From Bench to Product: Bridging Science and Technology through Academic-Industry Partnerships

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ABSTRACT

Scientific research and its translation into commercialized technology is a driver of wealth creation and economic growth. Partnerships to foster such translational processes between public research organizations, such as universities and hospitals, and private firms are a policy tool that has attracted increased interest. Yet questions about the efficacy and the efficiency with which funds are used are subject to frequent debate. This paper examines empirical data from the Danish National Advanced Technology Foundation (DNATF), an agency that funds partnerships between universities and private companies to develop technologies important to Danish industry. We assess the effect of a unique mediated funding scheme that combines project grants with active facilitation and conflict management on innovative performance, namely the quantity, citation count and collaborative nature of patents and papers, by comparing funded and unfunded firms. Because randomization of the sample was not feasible, we address endogeneity around selection bias using a sample of qualitatively similar firms based on a funding decision score. This allows us to observe the local effect of samples in which we drop the best recipients and the worst non-recipients.

Keywords: Economic Development, Technological Change and Growth -> Technological Change; Research and Development -> Government Policy

INTRODUCTION

Continued interest in understanding how ideas are produced and the means by which they are diffused is driven by the belief that technological inventions, which are grounded in basic scientific research for science-based industries, spur wealth creation and stimulate economic growth. The literature has identified three prevalent means of knowledge spillover from science that influences a firm's technological progress: publication in peer-reviewed journals and co-authorship with basic science researchers in other organizations such as universities (Cockburn & Henderson, 1998; Liebeskind, Oliver, Zucker, & Brewer, 1996), movement of human capital between academia and industry (Dasgupta & David, 1994), and geographically localized knowledge spillover (Zucker, Darby, & Brewer, 1998). In light of these results, many national governments have created, and increasingly invested in, funding programs and agencies that combine these mechanisms to accelerate and foster bridging between science and technology. Academic-industry partnerships are one such vehicle that target translational research and knowledge spillover between science and technology.

Examples of such funding schemes abound. In the United States, National Science Foundation (NSF) shared resources centers often require some form of partnership with private firms to accelerate product development, while the National Institutes of Health (NIH) academic-industry partnership program seeks to identify the most compelling cross-boundary opportunities that would link biomedical research with commercial opportunities. In Germany, the Fraunhofer-Gessellschaft is a partially state-supported application-oriented research organization that undertakes applied research of direct utility to private and public enterprises. The Technology Strategy Board in the United Kingdom supports a range of research collaborations and runs programs such as its Knowledge Transfer Partnerships, which support UK businesses wanting to improve their competitiveness and performance by accessing the knowledge and expertise available within UK universities and colleges. Though there are many such programs globally, little research has been performed to assess the impact of their intended purpose especially from the perspective of the firms that participate in them.

We examine academic-industry partnerships sponsored by the Danish National Advanced Technology Foundation (Højteknologifonden), a funding agency of the Danish government. In its unique mediated funding model, DNATF awards grants for projects that partner at least one academic institution and one firm. DNATF differs from traditional funding sources with its active follow up model, as well as what it calls a "1-2-3" funding structure that requires applicants to self-fund part of the project – academic partners provide one sixth of the budgeted amount, industry partners one third, while DNATF provides the remaining half. DNATF kindly provided a novel dataset for this study that enabled us to determine the efficacy of their academic-industry partnership model in terms of the quantity, citation count and collaborative nature of innovative outputs of participating firms. Specifically, we assess how collaborating with academic research institutions and receiving funding for such collaborations is effective in helping firms partake in explorative innovative activities translated from basic research. We contrast a sample of participating funded firms with those that applied for DNATF funding but did not ultimately receive a grant. Since all proposal applications to DNATF are ranked, we develop several sample specifications to ensure that the analysis does not suffer from selection bias by including qualitatively similar funded firms that participated and unfunded ones.

Our results show a consistent positive effect on filed and granted patent outputs for funded firms that participated in these academic-industry collaborations with subsamples of qualitatively similar small and medium enterprises and younger firms. For peer-reviewed publications, we find surprisingly no significant effect of funding and participation on neither the quantity of publications nor the quantity of co-authorship across institutions, although we do observe a significant uptick in forward citations. These results demonstrate that participation in academic-industry partnerships fosters knowledge spillovers from science to technology as measured by patents. The receipt of funds for these collaborations provides firms with more capital for research and development, while the "1-2-3" funding structure also induces funded firms to spend more of their own money on innovative activities. The significant increase in peer-reviewed publication forward citations also shows that basic research firms undertake is diffused more effectively.

This paper bridges the literature that explores the relationship between science and technology and that on innovation funding by lending empirical evidence on the effect of academic-industry partnership grants on spillover and the resulting knowledge created. It contributes to the knowledge spillover literature by assessing the effect on participating firms of a policy tool designed to foster bridging between science and technology. It takes a distinctive perspective from works that investigates the effect of academic scientists crossing scientific boundaries. Instead of focusing on participating scientists, this work centers on the firm as the level of analysis and investigates the impact of academic-industry projects on firm behavior and innovative performance. It also differs from studies in the entrepreneurial finance literature in that instead of focusing on more traditional sources of funding such as venture capital, debt, initial public offerings, or basic research grants, it investigates a setting that blurs the institutional boundaries between science and technology.

The structure of this work is as follows. We begin by presenting the theoretical framework from the literature and develop testable hypotheses. 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 several 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 the extant literatures and consider the implications for policymakers and managers.

THEORETICAL FRAMEWORK AND HYPOTHESES

Since Merton (1957), science has been seen as a different institution with a distinctive incentive system compared to technology. The scientific institution is primarily embodied in research universities where outputs are mainly in the form of peer-reviewed publications and the reward system is based on priority. The technology institution, in contrast, encodes ideas in protected modes, using patents, trademarks or copyrights, to facilitate commercialization and appropriation of economic rewards (Dasgupta & David, 1994). The two institutions also differ in the nature of goals accepted as legitimate and norms of behavior, especially with regard to the disclosure of knowledge. Science is concerned with additions to the stock of public knowledge, whereas technology is concerned with additions to the stream of rents that may be derived from possession of private knowledge. Within the well-delineated boundaries of science and technology, many studies have looked at the design and effect of various funding vehicles on organizational performance and innovative output in the form of grants for academic research (Azoulay, Graff Zivin, & Manso, 2011), early-stage funding such as angel investments (Kerr, Lerner, & Schoar, 2011) and venture capital (Kortum & Lerner, 2000), and of more mature financing outlets such as initial public offerings (Bernstein, 2012). They have found that funding relieves capital constraints thereby improving subsequent survival, exit, employment, patenting and financing, and also alleviates agency problems between entrepreneurs and investors through monitoring and improved governance.

The literature that studies the relationship between science and technology has illustrated their interplay using two models. The first perspective sees science exogenous to technology as depicted by a linear model, in which knowledge initiated from science spills over seamlessly into technology thereby creating positive externalities for innovation (Freeman, 1992; Mansfield, 1995). The second viewpoint, however, suggests that there is a more complex bidirectional relationship than the 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. However, as knowledge tends to be trapped in the ivory tower, there are many challenges that prevent it from being diffused easily across boundaries. Thus many papers have focused on pinpointing factors that enhance the spillover of knowledge created in one institution to the other as they co-evolve together. From the perspective of the academic scientist, one stream has investigated the roles that scientists take on crossing institutional boundaries (Murray, 2004) and the effect of such behavior on their research (Azoulay, Ding, & Stuart, 2009). From the perspective of science-based firms, various mechanisms of how science influences technological progress have been identified, such as publication in peer-reviewed journals (Henderson & Cockburn, 1994) and co-authorship with academic scientists (Cockburn & Henderson, 1998; Liebeskind et al., 1996), movement of human capital (Dasgupta & David, 1994), and geographic colocation (Zucker et al., 1998).

The setting of this paper is in line with the endogeneous perspective that science and technology co-evolve. Academic-industry partnerships are a different structure from the traditional model of separately funding for basic research and product development while scientific discoveries are translated into technology and commercialization through mechanisms such as licensing and entrepreneurship. Instead of such a sequential process, academic-industry partnerships create an environment where academic scientists and industry researchers work together concurrently to bridge from lab to practice.

Academic-industry partnerships offer firms a close relationship with academic researchers where they can reap first-hand benefits from knowledge spillovers (Henderson & Cockburn, 1994). Funding for these partnerships also alleviates capital constraints (Admati & Pfleiderer, 1994). Therefore, we posit that firms participating in academic-industry partnerships and successful in obtaining funding for such collaborations take on translational R&D projects with knowledge spillovers from the academic lab bench into applied inventions. They are therefore more likely to have resulting inventions encoded in patents.

Hypothesis 1: Firms that receive and participate in funded, mediated academic-industry partnerships produce more patents relative to non-funded firms

Firms have little incentive to undertake basic research because of the difficulty in protecting and patenting resulting knowledge since natural laws and facts are not patentable, and because very few firms are broad and diverse enough to directly benefit from all the new technological possibilities opened up by successful basic research. Moreover, they are also confronted with the free rider problem (Nelson, 1959). Thus, the high uncertainties and risks associated with basic research combined with difficult appropriability diminish incentives for firms to pursue basic research and may prompt those with limited funding to completely avoid it. With the support of governmental funding for academic-industry partnerships, we postulate that it provides firms with the motivation and the risk mitigation mechanism to assume more basic research, as encoded in peer-reviewed publications that they otherwise would not have undertaken. Thus, firms with basic research capabilities can make more effective decisions about applied activities, build the capability to monitor and evaluate research being conducted elsewhere such as in universities, and evaluate the outcome of applied research to recognize possible implications (Rosenberg, 1990).

Moreover, given the cross-institutional nature of academic-industry partnerships where academic scientists and firm researchers collaborate and work together on the funded project, we posit that the spillover effects from participating in such projects alter firms' behavior and stimulate them in partaking in basic research activities more deeply rooted within basic science (Liebeskind et al., 1996).

Hypothesis 2: Firms that receive and participate in funded, mediated academic-industry partnerships produce more peer-reviewed publications compared to non-funded firms

Firms must do more than simply hire the best scientists and invest in in-house basic research with appropriate pro-publication incentive systems in order to take advantage of public sector research (Cockburn & Henderson, 1998). Industry researchers must also actively collaborate with their academic colleagues, which improve access to public sector research and quality of research conducted within the firm (Cockburn & Henderson, 1998; Liebeskind et al., 1996). Thus we postulate that given the close interactions between scientists and technologists when working on academic-industry partnership projects, collaboration and co-authoring across institutions increase.

Hypothesis 3: Firms that receive and participate in funded, mediated academic-industry partnerships produce more cross-institutional collaborative outputs relative to non-funded firms

Finally as suggested by the above hypotheses, firms participating in funded academic-industry collaborations benefit from increased knowledge spillovers. These spillover effects are not only manifested in the number of patents, publications and cross-institutional co-authoring of participating firms, but also in how basic science performed by participating funded firms are subsequently used by follow-on research. Therefore, we postulate that their publications will receive more forward citations.

Hypothesis 4: Firms that receive and participate in funded, mediated academic-industry partnerships produce more frequently cited peer-reviewed publications relative to non-funded firms

METHODOLOGY

Setting

Our setting is the Danish National Advanced Technology Foundation (DNATF) founded in 2005 by the Danish government, whose broad objective was to enhance growth and strengthen employment by supporting strategic and advanced technological priorities. It was created with the aim of making Denmark one of the world's leading advanced-technological societies. DNATF provides governmental funding for academic-industry collaborations, facilitating bridge building between Danish public research institutions and companies to generate new technologies and economic growth that benefit Danish society as a whole.

DNATF is the only Danish governmental funding source that exclusively supports academic-industry research partnerships. Funding for such collaborations, however, can also be obtained from other Danish governmental sources.[1] DNATF uses a bottoms-up approach in the application process, where it seeks to fund the best ideas within the broad realm of relevant advanced technology. The investment portfolio covers sectors ranging from robotics, agriculture, livestock, biotechnology and medicine, to telecommunications and production technology. Considering all funded projects from DNATF's inception to 2011, the largest sector in DNATF's portfolio is biomedical sciences, making up 30 percent of all investments, while 26 percent are in energy and environment, 20 percent in IT and communication, 14 percent in production, 5 percent in agricultural produce and food, and 5 percent in the construction sector. Applications must include at least one academic scientist and one firm. DNATF screens applications based on three criteria: obvious business potential, internationally recognized high quality research and innovation, and entreneurship. Applications are screened in two stages by the board of DNATF, which consists of nine leaders from Danish industry and science who have extensive and unique knowledge in their respective fields.

The first application stage is the submission of a short expression of interest which identifies the core idea of the proposed project. Each expression of interest is read and scored A, B, or C by each board member before a board meeting. Individual board members form their own opinion *a priori*. At the meeting, the aggregate scores generated by board members are tallied at the beginning of the discussion prior to deciding whether to approve the individual expressions of interest for a second round. About 30 percent of the first round applications are approved and move into a second round, in which applicants prepare a more comprehensive

[1] The largest alternative state funding sources in Denmark are the Energy Technology Development and Demonstration Programme (EUDP), Green Development and Demonstration Programme (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.

proposal that explains the project idea in detail. These applications are then subjected to a peer review process by two independent reviewers, and armed with these peer reviews DNATF's board members again score each application with a score of A, B or C. Based on the aggregate scores and discussion, the board reaches a consensus on whether to fund each application. From the applications that proceed to the second stage, about 40 percent ultimately receive funding. During the final board meeting every year, a fixed budget is awarded until fully exhausted, thus eliminating the potential endogeneity issue of reverse causality where innovation drives funding.

DNATF's mediated facilitation model entails active follow-up on each investment throughout the project period. A Single Point of Contact (SPOC), an individual who is part of the small DNATF staff, is assigned to each investment to act as a gatekeeper and link between the project and DNATF for the project duration. The SPOC practices active follow-up by participating as an observer in steering-group meetings, engaging in day-to-day dialogue with project participants, reporting quarterly to the board, and challenging the project participants on progress and issues throughout the project period. The SPOC focuses on facilitating effective collaboration between projects participants, maximizing the collaborative gains for each project.

By the end of 2012, DNATF had made 238 investments with a total project budget of DKK 5,320[2] million of which DNATF invested half in accordance with its 1-2-3 investment model. The public research institution(s) fund one sixth of the total budget, private firm(s) one third while DNATF funds one half. Neither participating firms nor academic institutions are required to pay back the awarded funding, therefore using the self-financing scheme ensures that all parties have something at stake. Full requested amounts are committed at the time of award, but progress payments are contingent on performance. A project has a typical duration of 4 years and on average receives DKK 12 million from DNATF. Figure 1 shows the distribution of funded amounts awarded by DNATF.

[Insert Figure 1 about here]

DNATF project awards typically go to a team of one or two public research institutions teamed with an average of two companies. In 2012, 84 percent of all investments had one or more universities as the participating public research institution. The remaining 16 percent were either hospitals or universities and hospitals in cooperation. Foreign companies are allowed to

[2] DKK5,320 million is the equivalent of USD925 million at the October 2012 exchange rate of 5.75DKK/USD

participate but cannot receive funding. Of the unique companies in DNATF's portfolio (duplicates not included), 59 percent have 49 or fewer employees, 17 percent have 50-249 employees, 12 percent have 250-999 employees, and 12 percent have more than 1000 employees.[3] The age distribution for DNATF funded firms is skewed towards younger firms with 38 percent of firms aged 5-years and younger, 22 percent between 6 and 10 years old, 8 percent from 11 to 15 years old, and 36 percent being 15 years and older.

Outcome Variables

The data is in long panel form for each firm-year. Hypothesis 1 investigates the effect of academic-industry participation and funding on the quantity of knowledge produced as measured by the number of patents. We use the number of granted patents (*patents granted*) assigned to the firm as filed for each year up to four years after the year of application. For example, a patent granted in November 2013 but filed in July 2009 would count as a granted patent in 2009. We also employ the number of unissued patents filed (*patents filed*) for each year up to four years after the year of application.

Similarly in hypothesis 2 for peer-reviewed academic papers, we count the number of peer-review papers (*publications*) researchers of the firm have published for each year up to four years after the year of application.

Hypothesis 3 explores the co-evolutionary nature of science and technology in academic-industry partnership projects through co-authoring behavior. We count the number of instances where peer-review publications by a firm are published in collaboration with at least one co-author affiliated with an academic institution (*cross-institutions*) for each year up to four years after the year of application. 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.

Finally, hypothesis 4 focuses on how effective firms that participate in academic-industry collaborative projects are at generating academic research that is more applied and subsequently used. We count the number of citations (*forward citations*) garnered in all peer-reviewed publications for each year up to four years after the year of application.

[3] Additional numbers are provided by DNATF's yearbook.

Datasets

As described in the previous section, our dependent variables fell within two categories – patents and publications – which required different data sources.

Data for patent variables was collected at the firm level using Google patents. Firm name was matched to patent assignees, with some minor adjustments due to Danish letters not found in the English alphabet. The dataset for both filed and granted patents is in long panel form from time t_{-4} to time t_4, for fours years before and after the application year amounting to a total of nine years of data (four years prior to funding, four years after funding and t_0).

Publication variables were collected from the Web of Science. Again, we used firm name to search for publications with relevant organizational affiliation, where we extracted the number of publications and the number of forward citations garnered by these publications. One additional variable on cross-institutional co-authorship, the number of papers published in cooperation between firm(s) and universities, was also constructed. Similar to patents all publication variables were collected annually for four years before and after the year of funding application as well as the year of funding itself.

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

Empirical Approach and Identification Strategy

Full Sample from Second Stage of Selection Process

The two-stage application process that projects undergo enables us to eliminate projects that failed to advance to the second stage of selection and concentrate only on those that did. These projects are more similar in quality and partially resolve the problem of unobserved heterogeneity stemming from selection bias where the funded projects are more promising and have higher potential of success. Thus, our first specification is the entire sample of firms that proceed to the second round of the evaluation process.

At the end of 2011, a total of 49 investments had been finalized. These finalized investments were all funded between 2005 and 2008. Out of the projects that DNATF invested in, 47 were finalized as usual and two were stopped by DNATF before nominal project completion. Since there was no upper limit on the number of firms per project, the 49 invested projects corresponded to 102 participating companies. Among these 102 companies, 16 were duplicates, i.e. companies who participated in more than one of the 49 investments. Thus there were 86 unique companies in total which have been part of finalized DNATF investments, and these make up our funded group. For the matched control group, we used firms that applied for DNATF funding from 2005 to 2008 and selected into the second round of review but did not ultimately receive funding. These amounted to 105 companies. All firms in the control group were part of applications that would have been finalized by the end of 2011 or before. Among the 105 companies 8 were duplicates, which resulted in a total of 97 unique companies in the control group.

Sample of Qualitatively Similar Small and Medium Enterprises

A more detailed look at the sample of firms that participated and received funding shows that it encompasses an extremely heterogeneous set along the dimension of firm size. While most of the firms that participated and received funding are small and medium size enterprises (SME) defined as companies with 250 employees or less, some participants boasted headcounts into the thousands of employees. Given the limited range (DKK 2,550,000 to DKK 62,400,000) in the amount of funding provided by DNATF, its impact would be more substantially felt in small and medium enterprises where the size of the academic-industry project is a substantial portion of the firm's R&D activities compared to larger companies.

Despite dropping firms whose projects did not advance to the second round of the application process as well as those with more than 250 employees, it can still be argued that the difference between the best firms in the participating funded sample and the worst firms among the unfunded ones is still significant and that the sample specification still suffers from selection bias and unobserved heterogeneity. To address this issue, our second sample comprises of qualitatively similar *ex ante* projects except in their probability of funding. We exploit scores given by DNATF board members in their assessment for each application proposal as a quasi-ranking system, and drop from the sample the best of the funded firms and the worst of the unfunded firms. Interviews with DNATF staff revealed that an assessment of A for a project indicates that a board member believes that the project is highly worthy of support, B indicates that the project is worthy of support, whereas C indicates not worthy of support. We translate this evaluation into a normalized score as dictated by Equation 1 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.

$$\text{Equation 1} \qquad score_i = \frac{10 \cdot (\sum_k A - \sum_k C)}{\sum_k (A + B + C)}$$

Similar to the methodology used in Kerr, Schoar and Lerner (2011), we define tranches of normalized scores and identify the fraction of firms that are funded. In column 2 of Table 1, we observe that the fraction of funded firms increases monotonically as the normalized score increases. We see that at the lower end no applications with a normalized score of less than -2.5 were funded, and are therefore these dropped from the sample. We also drop the top 5 percent of firms with normalized scores above 8.5. Consequently, we define our narrow band of qualitatively similar firms to be those with normalized score in the range [-2.5, 8.5], effectively creating a matched sample of funded participants and unfunded firms.

[Insert Table 1 about here]

Several characteristics of the data lead us to believe that observable heterogeneity from sample selection can be eliminated. First, DNATF does not have explicit funding rules that lead to systematic funding decisions. The selection process hinges on board member assessment and votes, the cutoff score for funding is not known in advance to applicants, and therefore it cannot be gamed or manipulated. Second, if we were to use unfunded firms as a matched sample to the participating funded ones, there should be no significant difference in the observables for unfunded and funded firms within of narrow range of normalized scores. We test this criterion using two-sided t-tests. Table 2 shows that firms situated within this narrow band were not significantly different on all observable dimensions at the time of application. These results are critical in order to draw causal inferences on the effect of the funding and participation on firm innovative performance. Moreover, a predictive logit regression model of the probability of funding – regressing a dummy *funded* variable on all observable explanatory variables listed in Table 2 – yields no significant result on any variable.

Consequently, our second sample specification consists of the region in which firms are most comparable – those with normalized scores in the range of [-2.5, 8.5] – dropping from the sample firms at the lowest and highest ends of the normalized score distribution, which amounts to 39 funded and 43 unfunded firms.

[Insert Table 2 about here]

Sample of Qualitatively Similar Younger Firm

Instead of small and medium enterprises, we take another cut at the data using age of the firm. From the skewed age distribution of firms, we first define a subsample of firms that are 15 years and younger, which yields 55 funded and 74 unfunded firms. Then, following the same method described above, we determine qualitatively similar younger firms. We find the same normalized score range of [-2.5, 8.5], which amounts to 38 funded and 45 unfunded firms. Similar to Table 2, Table 3 shows that observable measures of younger firms are not significantly different for the funded and unfunded samples at the time of project application.

[Insert Table 3 about here]

Regression Model Estimation

To test for all hypotheses on each sample specification described above, we employ a diffence-in differences (DiD) model for our estimation, specified as follows:

Equation 1
$$Y_{i,s,t} = \alpha + \gamma funded_s + \lambda post_t + \beta_1(funded_s \cdot post_t \cdot t_1) + \beta_2(funded_s \cdot post_t \cdot t_2) + \beta_3(funded_s \cdot post_t \cdot t_3) + \beta_4(funded_s \cdot post_t \cdot t_4) + \beta X_{i,t_0} + \varepsilon_{i,s,t}$$

The outcome variable is $Y_{i,s,t}$ for firm *i* at time *t* for funded state *s*. Since we are assessing the effect of academic-industry partnership funding, the first difference is that between participating funded and unfunded firms, and the second difference is that 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 effect trends, we also interact the DiD with a time indicator of t_1 to t_4 for each year after funding. Thus coefficients β_1 to β_4 are our coefficients of interest. For each firm *i* in the vector X_{i,t_0} of length j, we also control for observables by including application year fixed effects and industry fixed effects.

Since all variables for patents and papers (number of patents and papers, number of cross-institutional co-authored papers and number of citations) are non-negative and over-dispersed counts, we used quasi-maximum likelihood Poisson models with cluster-robust standard errors to circumvent the assumption of equal mean and variance distribution for Poisson models and minimize estimation bias.

RESULTS

This section shows the results for the hypotheses we proposed earlier in an effort to empirically bring evidence to the research questions of how does academic-industry partnership participation and funding affect firm innovative performance. Table 4 shows the summary statistics including the mean, standard deviation, minimum and maximum for each dependent variable as well as the *funded* and *post* indicator variables.

[Insert Table 4 about here]

Placebo Test on Period Prior to Funding Event

Before presenting our main results for the period after the funding event, we show the results of our placebo tests that we ran to ensure trends in the outcome variables prior to the funding event were not significantly different between the would-be participating funded and unfunded firms. For all outcome variables, we ran DiD regressions using the same estimation model as in Equation 2 as if the funding event occurred at time t_{-4} and include as outcome variables four subsequent years of data after funding from time t_{-3} to t_0. For all outcome variables of innovative quantity, cross-institutional co-authorship and citation count, we found no significance in the DiD coefficients which implies that no significant difference in our outcome variables of interest existed between participating funded and unfunded firms prior to the actual funding event at t_0. Figure 2 graphically depicts one such trend for granted patents in the qualitatively similar younger firm sample with pre and post funding periods. The placebo test regression tables are not included herein but can be obtained from the first author upon request.

[Insert Figure 2 about here]

Effect on Quantity of Firm Patents

We first explore the knowledge spillover effect of participating in academic-industry collaborations and receiving funding on patents. Table 5 shows our results for the number of filed and granted patents. We find that especially for the two qualitatively similar sample specifications the number of filed patents after applying to DNATF is significantly higher for participating funded firms than for non-funded ones. Specifically, in models 2 and 5 for the narrowly defined qualitatively similar SMEs, we find that participating funded firms file between 3.6 times ($e^{1.282}$) and 4.7 times ($e^{1.557}$) more patents than unfunded firms in the four years after applying to DNATF, and participating funded firms receive between 2.3 times ($e^{0.834}$) and 3.7 times ($e^{1.316}$) more granted patents when filed up to three years after applying to DNATF. Comparable strong significant results are also observed for qualitatively similar younger firms. Models 3 and 6 respectively show that participating funded firms file between 2.1 times ($e^{0.723}$) and 2.3 times ($e^{0.812}$) more patents up to four years after applying to DNATF, and receive between 2.3 times ($e^{0.816}$) and 3.6 times ($e^{1.287}$) more granted patents when filed up to four years after applying to DNATF. Thus, we find strong empirical evidence that confirms hypothesis 1.

[Insert Table 5 about here]

Effect on Quantity of Firm Publications

Similarly we show results for the effect of academic-industry partnership participation and funding on the number of peer-reviewed publications in models 1 to 3 of Table 6. Surprisingly, we find no consistent significant result for the three sample specifications; although for the qualitatively similar sample of SMEs, results are weakly significant for one and three years after funding and significant four years after funding (funded firms publish 3.0 times ($e^{1.091}$) more peer-reviewed papers). Overall the results suggest that even though funded firms participate in boundary crossing projects that are arguably based on more basic science, they do not publish their findings in peer-reviewed papers more than unfunded firms. Thus hypothesis 2 is only weakly supported for the qualitatively similar SME sample.

[Insert Table 6 about here]

Effect on Cross-Institutional Co-Authorship

Models 4 to 6 in Table 6 show whether participation in cross-institutional projects changed the collaborative nature of the innovation produced. Our outcome variable is defined as the number of papers published up to four years after application in which co-authors are affiliated with different institutions. For a publication to count as cross-institutional at least one author has to be from academia while another one from a firm. Surprisingly again, all three sample specifications yield no significant results, which implies that despite working on an academic-industry partnership project researchers in participating funded firms do not collaborate more with their peers in academic institutions than those in unfunded firms. Thus, hypothesis 3 is also not verified.

Effects on Citation Count of Firm Innovations

Beyond assessing the quantity of innovative productivity, we also explore how effective participating funded firms are at generating academic research used and cited in subsequent work, and employ the measure of forward citations to operationalize it. Our results are shown in an analogous setup in models 7 to 9 of Table 6 for all three sample specifications. For qualitatively similar SMEs in model 8, we find the most consistently significant results with participating funded firms being cited between 3.3 times ($e^{1.196}$) and 9.6 times ($e^{2.261}$) more than unfunded firms. For qualitatively similar younger firms in model 9, even though the coefficients of interest are sometimes only weakly significant, publications from participating funded firms are still more cited than those from unfunded ones. Thus, we find evidence for hypothesis 4.

DISCUSSION AND CONCLUSION

Contributions to Literature

This work provides empirical evidence on the effect of a novel funding program of academic-industry partnerships on firm innovative performance. To the best of our knowledge this work is the first to show the effect of such policy tools using a setup that eliminates observable selection bias at the level of the firm. To summarize our results, we observe compelling evidence that participating and receiving funding for academic-industry partnerships increases the firm's number of filed and granted patents. In these partnerships, industry researchers work hand-in-hand with academic scientists thereby facilitating knowledge spillovers from science to technology, which firms capitalize on to create new inventions. They encode these inventions using patents, the common method used in a technological institution to protect against unwarranted appropriation by others. Moreover, with the receipt of funding for these collaborations, firms take advantage of the extra capital to invest more into (risky?) innovative activities to increase their stock of knowledge, and in turn encode this knowledge into patents.

However, we do not observe the same persuasive effects on peer-reviewed papers published by participating funded firms. Surprisingly, despite an environment conducive to spillovers during the projects while working alongside academic partners and extra capital from funding, participating in such partnerships did not increase the number of peer-reviewed publications nor did it increase the number of cross-institutional co-authorships, contrary to findings in prior studies (Cockburn & Henderson, 1998; Liebeskind et al., 1996). We can deduce from these results that partners are siloed and ingrained within their initial institutional logics, where traditional approaches and norms are still prevalent. This is despite participation in a setup designed to break away from established boundaries. Two potential mechanisms may be driving these findings. First, perhaps it is precisely because of these cross-institutional partner compositions that there is a clear division of labor between academia and industry where each partner focuses on their own area of expertise. Academic partners perform more basic research that ultimately gets published, while industrial partners do more applied research that they patent. Thus, contrary to what has been previously hypothesized, industry researchers in participating firms may not do more basic research because they leave it to participating academics. Second, it also may be that more basic research is indeed done in the firm, but because of the institutional norms that firms uphold, they still do not encode the knowledge produced in open science but do it in the form that they are most familiar with, i.e. patents, because they want to extract rents from the research. Interviews with a small set of participating and funded firms (*n=10*) reveal that they do more basic research, and collaborations between academic and industrial partners does not stop at the level of sharing equipment but also extendS to the exchange of ideas. However, for most of these firms, publishing is not a priority.

Finally, the other interesting result is the significant positive effect on the citation count of peer-reviewed publications in participating funded firms. It is an indication that even though the amount of basic research encoded in publications is not significantly higher for participating funded firms, the scientific knowledge that does get published garners more applications by subsequent research and is more easily diffused.

Implications for Practitioners and Policymakers

The academic-industry partnership structure that we studied in this paper creates the potential for a novel model of interaction between the realms of science and technology that moves away from the conventional model of dedicated gatekeepers that straddle both institutions. Instead of having single actors transfer knowledge back and forth between the independent silos of science and technology, our setting temporally breaks down the boundaries between the two institutions and enables teams of individuals from both sides to work together alongside one another. As evidenced by our results when implementing such funding programs, governments are able to incentivize firms in undertaking basic research that is more widely applied as evidenced by increased forward citations of peer-reviewed publications and more R&D projects translated into patents. As a way to help companies maintain competitiveness, governments can view this approach as a potential policy tool for faster and more effective application and commercialization.

However, we cannot ignore the fact that there are no improvements in the number of peer-reviewed publications nor cross-institutional co-authorships for participating funded firms. Even though a small sample of interview data shows that on average participating firms do perform more basic research, we cannot help but think that the lack of increased publications and co-authorship between scientists from different institutions may be an indication that institutional partners are still isolated within the project and that a division of labor between academic scientists and industry researchers is still parcticed. Perhaps if firms stepped out more from their initial institutional logics – publishing and co-authoring more with academic scientists – they would be even more effective in capitalizing on knowledge spillovers from science.

Limits and Weaknesses

Despite showing interesting outcomes of participation in funded academic-industry partnerships on firm innovative performance, 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 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 and funding, we strongly believe that the implications of our results can be interpreted more broadly. Moreover, even though we were very careful in our empirical design to address endogeneity concerns there may still be subtle selection issues not observable to us.

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 show the relationship between input – participation and funding, and output – firm performance – without delving inside what remains a black box. Preliminary qualitative interviews (*n =10*) with project managers of these academic-industry partnership projects indicated that some big challenges they faced were getting individuals from different institutions to align their goals, understand each other and collaborate effectively.

From a policy standpoint, this work did not emphasize nor tease apart the effect of providing funding from the novel mediated intervention model specific to DNATF since our sample of firms does not provide us with any source of variation on this intervention dimension. As explained in the Setting section, DNATF's mediated intervention model implies active follow-up on each project throughout the project period where a DNATF staff member is assigned and acts as the single point of contact throughout the funded project's lifetime. In effect, DNATF's model is a combination of the governance usually associated with private equity and venture capital models with the funding of pure government grants. Compared to more conventional funding schemes where funded projects are left on their own to meet pre-established deliverable deadlines, DNATF stays much closer to each project, frequently mediating conflicts that arise among funded parties.

Future Research

Despite these limitations and weaknesses, we have exposed several interesting future research topics beyond the research question explored herein of how participating in funded academic-industry collaboration affects firm innovative performance. From a management 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 these projects more successful. For policymakers designing effective funding programs, understanding DNATF's mediated funding and 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 lower our level of analysis to understand the effect of such partnerships on individual level productivity and subsequent impact particularly from the viewpoint of the academic scientist.

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Normalized score	Funded (%)	Number of applications	Applications (%)	Cumulative applications (%)
[-7.5,-5)	0.0%	9	7.3%	7.3%
[-5, -2.5)	0.0%	17	13.8%	21.1%
[-2.5, 0)	15.4%	13	10.6%	31.7%
[0,2.5)	37.1%	35	28.5%	60.2%
[2.5, 5)	42.1%	19	15.4%	75.6%
[5, 7.5]	86.7%	15	12.2%	87.8%
[7.5, 10]	100.0%	15	12.2%	100.0%

Table 1 – DNATF funding selection by normalized score

Characteristic	Unfunded	Funded	Two tailed t-test
age of firm	8.16	7.79	0.84
proposed duration	3.00	3.00	1.00
funding amount	12700000	12400000	0.85
number of parties	5.12	5.56	0.54
patents filed	3.29	1.16	0.29
patents granted	2.66	0.84	0.35
publications	4.02	6.44	0.46
forward citations	119.19	136.79	0.85
cross-institutions	2.28	3.28	0.62
n	43	39	

Table 2– Comparison of funded and funded firm observables for SMEs

Characteristic	Unfunded	Funded	Two tailed t-test
age of firm	5.16	5.26	0.89
proposed duration	3.09	3.00	0.63
funding amount	14800000	13200000	0.46
number of parties	5.13	5.37	0.73
patents filed	3.70	1.85	0.40
patents granted	2.98	1.34	0.43
publications	7.84	6.71	0.83
forward citations	147.13	141.80	0.96
cross-institutions	4.09	3.97	0.97
n	45	38	

Table 3 – Comparison of funded and funded firm observables for young firms

Variable	Observation number	Mean	Std. Dev.	Min	Max
normalized score	1629	2.0196	4.564143	-7.5	10
proposed duration	1845	3.063415	0.7333031	1	5
amount funded by DNATF	1728	1.35E+07	9756608	2550000	6.24E+07
number of parties	1845	5.663415	3.674086	2	19
funded	1845	0.4926829	0.500082	0	1
post	1845	0.4444444	0.4970387	0	1
SME	1737	0.6839378	0.4650714	0	1
young firm	1845	0.6292683	0.4831317	0	1
patents filed	1827	3.217843	11.19599	0	178
patents granted	1827	1.383142	4.961285	0	49
publications	1782	2.070707	18.09965	0	337
forward citations	1773	15.40835	80.91633	0	1553
cross-institutions	1773	0.6739989	2.536591	0	41

Table 4– Summary statistics

Poisson Models	Patents filed			Patents granted		
	Full	QS SME	QS Young	Full	QS SME	QS Young
	b/se	b/se	b/se	b/se	b/se	b/se
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
post	-0.012	-0.820**	-0.421	-0.565	-0.765**	-0.820**
	(0.35)	(0.16)	(0.27)	(0.40)	(0.24)	(0.25)
funded	2.504**	1.162+	1.684**	2.717**	1.501*	1.789*
	(0.42)	(0.65)	(0.48)	(0.57)	(0.70)	(0.88)
post*funded*t1	0.086	1.557**	0.723*	0.722+	1.316**	1.134**
	(0.37)	(0.33)	(0.29)	(0.41)	(0.39)	(0.43)
post*funded*t2	0.334	1.282**	0.792**	0.681	0.834**	1.287**
	(0.42)	(0.32)	(0.28)	(0.42)	(0.30)	(0.25)
post*funded*t3	0.416	1.319**	0.744*	0.614	0.834*	1.092**
	(0.36)	(0.48)	(0.30)	(0.41)	(0.39)	(0.25)
post*funded*t4	0.251	1.423**	0.812**	0.137	0.563	0.816**
	(0.38)	(0.37)	(0.31)	(0.45)	(0.50)	(0.27)
constant	-1.513+	-2.145	-0.152	-2.399*	-2.449	-0.451
	(0.79)	(11.19)	(1.15)	(0.94)	(10.63)	(3.00)
Lnalpha constant	1.727**	1.250**	1.297**	1.859**	1.078**	1.382**
	(0.14)	(0.26)	(0.19)	(0.13)	(0.26)	(0.19)
N.Obs	1818	729	738	1827	729	738
Log-Likelihood	-2720.374	-826.474	-1077.889	-1412.943	-380.596	-545.134

+ p<0.10, * p<0.05, ** p<0.01

Table 5 – Patent data. DiD QML Poisson count regression models with cluster robust standard errors for filed and granted patents filed up to four years after funding, run on all three sample specifications: full sample in second round selection, qualitatively similar SMEs, and qualitatively similar young firms.

Poisson Models	Publications			Cross-Institutions			Forward Citations		
	Full	QS SME	QS Young	Full	QS SME	QS Young	Full	QS SME	QS Young
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
post	0.343	0.441	0.41	0.526*	0.673	0.598	-0.177	-0.415	-0.42
	(0.21)	(0.36)	(0.30)	(0.23)	(2.83)	(0.56)	(0.35)	(0.31)	(0.42)
funded	1.447**	-0.507	0.214	1.296**	-0.46	0.364	0.861	-1.117	-0.233
	(0.55)	(1.12)	(1.13)	(0.41)	(3.27)	(1.48)	(0.70)	(1.75)	(2.04)
post*funded*t1	-0.003	0.771+	0.422	-0.182	0.618	0.182	0.518	2.023*	1.589+
	(0.29)	(0.47)	(0.47)	(0.27)	(4.02)	(0.74)	(0.62)	(0.82)	(0.82)
post*funded*t2	0.08	0.653	0.141	-0.105	0.707	0.079	0.3	1.483**	0.995
	(0.28)	(0.52)	(0.56)	(0.28)	(2.77)	(0.79)	(0.44)	(0.43)	(0.73)
post*funded*t3	0.148	0.896+	0.457	0.069	0.789	0.275	0.633	2.261*	1.784+
	(0.30)	(0.49)	(0.45)	(0.30)	(2.81)	(0.72)	(0.65)	(0.93)	(1.06)
post*funded*t4	0.275	1.091*	0.656	0.336	1.159	0.643	0.08	1.196+	0.783
	(0.30)	(0.45)	(0.48)	(0.33)	(2.77)	(0.74)	(0.51)	(0.69)	(0.69)
constant	-0.904	-1.404	-0.119	-0.624	-1.626	-0.303	2.422	1.772	3.129
	(0.96)	(5.57)	(1.21)	(1.02)	(4.89)	(1.85)	(1.81)	(4.09)	(2.34)
lnalpha constant	1.957**	1.666**	1.477**	1.871**	1.604**	1.409**	2.713**	2.446**	2.338**
	(0.14)	(0.31)	(0.26)	(0.14)	(0.39)	(0.37)	(0.14)	(0.21)	(0.19)
N.Obs	1773	729	702	1764	729	702	1764	729	702
Log-Likelihood	-1190.805	-392.433	-465.262	-1043.267	-352.015	-422.861	-14605.259	-5094.846	-6299.557

+ $p<0.10$, * $p<0.05$, ** $p<0.01$

Table 6 – Publication data. DiD QML Poisson count regression models with cluster robust standard errors for the number of peer-reviewed papers, cross-institutional collaborations of peer-reviewed papers and the number of forward citations up to four years after funding, run on all three sample specifications: full sample in second round selection, qualitatively similar SMEs, and qualitatively similar young firms.

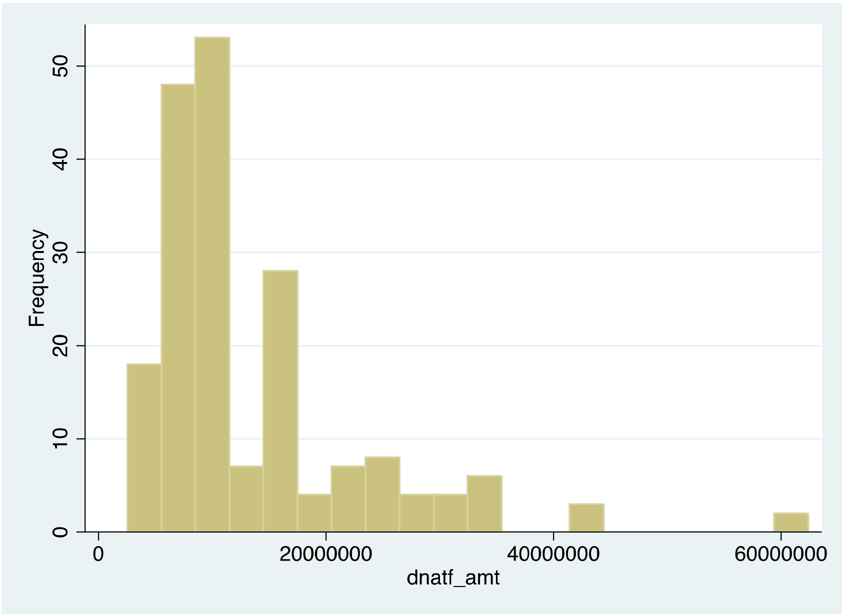

Figure 1 – Frequency distribution of amount funded by DNATF (in DKK)

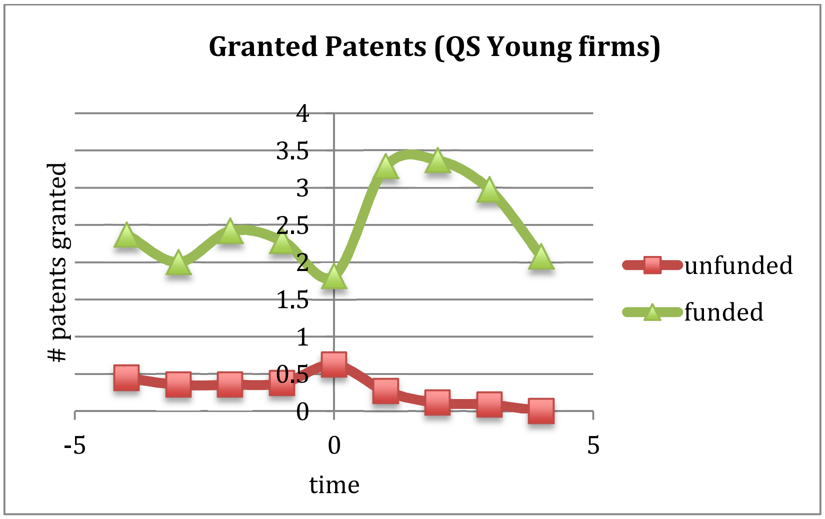

Figure 2 – Graphical depiction of the number of granted patents for both funded and unfunded firms for periods before and after funding at t_0 using the qualitatively similar sample of younger firms.