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Bridging science and technology through academic–industry partnerships

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ABSTRACT

Partnerships that foster the translation of scientific advances emerging from academic research organizations into commercialized products at private firms are a policy tool that has attracted increased interest. This paper examines empirical data from the Danish National Advanced Technology Foundation, an agency that funds partnerships between universities and private companies. We assess the effect on participating firms' innovative performance, comparing patent count, publication count and proportion of cross-institutional publications between funded and unfunded firms. Specifically, we measure the impact on each of these variables based on three dimensions – small and medium-sized enterprises (SME), younger firms, and size of the collaboration firms participated in – to establish boundary conditions. Our results suggest that receiving funding affects firms' innovative behavior differently depending on the type of firm, where (1) peer-reviewed publications increased significantly more for SMEs and larger projects, (2) granted patents increased significantly up to 4 years after funding for young firms and those in larger projects, and (3) proportion of cross-institutional publications increased significantly more 3 years after funding for all three sample specifications.

1. Introduction

How ideas are produced and the means by which they are diffused is an area of great interest to researchers. This is driven by the belief that technological innovations, which are grounded in basic research, spur wealth creation and stimulate economic growth. Research universities, with their primary missions of educating and creating knowledge, are an important source for such ideas. The Bayh–Dole act of 1980 in the US and similar legislation in European countries enabled universities to patent technologies resulting from government funded research, and as a consequence universities have undertaken a third role of fostering knowledge and technology transfer to spur economic growth (Etzkowitz et al., 2000). As a result, universities have employed many instruments to push newly generated knowledge into industry (Feldman et al., 2002; Mowery et al., 2004; Thursby and Thursby, 2002), while firms have used various ways to draw upon the research and pull new technology from academia (Henderson and Cockburn, 1996; Liebeskind et al., 1996). Despite these efforts knowledge still tends to be trapped in the ivory tower (Bikard, 2014). In light of these results, many countries have increasingly turned toward academic–industry partnership programs that combine these mechanisms to facilitate and foster the bridging between academic science and commercialization of technology.[1] Though there are many such programs globally, there is little research that assesses the impact of academic–industry partnership funding on participating firms' innovative performance compared to non-participants.

We examine academic–industry partnerships sponsored by the Danish National Advanced Technology Foundation[2] (DNATF), a funding agency of the Danish government. DNATF awards grants for projects that partner at least one academic institution and one

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[1] In the US, National Science Foundation Shared Resources Centers often require partnership with private firms to accelerate product development, while the National Institute of Health Academic–Industry Partnership Program seeks cross-boundary opportunities that link biomedical research with commercial opportunities. In Germany, the Fraunhofer–Gesellschaft is a partially state-supported application-oriented research organization with direct utility to private and public enterprises. The Technology Strategy Board in the UK runs programs such as its Knowledge Transfer Partnership that support businesses wanting to improve their competitiveness by accessing the expertise available within universities.

[2] Højteknologifonden in Danish, DNATF was merged into the InnovationsFonden in May 2014.

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firm in a co-funding structure where academic partners provide one sixth of the budgeted amount, industry partners one third, and the agency providing the remaining half. As few existing works explore how academic–industry funding affects subsequent firm innovative performance, our analysis is mainly exploratory. We contrast a sample of funded firms with those that applied for DNATF funding but did not ultimately receive a grant, comparing on an annual basis up to 5 years after funding. Since all proposal applications were ranked, we mitigate selection bias by including qualitatively similar participant and non-participant firms. We first assess how such partnerships affect collaborations with academic research institutions in helping firms partake in innovative activities translated from basic research by studying the quantity and the collaborative nature of peer-reviewed publications. We then explore how these partnerships affect commercialization by studying the quantity of granted patents. Finally, we investigate three dimensions – the size and age of the participating firms, and the size of the collaborations – in order to establish the boundary conditions of such a funding scheme.

Although our results do not show consistent significant effects of academic–industry funding on the full sample of heterogeneous participating firms, we find significant effects along the three dimensions. For the samples of qualitatively similar small and medium-sized enterprises (SMEs) and firms in large projects, peer-reviewed publications increased significantly among funded compared to unfunded firms. For the young firm and large project qualitatively similar samples, granted patents increased significantly for funded firms compared to unfunded firms up to 4 years after funding. Moreover, for all three sample specifications, the proportion of cross-institutional publications increased significantly for funded firms compared to unfunded firms, when looking at a point 3 years after the start of funding. Taken together, our findings suggest that receiving the grant affects firms' innovative behavior differently depending on characteristics of the firm.

This work departs from prior works in a number of novel ways. It showcases a hybrid model that incorporates both academic engagement (Perkmann et al., 2013) and university entrepreneurship (Rothaermel et al., 2007) – academic–industry partnerships – and lends empirical evidence to the effect of governmental grants that foster these bridging partnerships on the resulting scientific and technological knowledge that is created. It takes a distinctive perspective from most works that study university technology transfer. Instead of focusing on academic scientists who cross institutional boundaries (Ding and Choi, 2011; Stuart and Ding, 2006), this work centers on the firm as the level of analysis and investigates the impact of academic–industry projects on firm innovative performance. Finally, given the nine-year window that we employ in our analysis (4 years before and 5 years after funding), we possess a rare longitudinal dataset that shows the dynamic and longer-term effects of the funding on firm innovative performance.

The structure of this work is as follows. We begin by presenting the theoretical framework from the literature. We then describe the setting from which we compiled our data, detail the estimation methodology employed to run our analyses, and interpret our results. Finally, in the discussion we elaborate on our quantitative results with interviews of project managers working in funded firms and explore potential factors that explain our findings. We also discuss the contributions this work brings to extant literatures and consider the implications for policymakers and managers.

2. Academic engagement, university entrepreneurship and government funding

Merton (1957) first pointed out the distinctive incentive systems between the institutions of science and technology. Science is primarily embodied in research universities where scientists are free to choose the direction of research, outputs are mainly encoded in the form of peer-reviewed publications, and the reward system is based on priority. Technology, in contrast, encodes ideas in protected modes, using patents, trademarks or copyrights to facilitate commercialization and appropriation of economic rewards (Dasgupta and David, 1994). The two institutions also differ in the nature of goals accepted as legitimate, as well as norms of behavior, especially with regard to the disclosure of knowledge. Science is concerned with additions to the stock of open knowledge, whereas technology is concerned with additions to the stream of rents that may be derived from possession of private knowledge. Though theoretically the two institutions are distinct, starting with the Bayh–Dole act of 1980 (Mowery et al., 2001) and analogous policies in Europe, the boundary between science and technology have become blurred as universities started to transfer technology by patenting their research and increasing their involvement with industry.

The literature that examines the relationship between science and technology has illustrated their interplay using two models. The first perspective depicts a linear model with science exogenous to technology, in which knowledge initiated from science spills over into technology thereby creating positive externalities for innovation and commercialization (Freeman, 1992; Mansfield, 1995). The second perspective suggests that there is a more complex bidirectional relationship rather than a pure linear model, where progress in science may be due in part to feedback from technology (Murray, 2002; Nelson, 1995). In other words, science is not viewed as a self-contained exogenous process but rather endogenous to technical progress and commercialization. However, as knowledge tends to be sticky (von Hippel, 1994), there are many challenges that prevent it from being diffused easily across institutional boundaries.

Practically, both institutions have used various means to enhance the transfer of knowledge and technology that they create as they co-evolve together. From the perspective of science-based firms, a number of mechanisms of how science influences technological progress and ultimately financial performance through knowledge spillovers have been identified. These include publishing in peer-reviewed journals (Henderson and Cockburn, 1994), coauthoring with academic scientists (Cockburn and Henderson, 1998; Liebeskind et al., 1996), movement of human capital through hiring of academic talent (Dasgupta and David, 1994), and geographically collocating close to academic organizations (Zucker et al., 1998). From the perspective of research universities, academic researchers engage in knowledge-related collaborations with firms (Perkmann et al., 2013) in the form of collaborations, contract research, or consulting, and as well as the founding of science-intensive firms (Murray, 2004; Stuart and Ding, 2006; Stuart et al., 2007). Universities actively foster commercialization (Rothaermel et al., 2007) through technology transfer offices that patent and license inventions from academic laboratories (Bercovitz and Feldman, 2006; Debackere and Veugelers, 2005), science parks to create clusters of expertise and incubators to nurture university spin-outs (Phan et al., 2005), and equity investment in start-ups (Feldman et al., 2002). Conceptually, academic engagement pursued for broader objectives, such as to assess resources and obtain learning opportunities (Lee, 2000), is seen as separate from and precedes university technology transfer (Perkmann et al., 2013), with the main goal of reaping financial reward from universities technologies.

The setting of this paper is a hybrid model of academic engagement and university entrepreneurship. The academic–industry partnerships under study entail collaborations between university scientists and industry researchers with the goal of developing technologies important to industry. These partnerships differ from the traditional model of separately generating basic scientific discoveries and translating them into technology to be developed into a commercializable product through mechanisms such as licensing or entrepreneurship. Instead of a sequential process, academic–industry partnerships create an environment where academic scientists and industry researchers work together concurrently to bridge from lab to product. While most of the literature that explores academic engagement and university entrepreneurship examines the implications of such activities on their productivity and direction of research at the individual scientist level (Azoulay et al., 2009; Larsen, 2011), far fewer works have taken the perspective of the firm, with the exception of studies that focus specifically on new entrepreneurial ventures.

Consistent with the Triple Helix model of university–industry–government relations (Etzkowitz and Leydesdorff, 2000), this work adds another constituent – government – to the model of academic–industry collaborations, since we assess the effect of government funding on participating firm's subsequent innovative performance. The rationale behind policies that fund and foster such academic–industry collaborations is to alleviate market failures found in traditional mechanisms for technology transfer (Bozeman, 2000). As knowledge is notoriously sticky (von Hippel, 1994), both firms and universities face many challenges that prevent knowledge from being transferred easily across boundaries (Bikard, 2014). For instance, generating the first point of contact and early interactions with academic researchers for the purpose of establishing a collaborative relationship can be difficult, and the movement of human capital is limited as scientists have strong preferences for academic freedom (Stern, 2004).

Moreover, funding for academic–industry collaborations not only relieves market failure in the technology transfer mechanism, but also addresses the difficulty firms face in appropriating returns from the basic science they undertake (Nelson, 1959). Firms have little incentive to undertake basic research because of the free rider problem, compounded by the difficulty in protecting resulting knowledge since natural laws and facts are not patentable. In addition, few firms are broad and diverse enough to directly benefit from all the new technological possibilities opened up by successful basic research. Thus, funding for academic–industry collaborations can alleviate the high uncertainties and risks associated with basic research that inhibit firms from pursuing it.

Within the well-delineated boundaries of science and technology, researchers have studied the design and effect of various funding vehicles on organizational performance and innovative output in the form of grants for academic research (Azoulay et al., 2011), early-stage funding such as angel investments (Kerr et al., 2011) and venture capital (Kortum and Lerner, 2000), and of more mature financing vehicles such as initial public offerings (Bernstein, 2015). They have found that funding relieves capital constraints thereby improving subsequent survival rate, employment, patenting, exit and financing, and also lessening agency problems between entrepreneurs and investors through monitoring and improved governance. The few studies that have investigated the effect of government funding of academic–industry partnerships found positive results as measured by patents, employment and gross profits (Kaiser and Kuhn, 2012), return on assets (Bayona-Sáez and García-Marco, 2010), labor productivity and price cost margins (Benfratello and Sembenelli, 2002). However, to the best of our knowledge no study has considered how academic–industry funding affect firms' subsequent overall innovative behavior measured not only through patents but also using peer-reviewed publications.

Many works in the literature have also studied the relationship between firm size and age and their innovativeness as measured by patent productivity and quality, but the empirical results remain ambiguous. For instance, bigger firms have shown to benefit from economies of scale and therefore tend to have more patented outputs (Scherer, 1965). However, others have argued for diseconomies of scale in innovation productivity, as there are more complex bureaucratic procedures to navigate in larger firms (Link and Rees, 1990). Moreover, the relationship between firm size and innovation productivity also depends on the nature of innovation undertaken, whether it is more process or product innovation (Cohen and Klepper, 1996). Our setting is different from these prior works, as it explores how funding for academic–industry partnership affect innovative performance depending on the participating firms' size. Given the limited range of funding provided in our setting, its impact is likely to be felt more noticeably in SMEs where the size of the academic–industry project is a substantial proportion of the firm's research and development (R&D) activities compared to larger companies.

Firm age has been shown to improve R&D efficiency as firms become more experienced in executing organizational routines (Sørensen and Stuart, 2000), but as firms age a mismatch forms between their existing R&D capabilities and environmental demands (Sørensen and Stuart, 2000) and R&D technical quality decreases (Balasubramanian and Lee, 2008). Thus, age of the firm may play a defining role in the amount and risk of innovation they undertake, as older firms are more likely to have developed entrenched routines and suffer from more organizational inertia. To our knowledge, no studies have explored the relationship between firm characteristics and the type of innovation activities that these firms pursue on the continuum from basic to more applied research.

Empirical evidence in the literature on collaborations shows a continuing and increasing trend for teams or multiple parties to contribute to the production of knowledge through paper and patent publications in all natural and social science domains (Wuchty et al., 2007). Teams are more productive as they benefit from multiple idea sources and permit the recombination of more diverse components, and foster emergence of breakthroughs, as circulating ideas for critique by collaborators decreases the likelihood of poorer outcomes (Singh and Fleming, 2010). However, even though teams bring greater collective knowledge and effort, there remain significant costs to increased teamwork, including coordination losses (McFadyen and Cannella, 2004) and groupthink (Janis, 1971). Yet in our setting, in instances where the application of the university technology being developed was not obvious from the onset, a greater number of parties may also translate into more successful commercialization as this increases the chances that a project technology finds a suitable application.

3. Methodology

3.1. The Danish National Advanced Technology Foundation

Our setting is the DNATF which was founded in 2005 by the Danish government, whose broad objective was to enhance growth by supporting strategic and advanced technological innovations from the basic sciences. DNATF provided funding for partmership collaborations that included at least one academic scientist and one firm in order to facilitate bridge-building between the academic research institutions and firms. The goal was generating new technologies and economic growth that would benefit society as a whole.[3] DNATF used a bottoms–up approach in the

[3] Funding for such collaborations, however, can also be obtained from other Danish governmental sources. The largest alternative state funding sources in Denmark are the Energy Technology Development and Demonstration Program (EUDP), Green Development and Demonstration Program (GDDP), The Danish Counsil for Strategic Research, the Business Innovation Fund, The Danish Counsil for Technology and Innovation, and finally, The Danish Public Welfare Technology Fund.

application process, in which it sought to fund ideas across a broad range of advanced technology relevant to industry. In our dataset of funded projects from inception until 2010, biomedical sciences made up approximately 24.7% of all investments, while 25.7% were in energy and the environment, 27.4% in information technology and communications, 12.6% in production, 3.7% in agricultural produce and food, and 5.3% in the construction sector. Applications were evaluated based on obvious (1) business potential, (2) internationally recognized high quality research and innovation, and (3) entrepreneurship.

Applications were screened in two stages by the board. The first stage began with the submission of a short expression of interest identifying core ideas of the proposal. These expressions were individually scored *A*, *B*, or *C* by each board member *a priori*. At the meeting, all scores were tallied at the beginning of the discussion prior to deciding whether to approve the proposal for a second round. About 30% of applications from the first round moved onto a second round in which applicants prepared a more comprehensive proposal. These were submitted to two independent peer reviewers. Using the peer review feedback, board members again scored each application with the same system. Based on aggregate scores and discussion, the board reached a consensus on whether to fund each application. About 40% of second round applicants ultimately received funding. No explicit funding rules or cutoff scores that might have led to systematic funding decisions were known in advance to applicants, and therefore they could not be gamed or manipulated. A fixed budget for each granting cycle was awarded until fully exhausted, eliminating the potential reverse causality issue of innovation driving funding.

By the end of 2012, DNATF's portfolio totaled a project budget of DKK 5320 M.[4] The public research institution(s) funded one sixth of the total budget, private firm(s) one third, and DNATF funded one half, in accordance with its co-funding model. The self-financing scheme ensured that all parties had something at stake. Neither participating firms nor academic institutions were required to pay back the awarded amount nor did they offer equity in return.

3.2. Datasets and variables

Data is in long panel form for each firm-year, 3 years prior t_{-3} to 5 years after t_5 the year of application. We empirically tested the hybrid nature of academic–industry collaborations by using peer-reviewed publications as a proxy for academic engagement, and by measuring commercialization using granted patents. We counted the number of peer-reviewed papers (*publications*) firms published for each year in our sample period, collected from the Web of Science by searching for affiliation by firm name. For commercialization, we used the number of granted patents (*patents granted*) assigned to the firm filed during each year of our sample period. A patent granted in November 2013 but filed in July 2009 would count as a granted patent in 2009. Data for the patent variable was collected by matching to patent assignees using Google Patents, including US and European patents.

Finally, to explore the co-evolutionary nature of science and technology and knowledge spillovers in academic–industry partnerships, we measured the cross-institutional co-authorship of peer-reviewed papers. We tabulated the proportion of publications firms published in collaboration with at least one academic co-author (*proportion cross-institutions*) for each year. We wanted to include a similar measure for patents, but affiliation data for inventors do not show the organization they work for so we were not able to make any rigorous inferences as to their professional affiliation.

A number of variables were also obtained from DNATF's database and integrated into the dataset. These consisted mainly of descriptive information on the specific project or application each firm has been part of, such as the final *score* given to each project in the selection process, the year of application used to derive the *post* indicator, and whether a project was *funded* or not. Variables such as industry sector, project duration and amount of funding were all included as *ex ante* observables in the analyses.

3.3. Identification strategy and empirical approach

Because randomization of the sample was not feasible, we took advantage of the two-stage selection process and further developed a qualitatively similar sample of firms that mitigated the endogeneity problem from the selection bias of funding healthier firms with higher success potential. The two-stage application process that projects underwent enabled us to eliminate those that failed to advance to the second stage and concentrate only on the ones that did. These projects were similar in quality and partially resolved the issue of selection bias. By the end of 2013, a total of 101 investments funded between 2005 and 2010 had been finalized. These invested projects corresponded to 153 participating companies, among which 27 were duplicates, i.e. companies who participated in the program more than once. For the matched control group, we used firms that applied for DNATF funding during the same period and were selected into the second round of review but did not ultimately receive funding. These totaled 206 companies including two that were duplicates. All firms in the control group were part of applications that would have been finalized by the end of 2013 or before.

3.3.1. Qualitatively similar sample

Despite dropping firms whose proposals did not advance to the second round of the application process, the sample may still suffer from selection bias and unobserved heterogeneity. To address this issue, we limited our sample specification to qualitatively similar firms except in their funding. We exploited scores given by board members in their assessment for each proposal as a quasi-ranking system, and dropped the best of the funded firms and the worst of the unfunded firms. Interviews with the staff revealed that an assessment of *A* for a project indicated that a board member believed that the project was highly worthy of support, *B* indicated worthy of support, whereas *C* was not worthy of support. We translated this evaluation into a normalized score as dictated by $\text{score}_i = [10 \times (\Sigma_k\, A - \Sigma_k\, C)]/\Sigma_k(A + B + C)$ for firm i, where *A*, *B* and *C* are binary variables equal to 1 based on the assessment of board member k. Moreover an *A* assessment is assigned a score of 10, *B* a score of 0 and *C* a score of −10.

Similar to the methodology used in Kerr et al. (2011), we defined tranches of normalized scores and identified the fraction of firms that were funded. In column 2 of Table 1, the fraction of funded

Table 1
DNATF funding selection by normalized score.

Normalized score	Funded (%)	Number of applications	Applications (%)	Cumulative applications (%)
[−10, −7.5)	0.00	4	1.11	1.11
[−7.5, −5)	8.70	23	6.41	7.52
[−5, −2.5)	0.00	23	6.41	13.93
[−2.5, 0)	19.05	42	11.70	25.63
[0, 2.5)	43.06	72	20.06	45.68
[2.5, 5)	54.84	62	17.27	62.95
[5, 7.5]	96.97	66	18.38	81.34
[7.5, 10]	100.00	67	18.66	100.00

[4] DKK5, 320 million is the equivalent of USD968 million at the July 2014 exchange rate of ∼5.5DKK/USD.

Table 2
Summary statistics.

Variable	N. Obs.	Mean	Std. Dev.	Min	Max
Funded	4224	0.56	0.50	0	1
Post	4224	0.49	0.50	0	1
Normalized score	4224	2.50	4.61	−10	10
Proposed duration	4224	3.31	0.80	1.5	5.5
Amount funded by DNATF (in millions DKK)	4042	14.6	11.1	2.55	75
Number of parties	4224	5.37	3.24	2	19
Number of employees	2180	524.08	1733.32	0	25,063
Age	4094	16.03	18.19	0	109
SME	4224	0.64	0.48	0	1
Publications	4224	1.85	7.08	0	65
Patents granted	4224	1.71	7.24	0	120
Cross-institutional publications	4224	1.32	5.19	0	48

firms increases mainly monotonically as the normalized score increases. At the lower end, only two applications with a normalized score of <−2.5 were funded, and were dropped from the sample. We also dropped firms with normalized scores above 7.5 as all of them were funded. In effect, we created a more comparable sample of funded firms by dropping the stronger funded and the weaker unfunded firms. Consequently, we defined our narrow band of qualitatively similar firms to be those with normalized score in the range [−2.5, 7.5].

3.3.2. Boundary conditions

Given the heterogeneity in the size and age of participating firms as well as the number of collaborators in a given project, we ran our analysis on various sample specifications along these dimensions in order to establish the boundary conditions of these academic–industry funding schemes.

Of the firms in our sample, 59% had 50 or fewer employees, 17% had 51–250, 12% had 251–1000, and 12% had more than 1000 employees. While most firms that participated were SMEs defined (consistent with the European Commission) as companies with 250 employees or less, some participants boasted headcounts in the thousands of employees. The sample of qualitatively similar SME firms amounted to 78 participating and 73 unfunded firms.

The age of firms in our sample also varied broadly with 31% having been founded for 5 years or less, 24% between 6 and 10 years, 14% between 11 and 20 years, 22% between 21 and 50 years, and 8% more than 50 years, while the oldest one – Danisco A/S – has more than 100 years of history. We defined a young firm as one having 10 years or less of history, and also used 15 years as a cutoff point in our robustness checks and found similar results. The sample of qualitatively similar young firms totaled 63 funded and 70 unfunded firms.

Finally, the number of parties in each project varied from 2 to 19. Considering the distribution of number of parties in DNATF projects – 12% of firms are in projects with just one other party, 40% of firms are in projects totalling three and four partners, 43% between 5 and 10 partners, and 5% in projects with more than 10 partners – we defined large projects as having 5 or more parties. The sample of qualitatively similar firms in large projects totaled 55 participating and 62 unfunded firms.

3.4. Regression model estimation

We employed a difference-in differences (DiD) model for our estimations, specified as follows: $Y_{i,s,t} = \alpha + \gamma\,\text{funded}_s + \lambda\,\text{post}_t + \beta_1(\text{funded}_s \times \text{post}_t \times t_1) + \beta_2(\text{funded}_s \times \text{post}_t \times t_2) + \beta_3(\text{funded}_s \times \text{post}_t \times t_3) + \beta_4(\text{funded}_s \times \text{post}_t \times t_4) + \beta_5(\text{funded}_s \times \text{post}_t \times t_5) + \delta X_{i,t_0} + \varepsilon_{i,s,t}$.

The outcome variable is $Y_{i,s,t}$ for firm i at time t in funded state s. Since we are assessing the effect of academic–industry partnership funding, the first difference is between funded and unfunded firms, and the second difference is between the pre- and post-funding periods. Thus *funded* is an indicator of whether a firm i has participated and received funding at time t_0, while post is an indicator of being after the funding event. The difference-in-differences is captured by the interaction effects of funded_s and post_t, and since we are interested in dynamic trends up to 5 years after funding, we also interacted the DiD with a time indicator t_1 to t_5 for each year. Thus coefficients β_1 to β_5 are our coefficients of interest that showcase the longitudinal dynamics of the findings.

Although our sample specification strategy mitigated selection, board discussions could still affect project selection conditional on scores where there may be other unobservable variables driving the result. In order to eliminate fixed unobservable effects and tease apart selection from treatment, we used firm fixed effect panel regressions to remove fixed unobservables at the firm level with the caveat that the γ-term for the *funded* indicator drops out since there is no within firm variation for the variable. For count variables – number of patents and papers – that are non-negative and over-dispersed, we used quasi-maximum likelihood Poisson models with cluster robust standard errors to address the assumption of equal mean and variance distribution for Poisson models and minimize estimation bias. For the proportion of cross-institutional coauthored papers variable, we used OLS models with cluster robust standard errors.

4. Results

This section shows our empirical evidence for the research question of how does academic–industry partnership funding affect firm innovative performance. Table 2 shows summary statistics including the mean, standard deviation, minimum and maximum for each variable used in the analysis.

At first glance, results in Table 3 that cover the full sample of qualitatively similar firms that attained the second round of funding does not show much effect overall, except for granted patents filed 1 year after being funded in Model 2. Considering that there is usually a lag between receiving funding and performing patentable R&D, we cannot definitively attribute this positive effect in the first year after funding to the program itself. These results are surprising from a resource usage perspective, as the entrepreneurial finance literature suggests that firms that received funding should be more productive. A potential explanation comes from the counterfactual sample we built which consists of firms that applied for funding and made it to the second round of selection but did not ultimately receive any. Firms in this sample had intentions of pursuing the project and may have done so nonetheless either with their own funds or perhaps from other sources. Therefore, our estimated effects are insignificant because we are comparing firms that received funding and undertook the projects with ones that had intentions and may have undertaken the project anyways, as opposed to those that did not have any intent at all. To obtain a

Table 3
DiD QML Poisson count and OLS regression models with firm fixed effects and robust standard errors for number of publications published and granted patents filed as well as proportion of cross-institutional publications up to 5 years after funding, run on the full sample of qualitatively similar firms.

QS full sample	Model 1	Model 2	Model 3
	QML Poisson		OLS
	Publications	Patents granted	Proportion of cross-inst pubs
	b (SE)	b (SE)	b (SE)
Post	0.0755	−1.039*	0.110+
	(0.245)	(0.422)	(0.0598)
Post × funded × t_1	0.184	1.019*	−0.0494
	(0.263)	(0.464)	(0.0705)
Post × funded × t_2	0.151	0.657	0.0243
	(0.263)	(0.511)	(0.0696)
Post × funded × t_3	0.274	0.233	0.110
	(0.267)	(0.537)	(0.0741)
Post × funded × t_4	0.257	−0.183	0.152+
	(0.259)	(0.504)	(0.0771)
Post × funded × t_5	0.300	−0.752	0.106
	(0.274)	(0.501)	(0.0824)
Constant			0.283**
			(0.0131)
Firm fixed effects	Yes	Yes	Yes
N	966	843	966
R-squared			0.082
Log likelihood	−1209.6	−1543.7	

\+ $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.

Table 4
DiD QML Poisson count and OLS regression models with firm fixed effects and robust standard errors for number of publications published and granted patents filed as well as proportion of cross-institutional publications up to 5 years after funding, run on the qualitatively similar sample of SME firms with 250 employees or less.

QS SMEs	Model 1	Model 2	Model 3
	QML Poisson		OLS
	Publications	Patents granted	Proportion of cross-inst pubs
	b (SE)	b (SE)	b (SE)
Post	−0.129	−0.692**	0.111
	(0.252)	(0.114)	(0.0724)
Post × funded × t_1	0.802*	0.995**	−0.0452
	(0.358)	(0.355)	(0.0954)
Post × funded × t_2	0.901**	0.484	0.0765
	(0.303)	(0.371)	(0.0923)
Post × funded × t_3	1.159**	0.484	0.125
	(0.303)	(0.399)	(0.0959)
Post × funded × t_4	1.150**	0.112	0.246*
	(0.356)	(0.471)	(0.107)
Post × funded × t_5	1.320**	−0.511	0.226+
	(0.389)	(0.665)	(0.117)
Constant			0.228**
			(0.0187)
Firm fixed effects	Yes	Yes	Yes
N	541	443	541
R-squared			0.105
Log likelihood	−627.5	−387.5	

\+ $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.

more nuanced impact of the academic–industry funding program, we took different cuts of the sample and obtained findings that not only demonstrate that the effect of the funding is different for various types of firms but also enable us to better inform policy.

4.1. Qualitatively similar small and medium enterprises

For the sample of qualitatively similar SMEs, we find significant, strong and increasing effects on academic engagement of collaborations as measured by the number of peer-reviewed publications. Model 1 in Table 4 shows that participating firms publish 2.23 ($e^{0.802}$) times more publications compared to unfunded firms starting the first year after funding, and these effects steadily increase to 3.74 times ($e^{1.320}$) times more 5 years after the funding event. The first graph in Fig. 1 depicts the average number of firm publications by year, and corroborates our econometric findings in Model 1. Moreover, focusing on the period prior to funding to the left of the vertical time axis we find no discernible trend difference between the two groups thus assuring the causal effect of funding on publications. However, the effects on commercialization using the number of granted patents as a proxy is only significant the first year after funding, where participating firms were granted 2.70 ($e^{0.995}$) times more patents than unfunded ones when filed in the first year after applying for funding, as shown in Model 2. Again given the time it takes to develop a patentable technology, this positive effect in the first year after funding cannot be attributed to the program itself. Finally, we find that co-evolution between science and technology as measured by the proportion of cross-institutional publications increase significantly in the last 2 years of our sample. 4 and 5 years after funding in Model 3, the proportion of publications that funded firms coauthor with academics are 24.6% and 22.6%, respectively more than unfunded firms.

Overall, the evidence suggests that the effect of academic–industry partnership funding on participating SMEs' publications is particularly strong and progressively increases throughout the 5 years period after funding during which we track them. Moreover, the longer firms participate in these academic–industry partnerships the more they coauthor with academics.

4.2. Qualitatively similar young firms

For firms 10 years old or younger that are qualitatively similar, we find more significant and stronger effects for granted patents than publications. Model 1 in Table 5 shows that participating firms publish 49.0% ($e^{0.399}-1$) more publications compared to unfunded firms 5 years after funding, but this result is only weakly significant. Conversely, the effects on commercialization using number of granted patents filed, as a proxy is significant for the first 3 years after funding. Participating firms were granted 3.00 ($e^{1.097}$) and 2.00 ($e^{0.695}$) times more patents than unfunded firms 2 and 3 years after applying for funding as shown in Model 2. This positive effect can be more comfortably attributed to the program itself, especially for filings in years 2 and 3 after funding. Finally, similar to SMEs, we find that the proportion of cross-institutional publications increase significantly in the last 2 years of our sample. 4 and 5 years after funding, the proportion of publications that funded firms coauthor with academics is 27.4% and 22.1%, respectively more than unfunded firms, as shown in Model 3. Fig. 2 graphically depicts these regression results, where pre-participation time trends are similar for both groups ruling out potential continuation of prior tendencies.

In sum, the evidence for young firms suggests strong impact of academic–industry partnership funding on participating firms' granted patents filed up to 3 years after funding. Moreover, the longer firms participate in these partnerships the more they coauthor with academics.

4.3. Qualitatively similar firms in large projects

For the sample of qualitatively similar firms that participated in projects totaling five partners or more, we found very strong

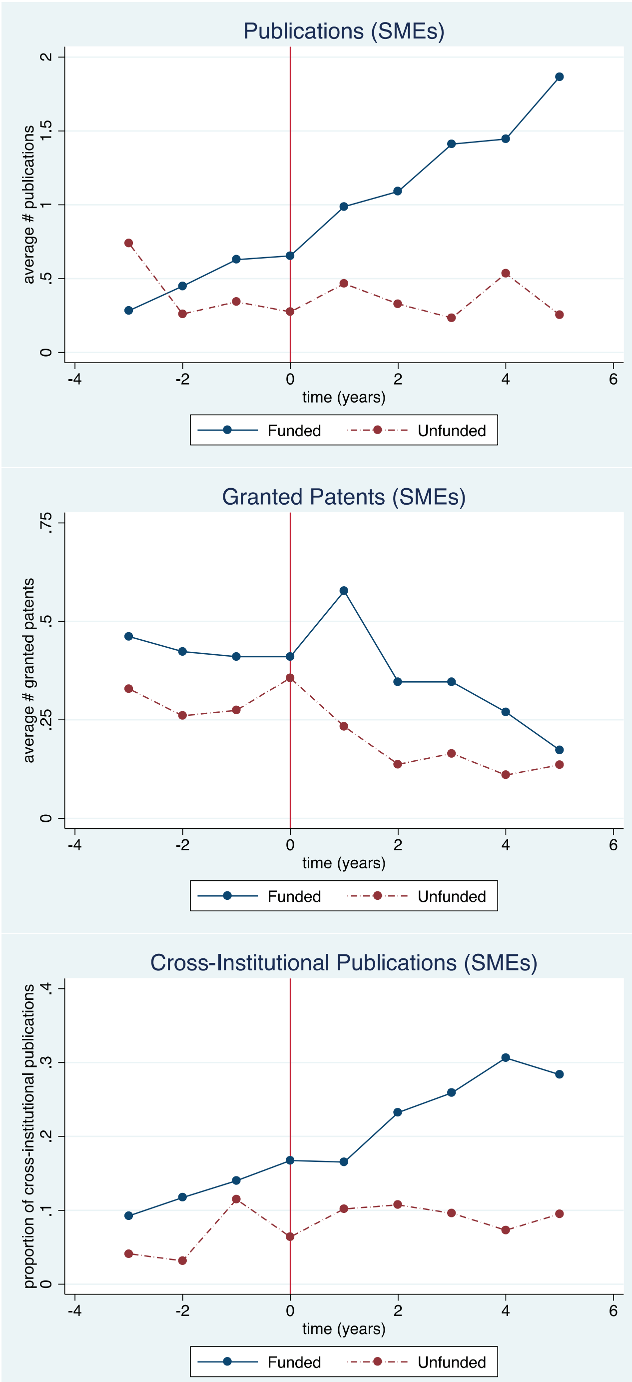

Fig. 1. Mean number of publications, granted patents and proportions of cross-institutional publications for both funded and unfunded firms each year before and after funding at t_0 using the qualitatively similar sample of SME firms with 250 employees or less.

and significant effects on publication output as well as granted patents. Participating firms' number of publications after funding increase relatively uniformly compared to unfunded firms in each of the 5 years after funding, ranging between 1.85 ($e^{0.617}$) and 2.36 ($e^{0.860}$) times more, as shown in Model 1 Table 6. The effects of academic–industry funding on the number of granted patents is very strong and significant up to 4 years after funding. Granted patents for participating firms peak when filed 2 years after funding. They were granted 6.19 ($e^{1.823}$) times more patents than unfunded ones, and even at the lowest impact when patents are filed 4 years after funding, participating firms were granted 3.05 ($e^{1.115}$) times more patents than unfunded firms as shown in Model 2. Lastly in Model 3, we find that the co-evolutionary nature between science and technology increases significantly 3 and 4 years after funding, where the proportion of publications that

Table 5
DiD QML Poisson count and OLS regression models with firm fixed effects and robust standard errors for number of publications published and granted patents filed as well as proportion of cross-institutional publications up to 5 years after funding, run on the qualitatively similar sample of young firms having been founded for 10 years or less.

QS young firms	Model 1	Model 2	Model 3
	QML Poisson		OLS
	Publications	Patents granted	Proportion of cross-inst pubs
	b (SE)	b (SE)	b (SE)
Post	0.130	−0.775**	0.0674
	(0.157)	(0.102)	(0.0812)
Post × funded × t_1	0.225	1.215**	−0.0157
	(0.199)	(0.212)	(0.0947)
Post × funded × t_2	0.120	1.097**	0.138
	(0.197)	(0.295)	(0.101)
Post × funded × t_3	0.285	0.695^{+}	0.163
	(0.216)	(0.366)	(0.105)
Post × funded × t_4	0.262	0.0330	0.274*
	(0.193)	(0.317)	(0.114)
Post × funded × t_5	0.399^{+}	−0.697	0.221^{+}
	(0.222)	(0.427)	(0.120)
Constant			0.263**
			(0.0203)
Firm fixed effects	Yes	Yes	Yes
N	508	410	508
R-squared			0.096
Log likelihood	−633.1	−523.7	

$^{+}$ $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.

Table 6
DiD QML Poisson count and OLS regression models with firm fixed effects and robust standard errors for number of publications published and granted patents filed as well as proportion of cross-institutional publications up to 5 years after funding, run on the qualitatively similar sample of firms that participated in a project with five collaborating parties and more.

QS firms in	Model 1	Model 2	Model 3
large projects	QML Poisson		OLS
	Publications	Patents granted	Proportion of cross-inst pubs
	b (SE)	b (SE)	b (SE)
Post	−0.503*	−1.559**	0.0225
	(0.247)	(0.355)	(0.0839)
Post × funded × t_1	0.617*	1.396**	0.0222
	(0.290)	(0.492)	(0.116)
Post × funded × t_2	0.860*	1.823**	0.0447
	(0.380)	(0.428)	(0.104)
Post × funded × t_3	0.844*	1.578**	0.244*
	(0.334)	(0.442)	(0.118)
Post × funded × t_4	0.737*	1.115*	0.301*
	(0.298)	(0.446)	(0.123)
Post × funded × t_5	0.784*	0.201	0.130
	(0.319)	(0.508)	(0.129)
Constant			0.215**
			(0.0235)
Firm fixed effects	Yes	Yes	Yes
N	362	254	362
R-squared			0.085
Log likelihood	−374.1	−345.8	

* $p < 0.05$.
** $p < 0.01$.

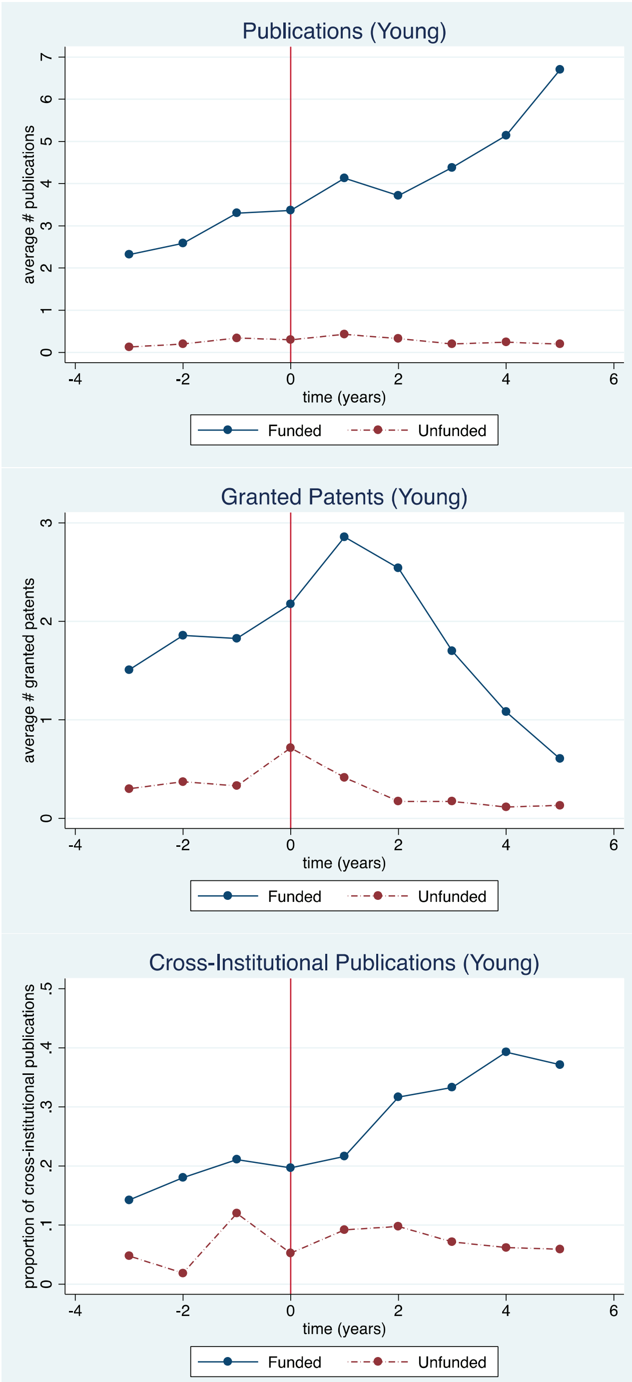

Fig. 2. Mean number of publications, granted patents and proportions of cross-institutional publications for both funded and unfunded firms each year before and after funding at t_0 using the qualitatively similar sample of young firms having been founded for 10 years or less.

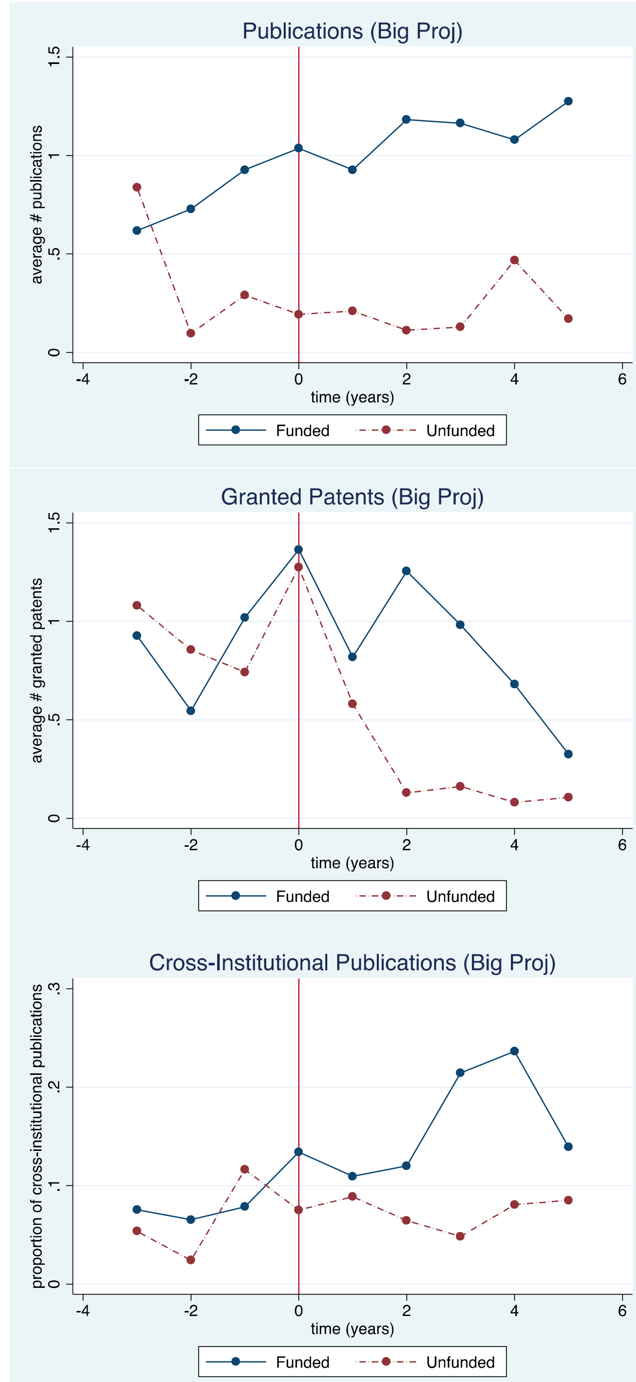

Fig. 3. Mean number of publications, granted patents and proportions of cross-institutional publications for both funded and unfunded firms each year before and after funding at t_0 using the qualitatively similar sample of firms that participated in a project with five collaborating parties and more.

funded firms coauthor with academics is 24.4% and 30.1% respectively more than unfunded firms. Fig. 3 graphically depicts these regression results.

Overall, the findings for firms that participate in larger projects indicate that academic–industry partnership funding's impact on participating firms' publications and granted patents are both strong throughout the years after funding. Once again, the longer firms participate in these partnerships the more they coauthor with academics.

4.4. Robustness checks

As robustness checks, we ran the same set of regressions using data up to 5 prior years to the funding event, and found no significant differences in the results. Finally, using random effects panel regressions and controlling for reviewer score, amount funded for the project, as well as application year and industry dummy fixed effects, we find reassuringly similar results. We are also able to obtain coefficient estimates for all DiD interaction β-terms and main effect terms on funded (γ) and post (λ) dummies using this specification. In the interest of conciseness, results are not shown herein but can be obtained from the corresponding author.

5. Discussion and conclusion

5.1. Empirical contributions to literature

This work provides empirical evidence on the effect of a funding program targeting academic–industry partnerships on firm innovative performance. To our surprise, we found no significant positive effect of funding on the full sample of qualitatively similar firms, especially for patents, as Kaiser and Kuhn (2012) documented an increase in filed patents in a similar program. We posit that the discrepancy in findings may be due to differences in how patents are measured as well as the counterfactual sample of comparison. In our design, we used patents filed up to 5 years after funding grants, whereas Kaiser and Kuhn use applications of patents that may or may not have been issued. Unless all filed patents are granted (which is relatively uncommon), firm's filed patents will be greater than granted patents. Moreover, we used in our counterfactual sample firms that were denied funding but still submitted a comprehensive proposal, whereas Kaiser and Kuhn employed a matched nearest neighbor sample of firms similar to funded ones based on observables. Our points of comparison are different, since we compare our funded firms to firms that already had the intention of pursuing the proposed project, while Kaiser and Kuhn compare their funded firms that may or may not have had the intention to pursue an R&D project.

For the samples of qualitatively similar SMEs, publications increased significantly and steadily for funded firms more than unfunded firms in all 5 years after funding while the impact on granted patents was not sustained. Referring back to our model of academic–industry partnerships as hybrid between academic engagement and commercialization, SMEs saw a heightened impact for academic engagement as measured by number of publications. The uptick in publications for SMEs, which is an unusual outlet for the encoding of firm knowledge, could be because organizational routines are easier to break in smaller firms than bigger ones. It could also indicate that SMEs take longer (outside of our span of analysis) to find commercializable consequences. The increase in granted patents for younger firms demonstrates that participation in academic–industry partnerships is more geared toward commercialization activities rather than academic engagement, and they may be more preoccupied with achieving or sustaining a profit, as this can take start-ups several years. These divergent findings for SMEs and younger firms may also suggest that government R&D funding is used for different purposes. SMEs participate in academic–industry partnerships with the goal of broadening their knowledge base by collaborating with academic experts, while young firms are more focused on directly commercializable outputs due to more imminent financial pressures. Future research could better understand the various motivations that bring different types of firms in engaging with such partnership funding.

Taken together, the null results of the full sample and positive results on publications for SMEs and early patenting for young firms also add to the debate on the additionality of R&D funding by governments (David et al., 2000). On the one hand, some works in the literature argue that public R&D funding is a complement and may stimulate private R&D investments (Aerts and Schmidt, 2008; Gonzalez and Pazo, 2008). While on the other hand, other works have also found evidence that public R&D funding is a substitute to private R&D funding and crowds it out (Busom, 2000; Lach, 2002; Wallsten, 2000). Our findings suggest that whether public R&D subsidies act as complement or substitute to private R&D is conditional on characteristics of the firm: when public R&D funding is provided to larger and older firms it crowds out their private R&D spent, whereas when SMEs and younger firms receive public R&D support the impact is additive.

For firms that participate in academic–industry collaborations with more partners, the consistent and large significant increase in both publications and patents in all 4 years after funding is an indication that more firms on a project not only increase the production of more basic knowledge as encoded in publications, but it also improve the chances of these project technologies of finding and being developed into suitable commercializable outlets.

Cross-institutional publications starting at 3 years after funding increased significantly for funded firms compared to unfunded firms for all three sample specifications. In these partnerships, industry researchers work hand-in-hand with academic scientists, thereby facilitating knowledge spillovers from science to technology. Partners are no longer ingrained within their own institutional logics where traditional approaches and norms prevail, as they participate in a setup designed to break through established boundaries. Interviews with a small set of participating firms ($n = 10$) corroborate these results and reveal that as firms do more basic research, collaborations between academic and industrial partners goes beyond the level of sharing equipment and extends importantly to the exchange of ideas.

Taken together, our results lead us to believe that academic–industry grants do fit the proposed hybrid model of concurrent academic engagement and commercialization, where participating firms do not always increase their traditional innovative productivity as measured by the generation of patents, but also steer the direction of their innovative outputs toward more basic research as demonstrated by our findings with publication data and the proportion of academic coauthoring of publications. Thus, participation in these partnerships has major effects on bridging science and technology and directing the focus of innovative output from more basic research. In the longer term, changes in research direction suggests that government support for academic–industry partnerships enables firms to invest more into risky and basic innovative activities, increasing their stock of knowledge (as encoded in publications) than they otherwise would have. Capabilities gained through basic research can in turn help firms make more effective decisions about applied research activities. Thus, we contribute to the knowledge spillover and industry–science relationships literatures by providing empirical evidence of an under-investigated area – a hybrid model of academic engagement and university commercialization.

5.2. Implications for practitioners and policymakers

The academic–industry partnership structure that we studied in this paper creates the potential for a different, hybrid model for bridging between the realms of science and technology. It moves away from the conventional model of separately generating basic scientific discoveries and translating them into commercialized technology through mechanisms such as licensing, startups, or dedicated gatekeepers that straddle both institutions. Instead of the unidirectional push of technologies into industry or having single actors transfer knowledge back and forth between the independent silos of science and technology, deliberate steps taken to break down the boundaries between the two institutions enable teams of individuals from both sides to work alongside one another. Our results suggest that governments can therefore motivate firms to undertake research that is more basic in nature yet still retain broad applicability – as evidenced by increased publications and cross-institutional collaborations that we found in this study. This is potentially highly significant, as it suggests laying the groundwork for early commercialization farther forward in the innovation pipeline.

These findings are also relevant for managers who do not necessarily rely on government funding to support advanced research. By initiating collaborations with academic scientists, and recognizing and then actively managing the institutional boundary and organizational impediments, they can improve the translation of novel technologies from more basic research and thereby broaden their organization's innovative focus. Moreover, when choosing how many collaborators to work with on a project, managers should err toward larger projects as these were found to have higher effect sizes on both patents and publications.

5.3. Limitations and future research area

Despite our careful analysis and resulting outcomes, this work still suffers from several limitations and weaknesses. Thus, the interpretation of our results should be made with care. Since we have studied one specific funding and management scheme, the generalizability of our results may have limitations. However, as we have not concentrated on the intricacies and idiosyncrasies specific to our setting, and instead attempted to explore at a higher level the effect of participation, we strongly believe that the implications of our results can be interpreted more broadly. Moreover, by exploring outcomes on samples of participating firms with different characteristics the policy implications of this work is more targeted.

Even though we were very careful in our empirical design to address endogeneity concerns, there may still be subtle selection issues. We do not know whether funded firms received other funding grants besides those from DNATF. If they did, our findings would be overestimated. However, given that we observe no significant increase for the full sample of qualitatively similar participating firms, we are less worried about this alternative explanation. We also do not have information on whether unfunded firms undertook their proposed projects, but if they did, our results would be underestimated and conservative as the counterfactual outcomes currently include the impact of these projects. Together, the underestimation from unfunded firms undertaking the project irrespective of funding and the overestimation from funded firms obtaining other grants likely should have a canceling effect.

We are unable to address an important question for practitioners: how partnerships in which team members come from very different institutional roots can be effectively managed. In effect, we explore the relationship between input – participation and funding, and output – firm innovative performance – without delving inside what remains a black box. Preliminary qualitative interviews ($n = 10$) with project managers of these academic–industry partnership projects indicate that some big challenges they faced were getting individuals from different institutions to align their goals, understand each other and collaborate effectively. This is consistent with guidance on managing across organizational and cultural boundaries.

From a policy standpoint, this work did not emphasize nor tease apart the effect of funding and participating from the active mediated model specific to DNATF since our sample of firms does not provide us with any source of variation on this intervention dimension. The mediation model implies active follow-up on each project where a DNATF staff member is assigned and acts as the single point of contact throughout the funded project's lifetime. In effect, the model is a combination of the governance usually associated with private equity and venture capital with the funding style associated with pure government grants. Compared to more conventional grant funding schemes where funded projects are left on their own to meet pre-established deliverable deadlines, DNATF stays much closer to each project, frequently intervening in and mediating conflicts that arise among funded parties. If the proactive identification of obstacles and active management across institutional boundaries yielded long-term benefits in fostering the desired spillovers, governments can use such an approach to facilitate the unlocking of knowledge created in academia, leading to faster and more effective commercialization as a way to help companies maintain competitiveness.

Despite these limitations and weaknesses, we have exposed several interesting future research topics. From a managerial perspective, understanding the challenges of managing conflict inside partnerships that are "virtual companies" with multiple cross-institutional stakeholders is vital. Research can explore how such projects can be effectively managed and what factors make them more successful. For policymakers designing effective funding programs, understanding DNATF's mediated intervention model can offer powerful insights into cross-discipline and cross-boundary project management. Finally, from the perspective of the literature on the micro-foundations of innovation we can study academic scientists – the other major stakeholder in these academic–industry partnerships. Understanding the effect of such partnerships from the perspective of an individual scientist's productivity and subsequent impact is also interesting and important. This would provide a complete picture of the impact of such bridging programs and whether similar effects will be seen or whether they generate distractions and end up diverting basic science research to more commercializable areas of focus.

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