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Working Paper

13-058

July 22, 2014

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

Acknowledgements: We would like to thank the Harvard Business School Department of Research and Doctoral Program for supporting this work. We are grateful to Lee Fleming, Richard Freeman, Carliss Baldwin, Vicki Sato, Anil Doshi, Shai Bernstein and participants of the NBER 2013 Conference on the Changing Financing Market for Innovation and Entrepreneurship, The Vienna Conference on Strategy 2013 and the 8th European Meeting on Applied Evolutionary Economics, for their insightful comments and feedback. We are also thankful to Casper Binow Hansen for his research assistance and DNATF for providing the data used in this study. All errors remain our own.

Bridging Science and Technology through Academic-Industry Partnerships

ABSTRACT

Scientific research and its translation into commercialized technology is a driver of wealth creation and economic growth. Partnerships to foster the translational processes from public research organizations, such as universities and hospitals, to 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 firm performance, comparing the likelihood of bankruptcy and employee count as well as patent count, publication count and their citations and collaborative nature between 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. Our results suggest that while receiving the grant does bring an injection of funding that alleviates financing constraints, its core effect on the firm's innovative behavior is in fostering collaborations and translations between science and technology and encouraging riskier projects rather than purely increasing patenting.

INTRODUCTION

How ideas are produced and the means by which they are diffused continues to be an area of great interest to researchers. This is driven by the belief that technological innovations, which are grounded in basic scientific research, spur wealth creation and stimulate economic growth. However firms often face difficulties appropriating returns from basic research because of knowledge spillovers and/or the inability to perfect intellectual property rights, thus private firms tend to underinvest basic research (Nelson, 1959). There is a widely held view that governments must fill this gap by investing in basic scientific research as a public good, which has led to the creation of agencies such as the National Institutes of Health (NIH), the National Science Foundation (NSF), and similar organizations in other countries that fund such research performed mainly at academic institutions.

Once new knowledge is generated by academic scientists finding ways to commercialize and unlock the research results created in universities and other public institutions is key to facilitating technological innovation and economic growth. Three predominant means of spurring the translation of science through knowledge spillovers to influence a firm's technological progress have been identified in the literature: publication in peer-reviewed journals and co-authorship with basic science researchers in other organizations such as universities (Henderson & Cockburn, 1996; Liebeskind, Oliver, Zucker, & Brewer, 1996), movement of human capital between academia and industry (Dasgupta & David, 1994), and geographic colocation (Zucker, Darby, & Brewer, 1998). Despite these findings, knowledge still tends to be trapped in the ivory tower (Bikard, 2014) while firms face many challenges that prevent knowledge generated in universities from being diffused easily across boundaries. For instance, generating the first point of contact and interaction with academic researchers in order to establish a collaborative relationship can be difficult, and the movement of human capital is limited as scientists have strong preferences for academic freedom (Stern, 2004).

In light of these results, many states have created, and increasingly have invested in academic-industry partnership programs that combine these mechanisms to facilitate and foster bridging between science and technology. In the United States, NSF Shared Resources Centers often require some form of partnership with private firms to accelerate product development, while the NIH Academic-Industry Partnership Program seeks to identify the most compelling cross-boundary opportunities that 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 stated purpose of bridging science and technology, especially from the perspective of participating firms.

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 partnership model. 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 mitigate selection bias by including qualitatively similar participant and non-participant firms. We first replicate findings from the entrepreneurial finance literature suitable to our setting that funding eases financial constraints and improves survival, employment and patenting. We then 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, citation count and collaborative nature of peer-reviewed publications of participating firms.

Although our results reveal significantly improved survival rates and increased employment in participating firms, surprisingly we found no significant effect on granted patent outputs for firms that participated in these academic-industry partnerships. However for peer-reviewed publications, we do observe significant positive effects of partnership participation on the quantity of publications, their forward citations as well as the quantity of co-authorship between academic and industry researchers. Our findings demonstrate that participation in academic-industry partnerships fosters knowledge spillovers from science to technology across institutional boundaries through collaborative publications and alters the innovative behavior of firms. The lack of a significant increase in granted patents indicates that participating firms' overall innovative productivity does not change when measured by patents, but the increase in peer-reviewed publications and co-authorship between firm and academic researchers point to a shift towards more basic research. Moreover, the significant increase in forward citations of publications also illustrates that the basic research firms undertake is diffused more effectively. Taken together, our findings suggest that receiving the grant does bring an injection of funding that relieves financing constraints, although its core effect on the firm's innovative behavior is more in fostering collaborations and translations between science and technology rather than purely increased patenting.

This paper bridges the literature that explores the relationship between science and technology and that on innovation funding. It lends empirical evidence to the effect of academic-industry partnership grants on spillovers and the resulting knowledge created. It contributes to the knowledge spillover literature by assessing the effect on participating firms of a tool, that can be used by both managers and policymakers, specifically 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 innovative behavior and performance. It also differs from studies in the entrepreneurial finance literature. 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 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

Merton (1957) first pointed out the different institutions and incentive systems of science 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, as well as 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, 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, 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 rate, employment, patenting, exit and financing, and also lessens agency problems between entrepreneurs and investors through monitoring and improved governance. Therefore, we posit that firms participating in academic-industry partnerships and successful in obtaining funding are less constrained financially. The extra funding improves the likelihood of firm survival and increases employment growth. Moreover, it allows participating firms to take on more innovative activities that result in more inventions encoded in patents.

Hypothesis 1: *Firms that receive and participate in funded, mediated academic-industry partnerships have higher survival rates relative to non-funded firms*

Hypothesis 2: *Firms that receive and participate in funded, mediated academic-industry partnerships grow employees more relative to non-funded firms*

Hypothesis 3: *Firms that receive and participate in funded, mediated academic-industry partnerships produce more patents relative to non-funded firms*

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 (Freeman, 1992; Mansfield, 1995). The second perspective 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 sticky (von Hippel, 1994), 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 science-based firms, a number of mechanisms of how science influences technological progress through knowledge spillovers 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). From the perspective of the academic scientist, another stream has investigated the roles that scientists take in crossing institutional boundaries (Murray, 2004) and the effect of such behavior on their research (Azoulay, Ding, & Stuart, 2009). The setting of this paper is aligned with the perspective that science and technology co-evolve. Academic-industry partnerships have a different structure than the traditional model of separate 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 a sequential process, academic-industry partnerships create an environment where academic scientists and industry researchers work together concurrently to bridge from lab to practice.

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, very few firms are broad and diverse enough to directly benefit from all the new technological possibilities opened up by successful basic research (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, we postulate that academic-industry partnerships provide firms with the motivation and the risk mitigation mechanism to undertake more basic research, encoded in peer-reviewed publications, than they otherwise might have pursued. 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 universities, and evaluate the outcome of applied research to recognize possible implications (Fleming & Sorenson, 2004; Rosenberg, 1990).

Hypothesis 4: *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). Researchers in industry must also actively collaborate with their academic colleagues. This improves access to public sector research and the quality of research conducted within the firm (Cockburn & Henderson, 1998; Liebeskind et al., 1996). Given the cross-institutional nature of academic-industry partnerships where academic scientists and firm researchers work together, they offer firms not only a link but also ensure a close relationship with academic researchers so they can reap first-hand benefits from knowledge spillovers. Thus, we posit that the spillover effects from participation alter firms' behavior and stimulate them in collaborating and co-authoring more on basic research activities.

Hypothesis 5: Firms that receive and participate in funded, mediated academic-industry partnerships produce more cross-institutional collaborative outputs relative to non-funded firms

Finally, the spillover effects of participating in academic-industry collaborations 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. Again because of the cross-institutional nature of these partnerships, basic research generated by participating firms will be from the beginning towards a more evident commercial application. Having a product in mind, basic research undertaken by collaborations between academic and industry researchers aims to solve a specific scientific or technological shortcoming, which is in turn translated and applied more efficiently into products. Therefore, we postulate that their publications will receive more forward citations.

Hypothesis 6: 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)[1] founded in 2005 by the Danish government, whose broad objective was to enhance growth and strengthen employment by supporting strategic and advanced technological priorities from basic science. It was created with the aim of making Denmark one of the world's leading advanced-technological societies.

[1] DNATF was merged into the InnovationsFonden in May, 2014.

DNATF provided 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 was the only Danish governmental funding source that exclusively supported academic-industry research partnerships. Funding for such collaborations, however, can also be obtained from other Danish governmental sources.[2] DNATF used a bottoms-up approach in the application process, where it sought to fund the best ideas within a broad realm of advanced technology relevant to Danish industry. The investment portfolio covers sectors ranging from robotics, agriculture, livestock, biotechnology and medicine, to telecommunications and production technology. In our dataset of funded projects from DNATF's inception until 2010, the biomedical sciences made up approximately 24.7% of all investments, while 25.7% were in energy and the environment, 27.4% in IT and communication, 12.6% in production, 3.7% in agricultural produce and food, and 5.3% in the construction sector. Applications must include at least one academic scientist and one firm. DNATF evaluated applications based on three criteria: obvious business potential, internationally recognized high quality research and innovation, and entrepreneurship. Applications were screened in two stages by the board of DNATF, which consisted of nine leaders from Danish science and industry who had extensive and unique knowledge in their respective fields.

The first application stage consisted of the submission of a short expression of interest which identified the core idea of the proposed project. Expressions of interest were 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 were tallied at the beginning of the discussion prior to deciding whether to approve the individual expressions of interest for a second round. About 30% of the first round applications were approved and moved into a second round in which

[2] 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.

applicants prepared a more comprehensive proposal that explained the project idea in greater detail. The second round applications were then subjected to a peer review process by two independent reviewers, and armed with these peer reviews, DNATF's board members again scored each application with their scoring system. Based on the aggregate scores and discussion, the board reached a consensus on whether to fund each application. From the applications that proceeded to the second stage, about 40% ultimately received funding. During the final board meeting every year, a fixed budget was awarded until fully exhausted, thus eliminating the potential endogeneity issue of reverse causality where innovation drives funding.

DNATF's mediated facilitation model entailed active follow-up on each investment for the duration of the project period. A Single Point of Contact (SPOC), an individual who was part of the small DNATF staff, was assigned to each investment to act as a gatekeeper who actively linked the project participants and DNATF for the project duration. The SPOC practiced active follow-up by participating as an observer in steering-group meetings, engaging in frequent dialogue with project participants, reporting quarterly to the board, mediating conflicts and challenging the project participants on progress and issues throughout the project period. The SPOC focused on identifying impediments and facilitating effective collaboration between project 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[3] million. The public research institution(s) funded one sixth of the total budget, private firm(s) one third while DNATF funded one half, in accordance with its 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, unlike traditional private sources of funding. Full requested amounts were committed at the time of award, but progress payments were contingent upon performance. A project had a typical duration of 4 years and on average received DKK 12 million from DNATF. Awards typically went to a team of one or two public research institutions

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

teamed with an average of two companies. Approximately 84% of all investments had one or more universities as the participating public research institution. The remaining 16% were either hospitals or universities and hospitals in cooperation. Foreign companies were allowed to participate but could not receive funding. Of the unique companies in DNATF's portfolio (duplicates not included), 59% had 49 or fewer employees, 17% had 50-249 employees, 12% had 250-999 employees, and 12% had more than 1000 employees.[4]

Datasets and Variables

Hypothesis 1 explores firm survival. We employed a simple binary measure of whether firms in our sample are *bankrupt* or not five years after they apply for DNATF funding. From hypothesis 2 onward the data is in long panel form for each firm-year. We obtained the number of *employees* by year for each firm to measure employment growth. For both bankruptcy and employment data our source is the BiQ Erhvervsinformation (BiQ) database that includes all registered Danish firms and provides yearly information updated daily from the Danish Business Authority, a governmental database that keeps comprehensive information on all Danish firms. Since all firms in our study applied for funding from 2005 onwards, we were able to collect employee data for three years before and five years after the application year (time t_{-3} to time t_5) amounting to a total of nine years of data (three years prior, five years after funding and t_0).

Hypothesis 3 investigates the effect of academic-industry participation and funding on the quantity of knowledge produced as measured by the number of patents. We used the number of granted patents (*patents granted*) assigned to the firm as filed for each year. 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 at the firm level using Google Patents that includes US and European patents. Firm name was matched to patent assignees, with some minor adjustments for Danish letters not found in the English alphabet. The data is from time t_{-3} to time t_5, three years before and five years after the application year.

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

For hypothesis 4 we counted the number of peer-reviewed papers (*publications*) researchers of the firm have published for each year three years prior and up to five years after the year of application. Hypothesis 5 explores the co-evolutionary nature of science and technology in academic-industry partnership projects through co-authoring behavior. We counted the number of instances where peer-review publications were published in collaboration with at least one co-author affiliated with an academic institution (*cross-institutions*) for each year three years prior and up to five years after 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 6 focuses on how effective firms that participate in academic-industry collaborative projects are at generating more applied and subsequently used research. We counted the number of citations (*forward citations*) garnered in all peer-reviewed publications for each year of three years prior to and up to five years after the year of the application. Publication variables were collected from the Web of Science by searching for firm name the publications with relevant organizational affiliation.

A number of variables were also 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 final *score* given to each project in the selection process and 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 *ex ante* observables in the analyses.

Identification Strategy and Empirical Approach

To mitigate the problem of unobserved heterogeneity stemming from the selection bias of DNATF funding healthier firms with higher success potential, we take advantage of the two-stage selection process and further develop a qualitatively similar sample of firms. We do not know whether unfunded firms undertook their proposed projects, but if they did, our results would be underestimated and conservative as the counterfactual outcome variables currently include the impact of these projects.

Full Sample from Second Stage of Selection Process

The two-stage application process that projects underwent enabled us to eliminate those that failed to advance to the second stage of selection and concentrate only on the ones that did. These projects were more similar in quality and partially resolved the issue of selection bias. Thus, our first specification is the entire sample of firms that proceeded to the second round of the evaluation process.

By the end of 2013, a total of 101 investments had been finalized. These finalized investments were all funded between 2005 and 2010. Since there was no upper limit on the number of firms per project, the 101 invested projects corresponded to 153 participating companies. Among these 153 companies, 27 were duplicates, i.e. companies who participated in the program more than once. Thus there were 126 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 2010 and selected into the second round of review but did not ultimately receive funding. These amounted to 206 companies. All firms in the control group were part of applications that would have been finalized by the end of 2013 or before. Among the 206 companies two were duplicates, which resulted in a total of 204 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 shows that it encompasses an extremely heterogeneous set along the dimension of firm size. While most firms that participated were small and medium size enterprises (SME) defined as companies with 250 employees or less, some participants boasted headcounts in the thousands of employees. Given the limited range (DKK 2,550,000 to DKK 75,000,000) of funding provided by DNATF, its impact is likely to be more noticeably felt in SMEs where the size of the academic-industry project is a substantial portion of the firm’s R&D activities compared to larger companies. The sample of firms that reached the second round of applications with 250 employees or less amounted to 117 participating and 113 unfunded firms.

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, the sample may still suffers from selection bias and unobserved heterogeneity. To address this issue, our final sample specification is comprised of qualitatively similar firms except in their funding. We exploited scores given by DNATF board members in their assessment for each application proposal as a quasi-ranking system, and dropped 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 translated this evaluation into a normalized score as dictated by $score_i = \frac{10\cdot(\sum_k A - \sum_k C)}{\sum_k (A+B+C)}$ 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, Schoar and Lerner (2011), we defined tranches of normalized scores and identify the fraction of firms that were funded. In column 2 of Table 1, the fraction of funded firms increases monotonically as the normalized score increases. At the lower end, no application with a normalized score of less than -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 best funded and the weakest 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].

[Insert Table 1 about here]

Several characteristics of the data led us to believe that observable heterogeneity from sample selection was alleviated. First, DNATF did not have explicit funding rules that led to systematic funding decisions. The selection process hinged on board member assessment and votes, where the cutoff score for funding was not known in advance to applicants, and therefore could not 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 the narrow range of normalized scores. We tested 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, except for total of amount of funding applied which we made sure to control in our regressions. These results are critical in order to draw causal inferences on the effect of participation on firm innovative performance. Consequently, our final sample specification consists of the region in which firms were most comparable dropping from the sample of SMEs at the lowest and highest ends of the normalized score distribution, which amounted to 78 participating and 73 unfunded firms.

[Insert Table 2 about here]

Regression Model Estimation

In testing Hypothesis 1, we conducted a simple logistic regression with cluster robust standard errors to test whether firms that obtained DNATF funding were more likely to survive five years after the potential funding event. The model is specified as follows:

$$Y_{i,s} = \alpha + \gamma funded_s + \delta X_{i,t_0} + \varepsilon_{i,s}$$

We are interested on the effect of $funded_s$ firms on the bankruptcy dependent variable $Y_{i,s}$ for firm *i* in funded state *s* as captured by the coefficient γ. We controlled for application year and industry fixed effects, reviewer scores, amount of funding requested and proposed duration in the X_{i,t_0} vector.

For all remaining hypotheses, we employed a difference-in differences (DiD) model for our estimation, specified as follows:

$$\begin{aligned} Y_{i,s,t} = \alpha + \gamma funded_s + \lambda post_t + \beta_1(funded_s \cdot post_t \cdot t_1) + \beta_2(funded_s \cdot post_t \cdot t_2) \\ + \beta_3(funded_s \cdot post_t \cdot t_3) + \beta_4(funded_s \cdot post_t \cdot t_4) \\ + \beta_5(funded_s \cdot post_t \cdot t_5) + \delta X_{i,t_0} + \varepsilon_{i,s,t} \end{aligned}$$

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 that between 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 interacted the DiD with a time indicator t_1 to t_5 for each year after funding. Thus coefficients β_1 to β_5 are our coefficients of interest. For each firm *i* in the vector X_{i,t_0}, we also controlled for observables by including application year fixed effects and industry fixed effects.

Although our sample specification strategy mitigated selection, board discussions could still affect project selection conditional on scores. Thus there may be other unobservable variables driving the result. In order to further eliminate fixed unobservable effects and tease apart selection from treatment, we used two regression model specifications. 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 are able to obtain coefficient estimates for all DiD interaction β-terms and main effect terms on funded (γ) and post (λ) dummies. With firm fixed effects panel regressions, we removed all fixed unobservables at the firm level with the caveat that the γ-term drops out completely since there is no within firm variation for the funded dummy variable.

Since all variables (number of employees, 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 address the assumption of equal mean and variance distribution for Poisson models and minimize estimation bias.

RESULTS

This section shows our empirical evidence to the research question of how does academic-industry partnership participation affect firm performance and innovative behavior. Table 3 shows summary statistics including the mean, standard deviation, minimum and maximum for each variable used in the analysis including the *funded*, *post* and *SME* indicators.

[Insert Table 3 about here]

Table 4 depicts the logistic regression results for the likelihood of bankruptcy five years after the potential funding event. We find in the full sample in model 1 and qualitatively similar full sample in model 2 that funded firms have significantly lower odds of going bankrupt. Interpreting the coefficient in model 2, we find that the odds for a funded firm to be bankrupt five years after applying for DNATF funding is 80.6% ($e^{-1.639}$-1) lower than the odds for non-funded firms. In models 3 and 4 although results are not significant, we find concurrence in the direction of the effect. Thus, hypothesis 1 is supported for the full sample of firms. As a robustness check, we also ran the Cox hazards model for survival analysis and found very similar results in that funding mitigates bankruptcy or death of the firm. In the interest of space, results are not included herein but can be obtained from the corresponding author.

[Insert Table 4 about here]

We analyze the effect of receiving academic-industry partnership funding on the number of employees and find consistent positive and significant effects for the qualitative similar samples, as shown graphically in Figure 1 through the mean number of firm employees per year and econometrically in Table 5. The impact is especially significant for SMEs with similar effect sizes for both the fixed and random effects panel regressions (respectively models 4 and 6), where for all five years after funding we find that funded firms have between 27.8% ($e^{0.245}$-1) to 41.8% ($e^{0.347}$-1) more employees than non-participating firms. We also find weakly significant positive result in the qualitatively similar full sample of firms three years after funding as shown in model 2. Coefficients for the fixed (model 4) and random (model 6) effect panel regression specifications are relatively close, meaning that our random effects model has accounted for most of the fixed unobservables. Moreover in the random effects regression shown, we find reassuringly that the funded variable is insignificant, which indicates that our specification is successful at mitigating the selection bias that funded firms have consistently more publications. These tendencies between the fixed and random models are present throughout our results. To ensure that the pre-period year-by-year trends are similar between the funded and unfunded so that results from our DiD regressions can be attributed to participating in the academic-industry partnership and not to the continuation of a prior tendency, we present in Figure 1 pre and post trends. Focusing on the period to the left of the vertical time axis, we discern no major trend difference between the two groups. These results verify hypothesis 2 and together with the decreased odds of bankruptcy in hypothesis 1, they suggest that receiving the grant helps firms alleviate financial constraints.

[Insert Table 5 and Figure 1 about here]

We explore the effect on the number of granted patents for participating in academic-industry collaborations. Figure 2 graphically depicts the mean number of granted patents per firm by year, and corroborates our econometric findings in Table 6. All six models in the table – no matter the sample or regression specification – consistently show that the number of granted patents is only significantly higher one year after participating. After the first year the effects disappear. Interpreting results for the qualitatively similar SME sample in models 4 and 6, we find very similar magnitudes for the fixed effect and random effect model specifications, respectively with participating firms granted 2.70 ($e^{0.995}$) and 2.77 times ($e^{1.018}$) more patents than unfunded firms in the first year after applying to DNATF. Given 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. This result is surprising given that the grant provided for the academic-industry projects should have helped in funding R&D activities and improved the innovative productivity of participating firms. Thus, we cannot empirically confirm hypothesis 3.

[Insert Table 6 and Figure 2 about here]

Table 7 shows results for the effect of academic-industry partnership participation on the number of peer-reviewed publications. We find consistently significant results for the qualitatively similar SME sample specifications in all five years following participation in models 4 and 6, where funded firms publish between 2.23 ($e^{0.802}$) and 3.74 times ($e^{1.320}$) more peer-reviewed papers. However, these effects disappear when including bigger firms in the sample. Overall the evidence suggests that the bridging effect of academic-industry partnerships is particularly strong for participating SMEs that led them to publish findings in peer-reviewed papers more frequently than unfunded firms. Thus, hypothesis 4 is supported for qualitatively similar SMEs. We present in Figure 3 the mean number of publications per firm by year, focusing on the period left of the vertical time axis we find no discernible trend difference between the two groups.

[Insert Table 7 and Figure 3 about here]

Table 8 shows whether participation in cross-institutional projects changed the collaborative nature of the innovation produced. We find again in the qualitatively similar SMEs but not the full sample that industry researchers of firms that participated in the DNATF academic-industry partnerships do collaborate more with their peers in academic institutions than those in unfunded firms. The effect on these cross-institutional collaborations is lagged for two years, becomes significant three years after project start and stays significant until the end of our dataset after five years. In models 4 and 6, we find similar effect sizes for both the fixed and random effects panel regressions, with 2.13 ($e^{0.756}$) to 2.74 times ($e^{1.007}$) more cross-institutional collaborations for participating firms then non-participants. These findings suggest that not only do SMEs publish more in peer-reviewed publications, but they also collaborate more with academic scientists under the project conditions. Pre participation time trends in Figure 4 also show similar trends for both groups ruling out potential continuation of prior tendencies. Thus, hypothesis 5 is also verified.

[Insert Table 8 and Figure 4 about here]

Finally, beyond assessing the quantity of innovative productivity and their collaborative nature, we also explore how effective participating funded firms are at generating basic research that is applied and cited in subsequent work. We find in Table 9 models 4 and 6 that qualitatively similar SMEs have between 2.65 ($e^{0.974}$) and 3.60 times ($e^{1.280}$) more forward citations counts of firm peer-reviewed papers than unfunded firms in the five years following project start. Figure 5 show similar time trends of mean forward citations per firm for both groups, again enabling us to rule out potential continuation of prior tendencies. Thus, we find evidence for hypothesis 6.

[Insert Table 9 and Figure 5 about here]

As robustness checks, we ran the same set of regressions using up to five prior years to the funding event, and find no significant differences in the results. In the interest of conciseness, results are not shown herein but can be obtained from the corresponding author.

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 summarize our results, we observe compelling evidence that participation in academic-industry partnerships where the collaboration is actively mediated improves the firm's survival and employment, and increases the number of peer-reviewed publications, collaborations with academic researchers and publication forward citations, but not granted patents. 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. The increased level of forward citations is particularly noteworthy, as they point to increased significance of the research as a foundation for future work. This could be because the work is more basic in nature, which means that it is riskier for a firm to undertake absent such a mechanism.

Interviews with a small set of participating firms (*n=10*) corroborate these results and reveal that firms do more basic research, and collaborations between academic and industrial partners goes beyond the level of sharing equipment and extends (importantly) to the exchange of ideas. The significant positive effect on the citation count of peer-reviewed publications in participating funded firms is an indication that published knowledge garners more applications by subsequent researchers and is more easily diffused.

Taken together, our results lead us to believe that these grants do not increase the traditional innovative productivity of firms as measured by the generation of patents, but rather they steer the direction of innovative outputs towards more basic research as demonstrated by our findings with publication data. Thus although receiving funding undeniably provides a capital boost for firms as depicted by the increase in survival odds and the number of employees, participation in these actively managed, mediated partnerships have major effects in bridging science and technology and directing the focus of innovative output into more basic research, rather than significantly increasing patenting activity. The change in research direction suggests that the support of governmental funding for academic-industry partnerships bridges the gap between science and technology and enables firms to invest more into risky and basic innovative activities to increase their stock of knowledge (as encoded in peer-reviewed 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 literature by providing empirical evidence of an under-investigated area.

Implications for Practitioners and Policymakers

The academic-industry partnership structure that we studied in this paper creates the potential for a novel model for bridging between the realms of science and technology. It 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, in our setting, deliberate steps are taken to break down the boundaries between the two institutions, enabling teams of individuals from both sides to work alongside one another. Our results suggest that governments can motivate firms to undertake research that is more basic in nature that still has broad application – as evidenced by increased peer-reviewed publications, cross-institutional collaborations and forward citations 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.

The proactive identification of obstacles and active management across institutional boundaries yielded long-term benefits in fostering the desired spillovers. As a way to help companies maintain competitiveness, governments can use such an approach to facilitate the unlocking of knowledge created in academia leading to faster and more effective commercialization.

These findings are also relevant for managers who do not 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 speed the translation of novel technologies from more basic research and broaden their organization's innovative focus.

Limits and Weaknesses

Despite presenting 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 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, even though we were very careful in our empirical design to address endogeneity concerns there may still be subtle selection issues.

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.

From a policy standpoint, this work did not emphasize nor tease apart the effect of funding and participating 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 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 intervening in and mediating conflicts that arise among funded parties.

Future Research

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 on individual scientist level productivity and subsequent impact particularly from the viewpoint of the academic scientist is also interesting and important so as to provide a complete picture of the impact of such bridging programs such as whether similar effects will be seen or whether they generate distractions from basic science to more commercializable research.

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Normalized score	Funded (%)	Number of applications	Applications (%)	Cumulative applications (%)
[-10,7.5)	0.0%	3	1.3%	1.3%
[-7.5,-5)	0.0%	18	7.9%	9.2%
[-5, -2.5)	0.0%	19	8.3%	17.5%
[-2.5, 0)	4.0%	25	11.0%	28.5%
[0,2.5)	60.9%	46	20.2%	48.7%
[2.5, 5)	54.8%	42	18.4%	67.1%
[5, 7.5]	94.6%	37	16.2%	83.3%
[7.5, 10]	100.0%	38	16.7%	100.0%

Table 1 – DNATF funding selection by normalized score

Characteristic	Unfunded	Funded	Two tailed t-test
age of firm	9.88	10.27	0.8
proposed duration	3.26	3.13	0.33
funding amount (M DKK)	15.8	11.2	0.013
number of parties	5.4	4.74	0.14
patents granted	0.36	0.41	0.77
publications	0.28	0.65	0.17
forward citations	13.68	14.07	0.97
cross-institutions	0.19	0.42	0.2
n	73	78	

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

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
SME	4224	0.64	0.48	0	1
bankruptcy	356	0.006	0.075	0	1
employee	2180	524.08	1733.32	0	25063
patents granted	4224	1.71	7.24	0	120
publications	4224	1.85	7.08	0	65
forward citations	4224	1.32	5.19	0	48
cross-institutional publications	4224	26.62	127.30	0	1913

Table 3– Summary statistics

bankruptcy	Model 1 Full b/se	Model 2 QS Full b/se	Model 3 SME b/se	Model 4 QS SME b/se
funded	-1.615*	-1.639*	-0.987	-1.004
	(0.659)	(0.742)	(0.749)	(0.831)
score	-0.0879	-0.0441	-0.0787	-0.000627
	(0.0617)	(0.109)	(0.0720)	(0.124)
ln(amount)	0.394	0.311	0.577	0.578
	(0.331)	(0.399)	(0.388)	(0.477)
_cons	-8.142	-6.079	-11.19	-10.54
	(5.822)	(6.718)	(6.846)	(8.012)
industry fe	y	y	y	y
application year fe	y	y	y	y
N	281	176	189	119
Log lik.	-82.98	-54.99	-65.62	-41.28

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

Table 4 – Logistic regression models with cluster robust standard errors for bankruptcy five years after the potential funding event, run on sample specifications: full sample in second round selection, qualitatively similar full sample in second round selection, SMEs and qualitatively similar SMEs.

employees	Model 1 Full b/se	Model 2 QS Full b/se	Model 3 SME b/se	Model 4 QS SME b/se	Model 5 SME b/se	Model 6 QS SME b/se
post	-0.110+	-0.135	0.000987	-0.0223	-0.0101	-0.0403
	(0.0641)	(0.0889)	(0.0840)	(0.113)	(0.0791)	(0.117)
funded					0.00239	-0.180
					(0.472)	(0.395)
post*funded*t1	0.133+	0.177+	0.230*	0.245*	0.241**	0.263+
	(0.0735)	(0.0934)	(0.0929)	(0.125)	(0.0845)	(0.139)
post*funded*t2	0.112	0.168+	0.275**	0.276*	0.286**	0.295*
	(0.0810)	(0.0956)	(0.0960)	(0.129)	(0.0971)	(0.145)
post*funded*t3	0.108	0.169+	0.314**	0.282*	0.325**	0.300+
	(0.0833)	(0.0957)	(0.103)	(0.129)	(0.104)	(0.156)
post*funded*t4	0.125	0.137	0.345**	0.306*	0.356**	0.324*
	(0.0762)	(0.0995)	(0.116)	(0.135)	(0.0980)	(0.155)
post*funded*t5	0.148	0.160	0.385**	0.328*	0.397**	0.347*
	(0.0823)	(0.108)	(0.128)	(0.145)	(0.110)	(0.152)
normalized score					0.0151	0.0559
					(0.0405)	(0.0639)
ln(amount)					-0.00454	0.0132
					(0.220)	(0.193)
constant					3.107	3.105
					(3.615)	(3.123)
lnalpha						
_cons					0.397**	0.311**
					(0.0725)	(0.0913)
firm fe	y	y	y	y		
industry fe					y	y
application year fe					y	y
N	1836	1284	1243	849	1217	815
Log lik.	-21997.3	-14336.7	-5299.5	-3641.2	-6497.8	-4385.0

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

Table 5 –DiD QML Poisson count regression models with fixed and random effects panel data and cluster robust standard errors for number of employees up to five years after funding, run on sample specifications: full sample in second round selection, qualitatively similar full sample in second round selection, SMEs and qualitatively similar SMEs.

granted patents	Model 1 Full b/se	Model 2 QS Full b/se	Model 3 SME b/se	Model 4 QS SME b/se	Model 5 SME b/se	Model 6 QS SME b/se
post	-0.968**	-1.039*	-0.709**	-0.692**	-0.724**	-0.715**
	(0.371)	(0.460)	(0.230)	(0.111)	(0.216)	(0.145)
funded					0.732	0.502
					(0.591)	(0.644)
post*funded*t1	1.030*	1.019*	0.912**	0.995**	0.926**	1.018*
	(0.410)	(0.468)	(0.346)	(0.348)	(0.315)	(0.401)
post*funded*t2	0.944*	0.657	0.581	0.484	0.595*	0.507
	(0.462)	(0.494)	(0.351)	(0.447)	(0.290)	(0.542)
post*funded*t3	0.580	0.233	0.363	0.484	0.377	0.507
	(0.434)	(0.545)	(0.357)	(0.519)	(0.439)	(0.655)
post*funded*t4	0.0144	-0.183	0.169	0.112	0.184	0.134
	(0.393)	(0.531)	(0.396)	(0.543)	(0.460)	(0.642)
post*funded*t5	-0.426	-0.752	-0.630	-0.511	-0.613	-0.485
	(0.463)	(0.557)	(1.579)	(4.891)	(3.018)	(8.737)
normalized score					0.0123	0.0299
					(0.0674)	(0.123)
ln(amount)					-0.0659	0.130
					(0.350)	(0.431)
constant					0.830	-2.378
					(5.865)	(7.146)
lnalpha						
constant					1.541**	1.592**
					(0.180)	(0.286)
firm fe	y	y	y	y		
industry fe					y	y
application year fe					y	y
N	1313	843	706	443	1914	1241
Log lik.	-2532.8	-1543.7	-656.3	-387.5	-1001.9	-596.3

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

Table 6 – DiD QML Poisson count regression models with fixed and random effects panel data and cluster robust standard errors for number of granted patents filed up to five years after funding, run on sample specifications: full sample in second round selection, qualitatively similar full sample in second round selection, SMEs and qualitatively similar SMEs.

publications	Model 1 Full b/se	Model 2 QS Full b/se	Model 3 SME b/se	Model 4 QS SME b/se	Model 5 SME b/se	Model 6 QS SME b/se
post	0.0354	0.0755	-0.136	-0.129	-0.135	-0.128
	(0.249)	(0.231)	(0.247)	(0.286)	(0.191)	(0.311)
funded					0.380	0.539
					(0.652)	(0.733)
post*funded*t1	0.306	0.184	0.572+	0.802*	0.571*	0.802*
	(0.261)	(0.249)	(0.293)	(0.401)	(0.286)	(0.404)
post*funded*t2	0.325	0.151	0.835**	0.901**	0.834**	0.900**
	(0.254)	(0.265)	(0.295)	(0.339)	(0.230)	(0.349)
post*funded*t3	0.406	0.274	0.939**	1.159**	0.938**	1.158**
	(0.253)	(0.263)	(0.295)	(0.313)	(0.229)	(0.324)
post*funded*t4	0.384	0.257	0.936**	1.150**	0.936**	1.150**
	(0.246)	(0.247)	(0.285)	(0.413)	(0.224)	(0.436)
post*funded*t5	0.413	0.300	0.915**	1.320**	0.914**	1.316**
	(0.259)	(0.280)	(0.327)	(0.433)	(0.290)	(0.484)
normalized score					0.150*	0.0933
					(0.0606)	(0.106)
ln(amount)					-0.0517	-0.124
					(0.454)	(0.550)
constant					0.758	1.631
					(7.653)	(9.102)
lnalpha						
constant					1.455**	1.474**
					(0.130)	(0.153)
firm fe	y	y	y	y		
industry fe					y	y
application year fe					y	y
N	1508	966	840	541	1914	1241
Log lik.	-2015.0	-1209.6	-968.3	-627.5	-1418.7	-915.0

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

Table 7 –DiD QML Poisson count regression models with fixed and random effects panel data and cluster robust standard errors for number of peer-reviewed publications up to five years after funding, run on sample specifications: full sample in second round selection, qualitatively similar full sample in second round selection, SMEs and qualitatively similar SMEs.

cross-inst. pubs	Model 1 Full b/se	Model 2 QS Full b/se	Model 3 SME b/se	Model 4 QS SME b/se	Model 5 SME b/se	Model 6 QS SME b/se
post	0.383*	0.490*	0.226	0.332	0.226	0.333+
	(0.191)	(0.199)	(0.221)	(0.241)	(0.232)	(0.185)
funded					1.079	1.234
					(0.714)	(0.927)
post*funded*t1	-0.0139	-0.210	0.349	0.351	0.350	0.351
	(0.208)	(0.219)	(0.270)	(0.389)	(0.318)	(0.453)
post*funded*t2	0.0559	-0.184	0.629**	0.605	0.630*	0.604+
	(0.216)	(0.219)	(0.243)	(0.331)	(0.313)	(0.322)
post*funded*t3	0.196	-0.0516	0.748**	0.757**	0.748**	0.756**
	(0.226)	(0.206)	(0.265)	(0.290)	(0.288)	(0.277)
post*funded*t4	0.186	-0.0324	0.841**	0.902*	0.841*	0.902*
	(0.224)	(0.215)	(0.271)	(0.367)	(0.338)	(0.399)
post*funded*t5	0.199	0.0170	0.760**	1.007**	0.761*	1.005**
	(0.213)	(0.228)	(0.288)	(0.367)	(0.317)	(0.339)
normalized score					0.130+	0.123
					(0.0698)	(0.127)
ln(amount)					0.358	0.871
					(0.494)	(0.561)
constant					-7.539	-15.47
					(7.907)	(11.09)
lnalpha						
constant					1.289**	1.219**
					(0.170)	(0.226)
firm fe	y	y	y	y		
industry fe					y	y
application year fe					y	y
N	1336	838	779	498	1914	1241
Log lik.	-1548.0	-893.9	-682.8	-422.3	-1078.8	-677.2

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

Table 8 –DiD QML Poisson count regression models with fixed and random effects panel data and cluster robust standard errors for number of cross-institutional collaborations for publications up to five years after funding, run on sample specifications: full sample in second round selection, qualitatively similar full sample in second round selection, SMEs and qualitatively similar SMEs.

forward citations	Model 1 Full b/se	Model 2 QS Full b/se	Model 3 SME b/se	Model 4 QS SME b/se	Model 5 SME b/se	Model 6 QS SME b/se
post	-0.448	-0.235	-0.754**	-0.566**	-0.754**	-0.566+
	(0.376)	(0.350)	(0.231)	(0.177)	(0.239)	(0.315)
funded					0.855	0.833
					(1.027)	(0.988)
post*funded*t1	0.605	0.44	1.233*	1.558*	1.233*	1.558*
	(0.428)	(0.501)	(0.519)	(0.774)	(0.551)	(0.738)
post*funded*t2	0.439	0.106	1.135**	0.974*	1.135**	0.974*
	(0.381)	(0.408)	(0.305)	(0.422)	(0.312)	(0.445)
post*funded*t3	0.421	0.34	1.256*	1.700*	1.256*	1.700*
	(0.399)	(0.505)	(0.579)	(0.755)	(0.639)	(0.734)
post*funded*t4	0.0606	-0.239	0.592	0.945	0.592	0.945
	(0.388)	(0.436)	(0.386)	(0.500)	(0.421)	(0.613)
post*funded*t5	-0.276	-0.226	0.62	1.280*	0.62	1.280*
	(0.419)	(0.538)	(0.626)	(0.643)	(0.649)	(0.629)
normalized score					0.211	0.192
					(0.133)	(0.195)
ln(amount)					0.416	0.556
					(0.792)	(0.948)
constant					-3.393	-5.568
					(13.280)	(16.130)
lnalpha						
constant					2.287**	2.218**
					-0.123	-0.159
firm fe	y	y	y	y		
industry fe					y	y
application year fe					y	y
N	1408	909	764	500	1914	1241
Log lik.	-31107.9	-19643.1	-19138.7	-11937	-19782.7	-12351.5

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

Table 9 –DiD QML Poisson count regression models with fixed and random effects panel data and cluster robust standard errors for number of forward citation of publications up to five years after funding, run on sample specifications: full sample in second round selection, qualitatively similar full sample in second round selection, SMEs and qualitatively similar SMEs.

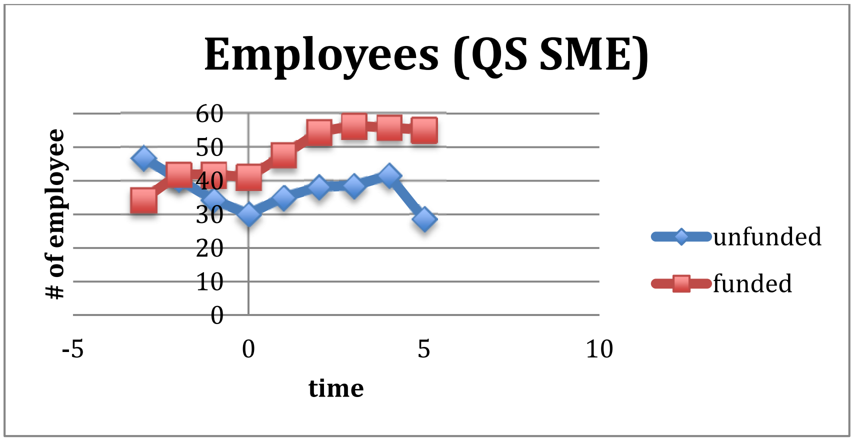

Figure 1 – Mean number of employees for both funded and unfunded firms for each year before and after funding at t_0 using the qualitatively similar sample of SME firms.

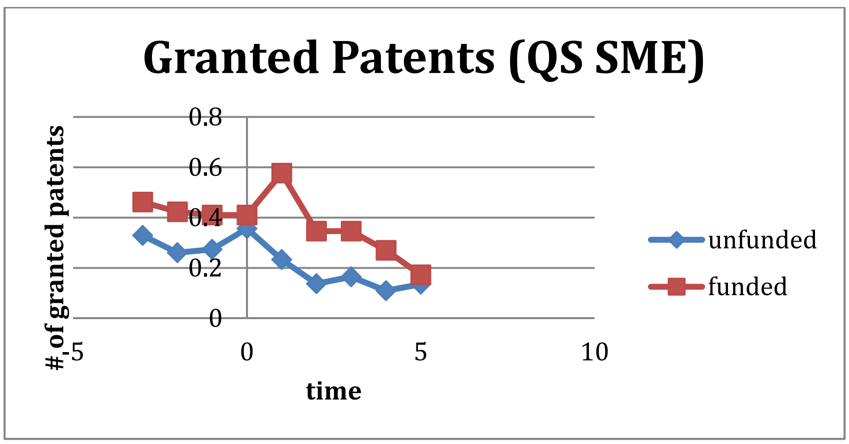

Figure 2 – Mean number of granted patents for both funded and unfunded firms for each year before and after funding at t_0 using the qualitatively similar sample of SME firms.

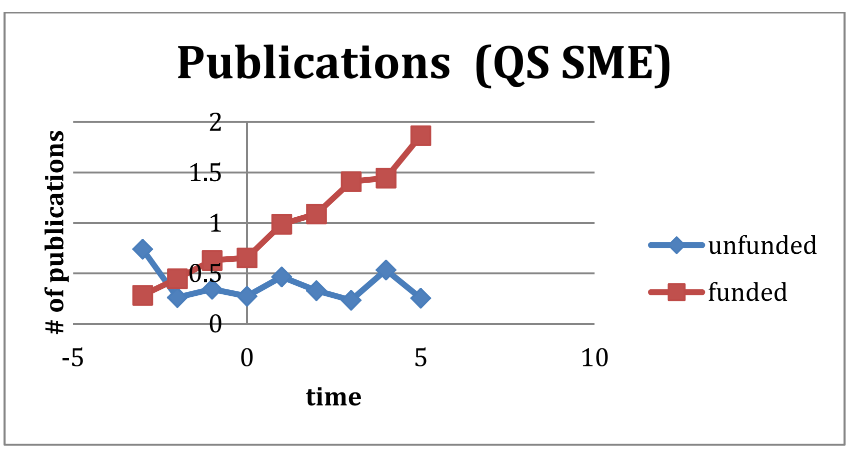

Figure 3 – Mean number of publications for both funded and unfunded firms for each year before and after funding at t_0 using the qualitatively similar sample of SME firms.

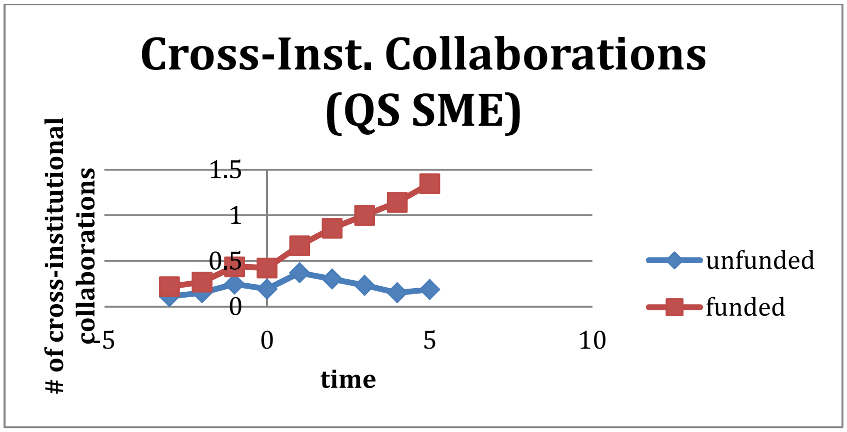

Figure 4 – Mean number of cross-institutional collaborative publications for both funded and unfunded firms for each year before and after funding at t_0 using the qualitatively similar sample of SME firms.

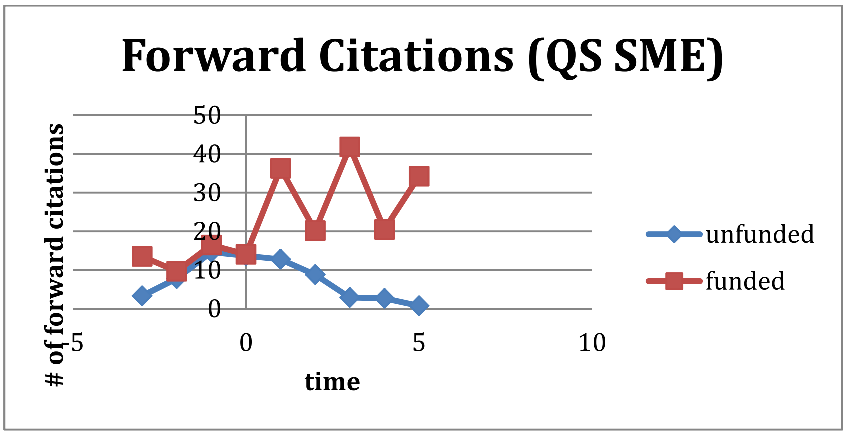

Figure 5 – Mean number of forward citations of publications for both funded and unfunded firms for each year before and after funding at t_0 using the qualitatively similar sample of SME firms.