimate the impact of the ARC Linkage program on the performance of the participating firms (i.e. firms named as partners on an ARC Linkage application). Our data is an unbalanced panel data of more than 2 million Australian companies observed over a period of 14 years. The overall grant success rate was 44.4 per cent.

The above setting presents us with two important challenges in identifying the impact of interest using the commonly employed difference-in-differences (DID) models. First, there

[12] 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.

[13] Production level is measured as sales revenue less non-capital purchases (i.e. inputs) in current $.

is likely to be a systematic selection both in the process that determined which companies applied for the grant and which of them are funded. The former may lead to violation of the identification assumptions of difference-in-differences models, namely parallel trends and no anticipation effect. Second, the ARC Linkage grant is a staggered intervention with each year, a new cohort of firms begins with the treatment (namely, funded U-I collaboration).

The first problem of identification mentioned above relates to the fact that the decision to conduct R&D collaboration between industry and university may involve systematic selection based on unobserved factors (Veugelers and Cassiman 2005; Segarra-Blasco and Arauzo-Carod 2008),.[14] For example, higher performing firms may self-select into the program based on their relatively higher level of readiness to benefit from extra-mural R&D. Therefore, we need isolate the effect of treatment (either applying for the grant or winning grant funds) from the unobserved selection factors. Similarly, even though funded and unfunded applicants have much in common – they both have signalled a desire to engage with university researchers – pre-determined firm attributes that are observable to application reviewers are expected to influence the funding decision.

Given our observational and longitudinal data, we do this by estimating our difference-in-differences model using matched sample. The basic idea is to construct a matched 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. There are 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). To assess whether the application process itself influences performance, we compared unsuccessful (that is, unfunded) applicant firms with a control group matched from the pool of firms which never apply for the grant. To assess whether getting funded influences firm performance, we matched funded applicants to unfunded applicants.

[14] 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).

Using a control group matched on observable characteristics means we are comparing like-with-like to ensure that the pre-treatment parallel-path and no anticipation assumptions behind our DID estimation are not violated (Lindner and McConnell 2019).[15] The matching variables are the averages of the following observed measures evaluated in the preceding 3 years prior to treatment: outcome (current, one period lag, and two period lag) and current values of export, investment, capital stock; and twenty one-digit industry division of the applicant firms.[16] The use of both covariates and current and lagged outcome measures as the matching variables is to reduce any potential bias from the matching process (Lindner and McConnell, 2019; Ham and Miratrix, 2024). The outcome variable is one of the following outcomes of interest: turnover, employment and the number of patent applications by the grant recipient firm. We find the best matching results, in terms of the parallel trend and no anticipation tests to be discussed later, if we perform a separate matching analysis for each outcome.[17]

Table 2 provides a summary of the results of matching analysis. As mentioned earlier, to estimate the impact of U-I collaboration on each outcome of interest (namely, turnover, employment, and patent application) we construct a separate matched sample. In each case, treated firms are matched to untreated firms based on current and two lagged value of the respective outcome variable and a set of covariates consisting of the current values of the other two outcome variables, exports, investment, capital stocks, and 20 one-digit industry division dummy. Table 2 provides the t-statistic and corresponding p-value of the mean difference between the treated (funded) and untreated (applied but unfunded) firms before and after matchings. 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 matching variables. For example, if we look at columns (3) and (4) for matching variable "Turnover(t)", we find the mean difference between treated and untreated

[15] This means we do not have to extrapolate and infer, say, the program effect on a large firm from data on small firms.
[16] We use three years prior to treatment for matching to ensure that we still have enough number of successful firms to analyse. For example, this setup means the first cohort we can analyse is the 2005 cohort. Our results are similar if we use two years prior to treatment; however, we lost too many observations if we use four years.
[17] The matching analysis is performed using STATA's psmatch2 command with the following options: logit function, common support, ties allowed, five nearest neighbours, and max calliper of 0.1. Despite of the five nearest neighbours setup, most of successful applicants can only be matched to one unsuccessful applicant.

firms is statistically significantly different from zero in the unmatched sample, with a t-statistic of 3.13 and a corresponding p-value of 0.002. However, after matching, the t-statistic (0.54) and p-value (0.588) suggest that the mean difference is no longer statistically significant. [18]

[18] When we match unfunded firms to firms which never applied, we obtain similar matching results: the matched treated and untreated firms no longer show any statistically significant difference in any of the matching covariates.

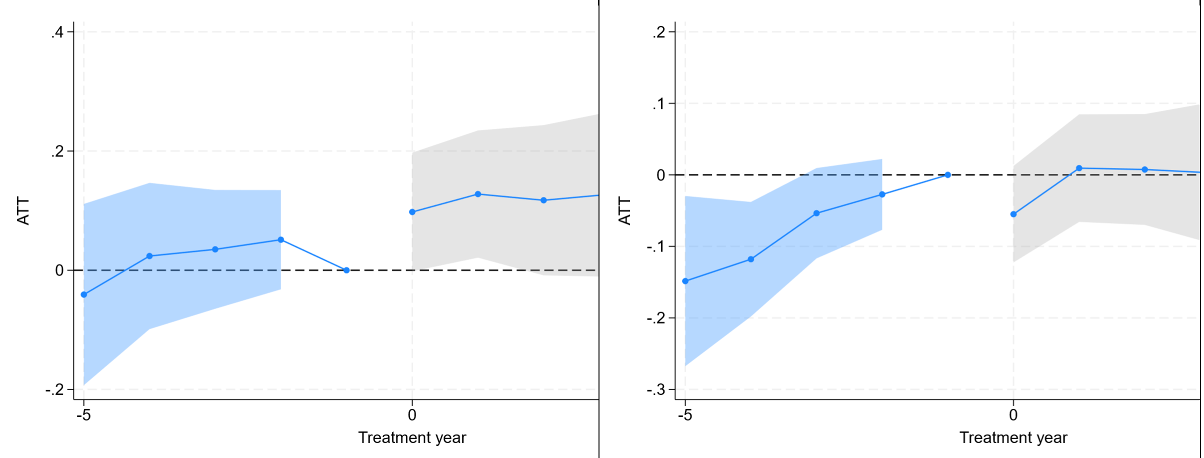
Table 2: Mean difference's t-statistics and p-value before and after matching, by separate outcome of interest, Funded vs Unfunded applicants

Matching variable	Sample	t-stat and p-value of mean differences between treated and control (for each outcome of interest matching analysis)					
		Turnover		Employment		No. patent apps.	
		t-stat	p-value	t-stat	p-value	t-stat	p-value
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Turnover(t)	Unmatched	3.13	0.002	3.19	0.001	2.22	0.027
	Matched	0.54	0.588	0.10	0.917	0.99	0.320
Turnover(t-1)	Unmatched	3.10	0.002				
	Matched	0.56	0.576				
Turnover(t-2)	Unmatched	3.37	0.001				
	Matched	0.47	0.642				
Employment(t)	Unmatched	3.21	0.001	3.13	0.002	2.30	0.022
	Matched	0.20	0.843	0.06	0.953	0.89	0.372
Employment(t-1)	Unmatched			3.15	0.002		
	Matched			0.00	0.956		
Employment(t-2)	Unmatched			3.08	0.002		
	Matched			-0.01	0.993		
No. patent app. (t)	Unmatched	1.23	0.219	1.21	0.225	1.30	0.195
	Matched	-0.24	0.807	0.97	0.332	-0.02	0.987
No. patent app. (t-1)	Unmatched					1.25	0.210
	Matched					-0.08	0.934
No. patent app. (t-2)	Unmatched					1.43	0.152
	Matched					-0.30	0.767
Export (t)	Unmatched	2.66	0.008	2.60	0.009	2.96	0.003
	Matched	0.34	0.730	0.41	0.683	0.49	0.627
Capital stock (t)	Unmatched	3.57	0.000	3.56	0.000	2.34	0.020
	Matched	0.20	0.839	0.23	0.816	0.64	0.520
Investment (t)	Unmatched	2.36	0.019	2.29	0.022	1.86	0.064
	Matched	0.32	0.753	0.09	0.929	0.16	0.869

Notes: The matched sample for estimating the impact on turnover consists of 474 funded firms matched to 359 unfunded firms. The matched sample for estimating the impact on employment consists of 487 funded firms and 364 unfunded firms. The matched sample for estimating the impact on number of patent applications consists of 565 funded firms and 416 unfunded firms. There is no statistically significant difference in terms of each of the 20 one-digit industry division dummy in the matched sample.

Figure 1 provides line plots of the average employment of matched funded v. unfunded firms and matched unfunded v. non-applicant firms across the time-to-treatment years.[19] For line plot (a), the treatment is *getting funded* by an ARC Linkage grant. For line plot (b), the treatment is *applying for* ARC Linkage grant. The pre-trend pattern in line plot (a) suggests support for the assumption of parallel trend between the firms in the matched funded and unfunded firms and the assumption of no anticipation. However, line plot (b) seems to suggest that either or both assumptions might be violated in the comparison of unfounded and non-applicant firms However, as discussed later, despite the visuals shown by line plot (b), a formal joint-test of the pre-trends may indeed conclude that the pre-trends are not statistically significantly different from zero.

Figure 1. Average Employment by Time-to-Treatment Years



(a) Funded vs Unfunded (b) Unfunded vs Non-applicant

Note: Solid and dashed lines represent the simple averages of the log employment of the firms in each treated and never-treated (control) groups. Shaded areas indicate the corresponding 95% confidence interval.

The second identification challenge comes from the staggered characteristic of the treatment: each year, a new cohort of firms receive ARC Linkage grant for the first time or, another cohort, apply for ARC Linkage grant for the first time. This staggered treatment is combined with the high likelihood for the treatment effect to be heterogeneous across cohort, time, and firm characteristics such as size. As shown and discussed by a rapidly growing number of recent econometrics and applied studies such as de Chaisemartin, C. and D'Haultfoeuille, X. (2020; 2022), Wooldridge (2021; 2023), Borusyak et al. (2024), and Nagengast and Yotov (forthcoming), under these conditions a naïve two-way fixed effect (TWFE) as specified in equation (1) below would likely to result in biased treatment effect estimates (τ) which are difficult to interpret:

$$Y_{it} = \alpha_i + \beta_t + \tau D_{it} + \varepsilon_{it} \qquad (1)$$

where Y_{it} and D_{it} denote the outcome of interest and binary treatment for year t and firm i, α_i and β_t denote firm and year fixed effects to account for cross-firm baseline variation and cross-year trendline variation. The source of the bias is what Borusyak and Jaravel (2017) and Borusyak et al (2024) refer to as 'forbidden comparisons': a comparison between observations from firms which are already treated to firms' later cohorts.

Fortunately, new estimators which are either robust against such biases or designed specifically to address the source of the bias are now available.[20] Recent applications of these new approaches suggest promising results including a forthcoming study by Nagengast and Yotov which implement Wooldridge (2023)'s Extended Two-Way Fixed Effect (ETWFE) estimator to estimate non-linear gravity trade model to assess the impact of regional trade agreement using difference-in-differences model.

In this paper, we implement the linear version of the ETWFE model (Wooldridge 2021). In essence, the model addresses directly the source of the bias discussed earlier by avoiding making the "forbidden comparisons". This is done by extending the basic structure of TWFE model in equation (1) by allowing for treatment effect heterogeneity at the cohort-year level (and possibly at some exogenous covariate level too) through the addition of cohort and calendar year interaction terms. A general form of Wooldridge's ETWFE model can be specified as follows:

$$Y_{it} = \alpha_i + \beta_t + \sum_{g=q}^{T} \sum_{s=g}^{T} \tau_{gs} D_{gs} + \varepsilon_{it} \qquad (2)$$

where g indexes cohort (with value $g = q$ for firms whose treatment starts in year q), T denotes the last year of the panel. Assuming treatment is absorbing, that is once treatment starts it will last forever, then D_{gs} is the cohort-year treatment indicator with a value of 1 for cohort g for $s = t$ in post-treatment years and 0 otherwise. Finally, τ_{gs} is the cohort-year specific treatment effects.

[20] See, for example, de Chaisemartin and D'Haultfoeuille (2020; 2022), Cengiz et al. (2019), Deshpande and Li (2019), Callaway and Sant'Anna (2021), Sun and Abraham (2021), Wooldridge (2021; 2023), Gardner (2022), and Borusyak et al., (2024). See also Roth et al. (2023).

The specified ETWFE model in equation (2) provides us with highly granular treatment effect estimates (τ_{gs}) for each possible cohort-year combination. Given our interest is in the aggregate effect (τ), we follow Wooldrige (2021)'s suggestion to construct a simple average of the following form:

$$\bar{\tau} = \frac{\sum_{g=q}^{T}\sum_{s=g}^{T}\tau_{gs}}{(T-q+1)(T-q+2)/2} \quad (3)$$

Different ways to aggregate τ_{gs} are possible, such as aggregating over treatment year or cohort. In practice, we follow Nagengast and Yotov (forthcoming) in using the **jwdid** package developed by Rios-Avila et al. (2022) for the STATA platform.[21]

A closely related imputational approach to solve the "forbidden comparison" problems has been proposed by Borusyak et al. (2024) based on a general formulation of the following dynamic even-study specification:

$$Y_{it} = \alpha_i + \beta_t + \sum_{\substack{s=-a \\ s\neq 1}}^{b-1}\tau_s\,\mathbf{1}[K_{it} = s] + \tau_{b+}\mathbf{1}[K_{it} \geq b] + \varepsilon_{it} \qquad (4)$$

where a ≥ 0 and b ≥ 0 denote the number of leads and lags to be included in the even-study equation. To obtain the estimates of τ_s, Borusyak et al. (2024) first estimates the fixed effects in $Y_{it} = \alpha_i + \beta_t + \varepsilon_{it}$ using untreated (never treated and pre-treated) observations. Under the parallel trend and no anticipation assumptions, the estimated fixed effects can be used to construct untreated potential outcomes which can be used to construct estimated treatment effect (τ_{it}). These τ_{it} can then be aggregated with appropriate weights to form the desired treatment effect estimates. For implementation, Borusyak et al. (2024) provided a STATA's package **did_imputation**. Thus, for robustness analysis, we discuss how similar the treatment effect estimates produced by our chosen Wooldridge's ETWFE model with the ones produced by Borusyak et al. (2024) estimator.

[21] In addition, for robustness, we compare our estimation results with the results from a similar imputation approach to Wooldridge's ETWFE model which avoids making "forbidden comparisons" in the staggered treatment setting as proposed by Borusyak et al. (2024) using their STATA's package **did_imputation** ().

5. Results

We investigate the impact of the ARC Linkage grant on company turnover, employment, and patenting activity. Results of our difference-in-differences estimate of the impact of ARC Linkage grants on turnover (sales[22]) are presented in Table 3. In each case, we compare firms with funded applications to a matched control group of applicants which did not receive funding. As discussed earlier, matching is based on average level of outcome variable (current and one- and two-years lag) in the 3 years preceding treatment as well as other pre-determined covariates (details of the matching procedure are provided at Section 4). Column 1 presents the Two-Way Fixed Effects (TWFE) estimate, and these indicate a significant 10% increase in turnover post-treatment for funded firms.

As discussed in Section 4, estimation of staggered treatment design difference-in-differences using TWFE suffer from bias associated with contamination of control group trends with previously treated units. To address potential biases in the standard TWFE approach, we employ the extended TWFE method proposed by Wooldridge (2021) (henceforth referred to as ETWFE). ETWFE based on a control group comprising purely never-treated firms are presented in Column 2, while Column 3 presents the more efficient ETWFE using both never-treated firms and not-yet-treated firms as controls. These estimates indicate that while there is no statistically significant difference in turnover for funded firms as compared to firms that did not receive funding, the size of the coefficient is as high as 0.0825, which is around 25% lower than the TWFE estimate. In other words, the TWFE estimate seems to have an upward bias.

[22] Although these terms are used interchangeably, strictly sales is the total value of goods and services a business sells and turnover (sales turnover) is how much the company sold its products and services within a given period.

Table 3. Aggregate annual average ATT of getting ARC Linkage grant on turnover, employment and patenting. Estimates over 5 years.

	Turnover			Employment			Patenting		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	TWFE	ETWFE (Never treated)	ETWFE (Not-yet treated and Never treated)	TWFE	ETWFE (Never treated)	ETWFE (Not-yet treated and Never treated)	TWFE	ETWFE (Never treated)	ETWFE (Not-yet treated and Never treated)
ATT	0.121**	0.053	.0825	.1184**	.1382**	.1182**	.0075	-.0238	-.0009
ATTSE	(0.057)	(0.067)	(.0659)	(.0508)	(.0618)	(.0577)	(.0204)	(.0415)	(0219)
N-obs. (firm-year)	9483	9486	9486	9721	9725	9725	13734	13734	13734
N-funded (firm)	356	359	359	362	364	364	416	416	416
N-unfunded (firm)	474	474	474	485	487	487	565	565	565

Estimates of the impact of ARC Linkage funding on firm employment are presented in Columns 4-6 of Table 3. As in the case of turnover, we present conventional TWFE, as well as the two variants of ETWFE. We find a positive and statistically significant effect on employment for all firms, with preferred estimates showing funded firms exhibit approximately 11.82 per cent higher employment post-treatment than non-funded firms. It is interesting to note that for employment, the three different models produce relatively similar treatment effects. This suggests that treatment effect heterogeneity in terms of employment may be not as significant as in the case of turnover.

We also evaluate the impact of ARC Linkage grants on patent applications. Headline results are presented in Columns 7-9 of Table 4 indicate no significant divergence in patent applications between funded and unfunded firms. The lack of effect on patenting is not altogether surprising. Although R&D collaboration may improve business performance, this result is consistent with previous studies that found a significant share of R&D collaboration did not generate additional patents (Lhuillery and Pfister 2009; Schwartz et al. 2012).

Robustness analysis

To empirically validate the assumption of parallel trends and no anticipation, we estimate an extended event-study design including treatment group x year-relative-to-treatment dummies in the *5 years* preceding treatment. Estimates use ETWFE and never-treated firms as a control group. Results for joint significance test for pre-treatment dummies for models of each dependent variable are reported in table 4 below. In each case, the dummy variables for years before treatment are collectively indistinguishable from zero, supporting the validity of our difference-in-differences approach.

Table 4. Testing for the null hypothesis of no pre-trend (Funded v. Unfunded)

	Turnover	Employment	Patents
p-value	0.1146	0.4847	0.4190
Decision	Fail to reject H0	Fail to reject H0	Fail to reject H0

As we noted earlier, we also implement Borusyak et al. (2024)'s approach. Despite the difference in the method to construct the treatment effect estimates, the resulting estimates from both approaches are quite similar. A statistically significant and positive and slightly higher treatment effect is observed from Borusyak et al. (2024)'s model in terms of employment. There is no effect in terms patent application. In terms of turnover, the estimated effect is very close (to the third decimal) to the TWFE estimate, suggesting that Borusyak et al. (2024)'s model may suffer from the same TWFE upward bias. Lastly, Borusyak et al. (2024) shows that their separation of the untreated observation allows for a more powerful test for the presence of pre-trend which may indicate violation of the parallel trend and/or the no anticipation assumption. Consistent with the results presented in Table 4, the pre-trend test produced by Borusyak et al.'s **did_imputation** command in STATA failed to reject the null of no pre-trend.

An obvious puzzle emerging from the results presented in Table 3 above in our results is why government support for U-I collaboration leads to an observable impact on employment, but an observed impact on turnover that is statistically indistinguishable from zero. One possible explanation may be that turnover effects are being obfuscated by dynamic adjustments such that firms with more successful innovation pipelines pre-emptively ramp up employment in preparation for ongoing product launches; in this case employment may raise initially with sales volumes increasing outside the five-year time horizon of our analysis. That is employment growth could reflect a strategic response to anticipated market expansion, where firms prioritize capacity building over short-term revenue increases.[23] We investigate this possibility further below by way of an even study design model.

Event-Study Design: Dynamic effect of ARC Linkage funding

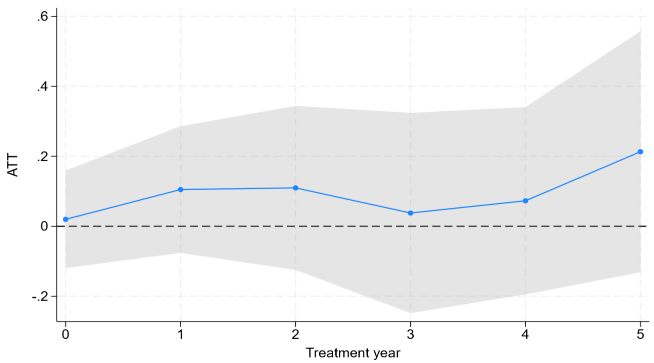
To provide a more granular assessment of the impacts of ARC Linkage funding, and on the dynamics of ARC funding impact, we use the τ_{gs} estimates from equation (2) to form a year-by-year event-study design using separate subsamples for large and small firms.[24] Our event-study design model includes a full set of year-relative-to-treatment dummies and are estimated via ETWFE incorporating never treated as implicit controls. Event study results are depicted in Figure 3. The right two panels (b and d) trace the dynamic effects of ARC Linkage grant on employment over time for large and small firms, respectively. In panel (b), the results indicate that for large firms the effect of funding appears to be increasing over time. This result which could suggest that the benefits of U-I collaboration take time to fully materialize in terms of employment growth. In contrast, for small firms, the effects are never statistically significant and begin to dissipate by the third year of the treatment.

[23] A less likely possibility may stem from the fact that we use conventional industry specific deflaters firm specific output prices. If output prices for funded firms fall more than for non-funded firms, we therefore underestimate the effect on real sales of treated firms.

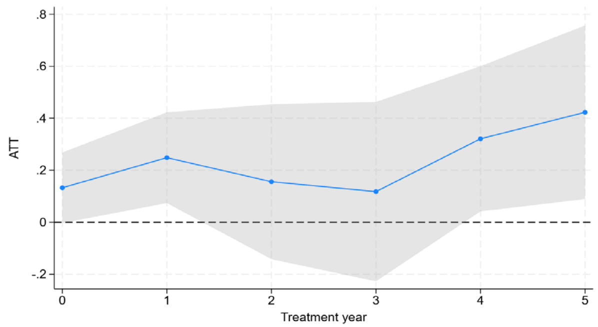
[24] In unreported results, we estimated models conditioned on university quality and industry, but these were not significant. It is unclear whether this reflects their lack of relevance as conditioning variables or limited statistical power due to sample constraints.

Figure 3. (2x2 panel) Event Study Results

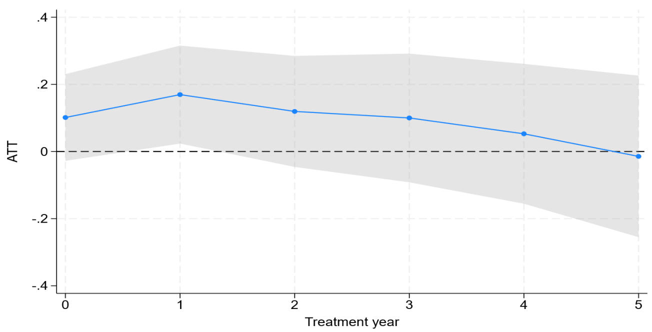
Panel (a) Turnover Large Firms



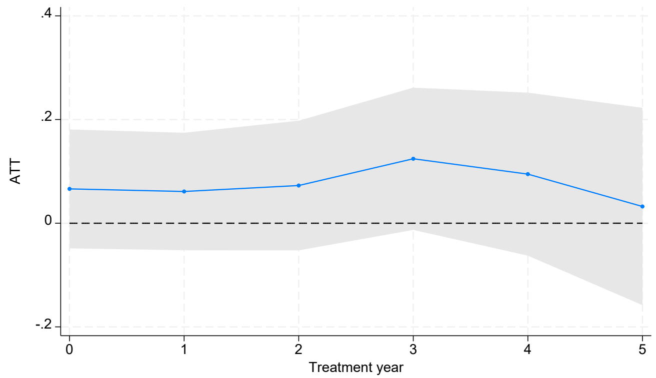
Panel (b) Employment Large firms



Panel (c) Turnover Small firms



Panel (d) Employment Small firms



The left panels of Figure 3 (a and c) depict event-study estimates of the effect of ARC Linkage funding on turnover. The point estimates are not statistically significant but can be seen to follow a distinct upward trajectory in large firms. We argue that these results provide suggestive evidence in favour of our previous explanation as to why we see a significant impact on employment over 5 years but not turnover: namely that this reflects pre-emptive capacity expansion and company growth not yet manifest in sales within our 5-year window.

Does the Application Process Benefit Firms?

Although the unfunded applicants did not receive the subsidy, they did engage in enough negotiations with the university partner to understand each other's issues and problems to devise a plausible application. Several authors have noted systematic differences in performance of applicant firms when compared with non-applicant firms, subsequent to the application date (Jaffe et al 2017; Ayoubi et al., 2019). To investigate the extent to which the performance trajectory of unfunded applicants diverged from non-applicants using analogous difference-in-differences model where treatment reflects the year of unfunded application for the grant. Results in Table 5 indicate no difference in post-treatment (application) turnover, statistically significant positive difference in post-treatment employment and a small and weakly statistically significant but negative difference in the post-treatment patenting of applicant firms as compared to a matched control non-applicant firms. The corresponding null hypothesis testing of No pre-trend for the employment effect seems to suggest that the positive outcome may be due to violation of the parallel trend and/or no anticipation assumption.

Table 5. Aggregate annual average ATT on turnover, employment and patenting behaviour over 5 years. ETWFE estimates (never treated & not yet treated): unsuccessful vs. never applied

	Turnover	Employment	Patents
ATT	.0393	$.0777^{**}$	$-.0193^{*}$
ATTSE	(.0547)	(.0432)	(.0105)
H0: No pre-trend	Accept. (pv=0.1019)	Reject. (pv=0.0302)	Accept. (pv=0.2108)

Before offering concluding remarks, we acknowledge several remaining caveats and limitations to our analysis. First, we do not observe the level of funding provided to each project, so we are restricted to estimate the average effect of funding, though we note that the program has a relatively narrow range in funding dollars per project. Second, we don't observe whether unfunded firms had access to alternative funding sources that may have been available. Our estimation strategy will not be biased as a result, but analysis of alternative funding mechanisms would be a valuable step in understanding the mechanism of benefit.

6. Concluding Comments

Despite the widespread adoption of government subsidies to promote university-industry collaboration across the OECD, robust causal evidence regarding their impact on firm performance is limited. 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 relating to applications that were not funded. In the case of general subsidy programs for R&D, the situation has been changing in recent years with a proliferation of quasi-experimental evaluations. However, large scale 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 funded and unfunded applications.

The Australian Government has had collaborative research grant schemes since the 1990s, in-line with other developed economies. The longstanding Linkage program provides around AU$300 million annually (~US$220 million) with the aim of encouraging and extending cooperative research between researchers in universities and business. 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 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.

Comparing funded and unfunded grant applicants, we find clear evidence that grant recipients have, on average, over the 5 years following grant, 12 percent higher employment compared with their counterfactual which were not funded. We also find that both employment and turnover reported by ARC Linkage grant recipients appear to diverge increasingly over the period following grant award suggesting that firms embark on progressive expansion in response to opportunities arising from research outcome, but it takes time for the impact on turnover to accrue. We do not find any systematic differences in funded firms patenting activity. We speculate that this may reflect that collaborative projects focus on outcomes that can be appropriated without intellectual property protection, possibly an outcome of the type of projects that can meet the disclosure objectives of firms (who preference no disclosure) and university scientists (who preference dissemination).

Unlike several previous studies, we do not find evidence that applying for a grant – finding a partner, negotiating and engaging in the application process – affects SME performance. Instead, we find evidence of selection into 'treatment' of grant application. That is, even unsuccessful grant applicants have pervasively different trends in re-application performance than otherwise observably similar companies that do not apply. This sounds a strong cautionary note regarding previous studies that compare program participants (i.e. funded applicants) with observationally similar firms from the general population when evaluating university-industry collaboration grants. From our perspective, these estimates of the supposed benefits of university-industry collaboration are likely to be biased.

Our evidence supports the efficacy of grants in changing firm behaviour to enhance their growth prospects and performance. Yet, it would be premature on this basis to conclude that such grants are welfare-enhancing. A firm performance effect is arguably a necessary but not sufficient criteria for a good policy. It would be valuable to see if public support for innovation is more effective in the context of complementary programs – training, exports, networking, logistics, planning – to enhance innovative activities; the role of agglomeration; and the role of champion firms in the innovative ecosystem.

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