Funding Private-Public Partnerships and Impact on Firm Performance & Innovative Performance: Evidence from Denmark

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Abstract

While public-private partnerships between public research organizations, such as universities and hospitals, and private firms are an established policy tool around the world for the delivery of social or public services, their use as a tool to spur innovation and translational research to spur the flow of investments in the basic sciences into commercial application has attracted renewed interest. This article examines empirical data from the Danish National Advanced Technology Foundation (DNATF or Højteknologifonden in Danish), an agency that funds partnerships between universities and private companies to develop technologies important to Danish industry. Using regression discontinuity methods, we causally assess the effect of such funding schemes on firm performance – survival, employment and growth – and firm innovative performance – quantity, quality and nature of patents and papers – by comparing funded and unfunded firms. We use a regression discontinuity subsample of small and medium enterprises just above and just below the funding cutoff threshold, and find convincing evidence that receipt of funding has a compelling effect on firm performance and innovative performance three to four years after receipt of funds. Selection of a firm to receive funding helps it to stay financially viable and significantly decreases the likelihood of bankruptcy by up to 1.11 times four years after funding application. Funding also increases the average number of headcount by 10.3 to 12.7 more employees for funded firms, respectively two and three years after application. For innovative performance, funding increases granted patents by 13.3 times and peer-reviewed publications 7.8 times, but its effect is mainly felt on quality of the innovations as peer-reviewed citations for funded firms are 38.1 times greater than those of unfunded firms. Finally, public-private partnership funding also alters the nature of knowledge produced as well as the collaborative behavior of scientists since funded firms collaborate 6.1 times more with colleagues in academia.

Keyword: innovation; firm performance; public-private partnership funding; translational research; small and medium enterprises; regression discontinuity

Introduction

A common question in the innovation literature is the comparative impact of different types of funding on firm performance and innovative output. In scientific research, understanding the effect of research grants on output is important for policymakers and academics alike (Azoulay, Graff Zivin, & Manso, 2011). In the technology sector, particularly in the literature of entrepreneurial finance, the effect of angel investments (Kerr, Lerner, & Schoar, 2011), venture capital (Kortum & Lerner, 2000; Samila & Sorenson, 2011), banks (Black & Strahan, 2002) and initial public offerings (Bernstein, 2012) on innovation and entrepreneurship is an area of great interest. These studies mostly investigate the effects of various funding schemes on innovation within the well-defined boundaries of the scientific and technological institutions. Inherent in these works is a clear dichotomy between the knowledge created in science and that produced for technological and commercial purposes.

The relationship and the differences between science and technology have been extensively studied and follow three major research streams. The first stream, the new economics of science, adopts an institutional stance (Merton, 1957; Dasgupta and David, 1994). A second stream looks at the role that science and technology play respectively in generating new knowledge (Stokes, 1997), and a third takes an information flow perspective (Allen, 1977). The interest in understanding how ideas are produced in both science and technology have been driven by the belief that scientific research and its subsequent translation into technology is a driver for wealth creation and economic growth (Scherer & Harhoff, 2000), where increased university research spending have been empirically shown to be associated with greater rates of local patenting (Jaffe & Trajtenberg, 1996), and cumulative published research leads to accelerated economic growth (Adams, 1990). Many of these works have assumed that knowledge created in the scientific and technological realms are produced independently.

Besides prevalent funding schemes separately targeting science and technology many countries have public-private partnership funding schemes that target translational research at the intersection of science and technology as well. In the United States, National Science Foundation (NSF) shared resources centers often require some form of partnership with private firms. The NSF Energy Resource

Centers, for example, require translational research partnerships between principal investigators and small firms to accelerate product development. The National Institutes of Health (NIH) launched a public-private partnership program in 2005 that sought to identify the most compelling opportunities for cross-boundary research that would link biomedical research to commercial opportunities. The NIH programs tended to be far reaching, including programs like a biomarkers consortium, a neuroimaging consortium targeting Alzheimer's Disease, and a Grand Challenges for Global Health initiative. The Fraunhofer-Gessellschaft in Germany 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. In other Scandinavian countries, the Finnish Funding Agency for Technology and Innovation is another example of a governmental agency funding firms and public research institutions, and the Swedish Governmental Agency for Innovation Systems VINNOVA supports different innovative projects including constellations of firms and public research institutions. Despite many such programs internationally little research has been performed to assess the impact of these approaches on the quantity and nature of knowledge produced and the performance of firms that receive them.

This paper examines the public-private partnership model of the Danish National Advanced Technology Foundation (DNATF or Højteknologifonden in Danish), an agency of the Danish government. DNATF awards funding for projects that are partnerships between at least one academic institution and at least one firm. It has a unique "1-2-3" funding model in which 1/6 of the total project funding is provided by the public sector research group(s), typically a university, 2/6 is provided by private firm(s) and 3/6 is funded by DNATF. Full requested amounts are committed at the time of award, but progress payments are contingent on performance. DNATF employs an active intervention model in which a small team of managers actively engages in project steering committee meetings. It provided a novel dataset for this

study that enables us to causally determine the effect of governmental funding on projects at the boundary between science and technology both on the economic performance of the firms and in the quality and quantity of innovative outputs.

This paper bridges the literature between innovation funding and the economics of science. It contributes to the former by lending empirical evidence on the impact of the change from traditional sources of funding such as venture capital, debt and initial public offerings to public-private partnership models. Moreover, it sheds light on how this novel funding scheme impacts the nature of knowledge creation within the institutions of science and technology when the boundaries are blurred.

We assess how DNATF funding is effective in helping firms survive, hire more employees and partake in riskier and wider exploration activities that serve to spur innovation. Using a regression discontinuity approach (Lee & Lemieux, 2010) we compare how this style of public-private partnership affect firm performance (survival), employment and growth, and innovative performance in the quantity, quality and nature of knowledge produced. We compare a treated sample – firms that obtained DNATF funding – with a control sample – firms that applied for DNATF funding but did not receive funding. Since all proposal applications to DNATF are ranked, we develop several sample specifications to robustly insure that funded and unfunded projects are most similar by including firms just above and just below the funding cutoff.

Our results show that with the subsample – small and medium enterprises just above and just below the funding threshold – built for a regression discontinuity design, the receipt of funds has the strongest effects on firm performance and innovative performance 3-4 years after funding application. It helps firms stay financially stronger and significantly decreases the likelihood of bankruptcy by up to 1.1 times 4 years after funding application. Funding also increases the average employment by 10.3 to 12.7 more employees for funded firms respectively 2 and 3 years after application. For innovative performance, funding increases granted patents 13.3 fold, and peer-reviewed publications 7.8 fold. More significantly, its impact on the quality of the innovations is dramatic, with a 38.1 times greater number of peer-reviewed citations for funded firms compared to unfunded ones. Finally, public-private partnership

funding also alters the nature of knowledge produced as well as the collaborative behavior of scientists since those firms that receive funding collaborate 6.1 times more frequently with colleagues in academia.

The structure of this paper is as follows. We begin by presenting the theoretical framework from the literature and develop testable hypotheses. We then elaborate on the setting from which we compiled our data, detail the estimation methodology employed to run our analysis, and interpret our results. Finally we discuss the contributions this paper brings to the extant literatures that we inform as well as implications for policymakers and managers.

Theoretical Framework and Hypotheses

Impact of Funding on Firm Performance

Literature on the financing of innovation has broadly explored the effect of funding on organizational performance and innovative output in the form of grants for academics research (Azoulay et al., 2011), of early-stage funding such as angel investments (Kerr et al., 2011) and venture capital (Kortum & Lerner, 2000), and of more mature financing outlets such as initial public offerings (Bernstein, 2012).

Scholars in entrepreneurial finance have extensively studied both theoretical and empirical consequences of early-stage funding such as venture capital and angel investors on firm performance. Theoretical work suggests that the role of entrepreneurial financiers is not only to provide funding that relieves capital constraints but also alleviates agency problems between entrepreneurs and investors through monitoring and improved governance (Admati & Pfleiderer, 1994; Hellmann, 1998).

Empirical researchers have causally demonstrated the impact of such early-stage investments on firm performance and innovative performance using identification strategies such as regression discontinuity or exogenous shocks from policy changes. Kerr, Lerner and Schoar used angel investor data and took advantage of a full dataset of ventures with successful and rejected angel funding with the application of regression discontinuity to show that funded ventures have improved subsequent survival, exit, employment, patenting and financing (2011). Exploiting exogenous shocks, venture capital funding

has been shown to be causally associated with higher patenting rates (Kortum & Lerner, 2000) and positively impacts on employment and aggregate income (Samila & Sorenson, 2011).

Although the firms in our setting are not necessarily entrepreneurial, they suffer from the same capital constraints that prevent them from undertaking risky innovative projects. Therefore we posit that firms successful in obtaining funding in the form of public-private partnerships are less likely to file for bankruptcy, and will also benefit from more employment and higher economic growth.

Hypothesis 1: *Firms funded in public-private partnerships have a higher likelihood of survival compared to non-funded firms*

Hypothesis 2: *Firms funded in public-private partnerships have a higher increase in the number of employees relative to non-funded firms*

Hypothesis 3: *Firms funded in public-private partnerships have higher growth relative to non-funded firms*

Private firms have little incentive to undertake basic research because of the difficulty in patenting and protecting basic research results (natural laws and facts are not patentable). Several reasons underpin this incentive misalignment. Very few firms are broad and diverse enough to directly benefit from all the new technological possibilities opened by successful basic research. Therefore with the absence of strict and pervasive enforcement of intellectual property rights, firms that perform basic research with their own capital are confronted with the free rider problem that enhances use by others (Nelson, 1959). Consequently, the combination of non-rivalry and imperfect excludability suggests that investments in innovation will be a public good. Furthermore, since basic scientific research is considered a long-term investment, objective timelines are also misaligned. Firms are concerned with short-term survival whereas basic research requires long-term forecasting and thinking. The high uncertainties and risks associated with basic research may prompt small risk-averse firms with limited funding to avoid it. Thus, combined with the difficult appropriability problem, firms lack incentives to perform basic research.

As a response to this classical economist's view, Rosenberg (1990) argues that it is not necessary for private firms to capture all the benefits of basic research, as long as they capture enough to yield a sufficiently high return on investment, it is worthwhile for them to pursue it. Private firms should still perform basic research with their own money because three reasons. First, basic research capability is essential to making effective decisions about their applied activities. Second it is crucial in order to monitor and evaluate research being conducted elsewhere such as in universities, and finally needed for evaluating the outcome of applied research to recognize possible implications.

Thus we postulate that governmental funding for public-private partnerships provides motivation for private firms to undertake basic research that they otherwise would not have undertaken while simultaneously limiting risk, and facilitating monitoring of the scientific landscape. Since public-private partnership projects condense interactions between scientists and technologists, firms will also be more effective at applying basic science results and translating them into patents, commercializable products and optimized processes.

Hypothesis 4a: *Firms funded in public-private partnerships produce more patents relative to non-funded firms*

Hypothesis 4b: *Firms funded in public-private partnerships produce more peer-reviewed publications compared to non-funded firms*

Science versus Technology and the Interplay between Science and Technology

In the institutional view, science is seen as having a distinctive incentive system compared to technology. The scientific institution is primarily embodied in research universities based on a priority-based reward system where the output is mainly in the form of peer-reviewed publications. The technology institution, in contrast, encodes ideas in protected modes, for example using patents, to facilitate commercialization and appropriation of economic rewards (Dasgupta & David, 1994). Moreover, the two institutions differ in the nature of the goals accepted as legitimate and the 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 adding to the stream of rents that may be derived from possession of private knowledge.

Merton (1957) first proposed science as an institution with its own reward system and behavioral norms of universalism, communalism, disinterestedness and organized skepticism. The priority based reward system puts emphasis and a premium on originality. The property rights of science only extend to the recognition by others of the scientist's unique role in generating the result or theory rather than the intellectual protection rights that patents benefit from, because as soon as the work is published the scientist no longer has exclusive rights of access to it. Consequently, the knowledge becomes part of the public domain of open science and reflects the norm of communalism. The reward system that supports this norm of priority is not pecuniary but rather recognition of scientific achievements through the award of various prizes, medals, memberships in honorary academies and societies, eponymy, etc. The relationship between science and technology can also be depicted by the nature of knowledge creation (Stokes, 1997). Science or basic research concentrates on demonstrating *why* through a process of posing hypotheses that are empirically tested so as to refine theory, while technology or applied research searches for recipes for *how* by developing practical and useful techniques.

Initial works that studied the interaction between science and technology suggested a linear relationship, in which knowledge introduced from science spills over seamlessly into technology thereby creating positive externalities for innovation (Freeman, 1992; Mansfield, 1995). In more recent research, scholars have suggested that the relationship between science and technology is more complex than the linear model, and that there exists a complex bidirectional relationship between the two. In other words, science is no longer viewed as a self-contained exogenous process but rather endogenous to technical progress. Nelson (1995) coins this phenomenon as the endogeneity of science and technology where progress in science may be due in part to feedback from technology.

Stokes critiques the conventional one-dimensional basic-applied spectrum in which basic research refers to fundamental studies carried without a specific application aim, while applied research, which encompasses engineering and technology aims primarily at practical application (Stokes, 1997). He

proposes instead a two-dimensional continuum where the vertical axis represents the quest for fundamental understanding or the degree to which a given body of research seeks to extend the frontiers of fundamental understanding, and the horizontal axis the degree to which the research is guided by considerations of use. Pasteur's quadrant emerges at the intersection of these two axes and includes not only basic research that seeks to extend the frontiers of understanding but is also simultaneously inspired by applicability. The public-private partnership setting that we are studying is a model in which knowledge produced is situated in Pasteur's quadrant, where the institutional boundaries between science and technology have been temporally blurred by the partnership project.

Science has also been presented as providing three mechanisms to explore a technological map (Fleming & Sorenson, 2004). First, it facilitates effective search by providing a theoretical understanding of underlying properties of technological components and their interactions. Second, science reduces the size of the combinatorial search space by ruling out and eliminating fruitless avenues. And third, science encourages inventors to continue in a certain direction of search despite initial unfruitful set of components since theoretically it is possible. Since a principal objective of public-private partnerships is to foster close collaboration between scientists and technologists, we posit that patents generated from these projects are of higher quality.

Hypothesis 5a: *Firms funded in public-private partnerships produce more cited patents relative to non-funded firms*

Other studies examining the interplay of science and technology have more specifically investigated the effect of patenting on scientists' efforts to engage in subsequent scientific research. Findings on the impact of university patenting on productivity, quality and direction of basic scientific research output show that both the flow and the stock of scientists' patents are positively related to subsequent publication rates (Azoulay, Ding, & Stuart, 2009). In academic research settings, even though patent volume does not predict publication volume, patent volume positively affects paper citations, providing insight on the research impact of patents (Agrawal & Henderson, 2002). The implication from

these studies is that patenting is a complementary activity to fundamental research as opposed to being a substitute.

However, the role of intellectual property rights (IPR) on scientific research has long been debated amongst academics and policy makers. On the one hand, IPR may facilitate the creation of a market for ideas, encourage further investment in ideas with commercial potential, and mitigate disincentives to disclose and exchange knowledge which might otherwise remain secret. IPR may enhance the ability of society to realize the commercial and social benefits of a given discovery. On the other hand, the anti-commons perspective argues that IPR privatizes the scientific commons, limits scientific progress, and inhibits the free flow of scientific knowledge and the ability of researchers to build cumulatively on each other's discoveries. Murray and Stern (2007) found evidence for a quantitatively modest but statistically significant anti-commons effect, where paper citation rates decline by approximately 10 to 20 percent after a patent grant. Consequently, the results of these studies are contradictory and largely unresolved.

Hypothesis 5b: *Firms funded in public-private partnerships produce more frequently cited peer-reviewed publications relative to non-funded firms*

Hypothesis 5c: *Firms funded in public-private partnerships produce less frequently cited peer-reviewed publications relative to non-funded firms*

Only a few articles have empirically assessed the extent of overlap between science and technology (Murray, 2002, 2004). Cockburn and Henderson (1998) build on Cohen and Levinthal's concept of absorptive capacity (1990), and provide empirical evidence that spillover effects between science and technology are not a simple waterfall model in which the public sector produces knowledge that spills over costlessly to downstream researchers. The authors show that in order to take advantage of public sector research, these firms must do more than simply hire the best scientists and invest in in-house basic research with appropriate pro-publication incentive systems. They must also actively collaborate with their public sector colleagues. This improves access to public sector research and quality of research conducted within the firm.

Thus we postulate that given the close interactions between scientists and technologists when working on public-private partnership projects, collaboration and co-authoring across institutions increases.

Hypothesis 6: *Firms funded in public-private partnerships produce more cross-institutional collaborative output 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 is 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 public-private research collaborations, facilitating bridge building between Danish public research institutions and Danish companies in order to generate growth and technologies that benefit Danish society as a whole.

DNATF is the only Danish governmental funding source that exclusively supports public-private research collaborations. Funding for such collaborations, however, can also be obtained from other Danish governmental sources. The largest alternative state funding sources in Denmark are the Energy Technology Development and Demonstration 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.

DNATF uses a bottom-up approach in the application process. It seeks to fund the best ideas within the broad boundaries of advanced technology. The investment portfolio covers a broad range of technologies ranging from robotics, agriculture, livestock, biotechnology and medicine, all the way to telecommunications. Based on all funded projects since DNATF's inception in 2005 to 2011, The largest

sector in DNATF's portfolio is biomedical, making up 28% of all investments, while energy and environment represents 21%, IT and communication 18%, production 17%, produce and food 10%, and 6% in the construction sector.

Applicants must include at least one academic scientist and one firm. In choosing the best ideas, DNATF screens on three main criteria: obvious business potential, internationally recognized high quality research and innovation, and entreneurship. Applications are screened in two stages by the board of DNATF. The board consists of nine leaders from Danish industry and science who have extensive and unique knowledge in their respective fields.

The first application stage is 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 member forms his or her own opinion *a priori*. At the meeting, the aggregate scores by all board members form the basis of discussion on whether to approve the particular expression of interest for the second round of application. About 30% of the first round applications are approved and move into a second round, in which applicants prepare a more comprehensive 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 score each application with an A, B or C. Based on the aggregate scores and discussion, the board reaches a consensus on whether to fund the application. From the applications that proceed to the second stage, about 40% ultimately receive funding. During the final the board meeting every year, a set funding is awarded until fully exhausted. Thus this setting does not suffer from the potential endogeneity issue of reverse causality where innovation drives funding.

DNATF intervenes throughout the project period. A Single Point Of Contact (SPOC), an individual part of the small DNATF staff, is assigned to each investment to act as a gatekeeper between the project and DNATF for the duration of the project period. The SPOC practices active follow-up by participating as an observer in steering-group meetings, handling the day-to-day dialogue with the project participants, reporting quarterly to the board, and generally challenging the project participants on

progress and challenges throughout the project period. Moreover, the SPOC focuses on ensuring a dedicated collaboration between the projects participants thereby maximizing the collaborative gains in the project.

By the end of 2012, DNATF has made 208 investments with a total project budget of DKK 4,701[1] million of which DNATF has invested half as per its 1/6 – 2/6 – 3/6 investment model described earlier, which implies that public research institution(s) fund 1/6 of the total budget, private firm(s) 2/6 while DNATF funds 3/6. 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. An average investment has a duration of 4 years and receives DKK 12 million from DNATF. Figure 1 shows the distribution of funded amounts by project 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 on average two companies. In 2012, 84% of all investments have one or several universities as the participating public research institution. The remaining 16% are either hospitals or universities and hospitals in cooperation. Foreign companies are allowed to participate but cannot receive funding. Of the companies in DNATF's portfolio, 59% have 49 employees or less. Seventeen percent of the companies have 50-249 employees, 12% have 250-999 employees, and 12% have more than 1000 employees.[2]

Empirical Approach and Identification Strategy

Full Sample from Second Stage of Selection Process

The two stage application process that projects undergo for funding enable 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 our problem of unobserved heterogeneity stemming from

[1] DKK4,701 million is the equivalent of USD818 million at the October 2012 exchange rate of 5.75DKK/USD
[2] Additional numbers are provided in the Yearbook 2012 by DNATF.

selection bias (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 chose to invest in, 47 were finalized as usual and two were stopped before nominal project completion by DNATF. Since there is no upper limit on the number of firms per project, the 49 invested projects translated into 102 participating companies. Among these 102 companies, 16 are duplicates, i.e. companies which participated in more than one of the 49 investments. Thus, in total there are 86 unique companies which have been part of finalized DNATF-investments and these make up our treatment group. For the control group, we use firms that applied for DNATF funding from 2005 to 2008 that were selected into the second round of review, but who did not receive funding. Therefore, these applications have been screened and tested in the first round of applications along with the 49 investments which make up our treatment group. As the treatment group, all firms in the control group were part of applications that would have been finalized and funded at the end of 2011 or before. The control group consists of 105 companies. Among the 5 companies 8 are duplicates, i.e. companies which are found more than one time among the unfunded applications. This amounts to 97 unique companies as the control group.

Our model estimation for this specification is as follows:

(eq. 1) $$Y_{i,t+1} = f(\beta_1 \cdot funded_{i,t} + \beta_j \cdot X_{i,t})$$

The outcome variable is $Y_{i,t+1}$ for firm *i* at subsequent time period *t+1*. Since we are assessing the effect of public-private partnership funding, the treated variable (*funded*) is an indicator of whether a firm *i* has received funding at time *t*. For each firm *i* in the vector $X_{i,t}$ of length *j*, we also control for observables by including application year (at time *t*) fixed effects and industry fixed effects.

Sample of Small and Medium Enterprises

A more detailed look at the sample of firms that received funding shows that it encompasses an extremely heterogeneous set along the dimension of firm size. While most of the firms that received funding are small and medium size enterprises (SME) – defined as companies with 250 employees or less – some funding recipients boasted headcounts into the thousands of employees. Given the limited range (DKK 2,550,000 to DKK 62,400,000) in the amount of public-private partnership funding provided by DNATF, the impact of this funding will have more impact in small and medium enterprises where the amount of funding comprises a sizable portion of the firm's R&D budget. Although larger companies still benefited from the influx of capital brought by funding, its impact was likely less evident, as the amount funded only represented a small fraction of the firm's R&D budget.

For our second specification, we restrict our analysis to small and medium size enterprises and dropped firms with more than 250 employees at the time of funding application from the sample. This left us with 55 SME firms in the treated group received DNATF funding and 77 firms in the control group that did not receive funding. The model estimation for this second sample specification is the same as in equation 1, except we have now restricted the treated and control samples to only include firms with 250 employees and less at time of application.

Regression Discontinuity Sample for Small and Medium Enterprises

Despite dropping firms whose projects that did not advance to the second round of the application process as well as those with more than 250 employees, the informed reader may still argue that the difference between the top firms in the funded sample and the worst firms among the unfunded ones is still significant and that the sample specification still suffers from unobserved heterogeneity. To address this issue, we employ regression discontinuity (Lee & Lemieux, 2010) to assess the causal impact of partnership projects on firm survival, employment, and growth, as well as the quantity, quality and nature of knowledge created. We essentially are comparing firms with projects situated just above and below the funding cutoff.

To determine the funding cutoff, we exploit scores given by DNATF board members in their assessment for each application proposal as a quasi-ranking system. Interviews with staff at DNATF revealed that an assessment of A for a project indicates that a board member believed that the project is highly worthy of support, B indicates that the project is worthy of support, whereas a C indicates not worthy of support. We translate this evaluation into a normalized score 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. The numeric score is calculated as follows:

(eq. 2) $$score_i = \frac{10 \cdot (\sum_k A - \sum_k C)}{\sum_k (A+B+C)}$$

From this normalized score we establish the cutoff boundary for funding. Since DNATF does not have explicit funding rules that lead to systematic funding decisions, we need to show three patterns in our data in order to infer causality using the regression discontinuity approach (Lee & Lemieux, 2010). First, applicants to the funding cannot know in advance the cutoff score for funding to avoid potential manipulation. Given DNATF's selection process which ultimately hinges on board member assessment and its lack of a systematic funding rule, we believe this first assumption is met.

Second, a discontinuity must be present between the normalized score and the probability of funding. In other words, there must be a point in the distribution where a small change in the normalized score would drastically change the probability of funding. Following the method employed in Kerr, Lerner and Schoar (2011) where a similar inexplicit relationship between angel investor interest level and angel funding is present, we identify using the third column of Table 1 the fraction of firms in each tranche of the normalized score that are funded. We observe that the fraction of funded firms increases mostly monotonically as the normalized score increases. We also see a drastic increase in funding probability, from 33% to 58%, between the normalized score ranges of [2,4) and [4, 6), which we identify as the discontinuous point in the distribution. From this cutoff we define a bandwidth of firms just above and below where the quality and funding prospect for these firms are most comparable. Referring back to Table 1, we see that at the lower end no applications with a normalized score of less than -2 was funded

and on the upper end one hundred percent of applications were funded if the application received a normalized score above 6. Consequently, we define our narrow band of firms just above and below the cutoff to be those with normalized score in the range [-2, 6).

[Insert Table 1 about here]

The third criterion was that we needed to ensure that there was no significant difference in the observables for firms just above and below the cutoff. We test this criterion using two-sided t-tests. Table 2 shows that firms situated within this narrow bandwidth around the cutoff were not significantly different on all observable dimensions. Not only do we look at cross-sectional data at points in time prior to funding, but we also included growth trends in the years prior to funding in order to rule out selection biases based on firm quality and growth trends. These results are critical in order to draw causal conclusions on the effect of public-private partnership funding on firm performance and innovative performance.

[Insert Table 2 about here]

Our third sample specification consisted of the region in which firms were most comparable – those with normalized scores in the range of [-2, 6) – and dropping from the sample firms at both extremes of the normalized score distribution. Again the model estimation for this final sample specification is the same as in equation 1, except this time we not only restrict the treated and control samples to only include firms with 250 employees and less at the time of application but also to those within the established normalized score range.

Regression Models

Given the different natures of our outcome variables, we used corresponding regression models to minimize estimation bias. For instance, survival data is depicted by an indicator variable for survival, so we employ Probit models with robust standard error. Employment and growth data consisted of both negative and positive values, which were best fitted using ordinary least squares and robust standard errors. Finally, variables for patents and papers (number of patents and papers and number of citations)

are non-negative and over-dispersed counts where we use quasi-maximum likelihood Poisson models with robust standard error to circumvent the assumption of equal mean and variance distribution for Poisson models.

Outcome Variables

Variables

Hypothesis 1 explores whether receiving DNATF funding increases the likelihood of survival for firms. We obtain data on whether a firm in our sample is bankrupt in the years subsequent to funding application. These outcome variables are indicators that take on the value of 1 if the firm is bankrupt a certain year after funding application and 0 if it is still operating. We trace the bankruptcy of firms as time passes for two periods after funding – survival 2 years (*bkrupt_1-2ya*) and 4 years (*bkrupt_1-4ya*) after application. If a firm goes bankrupt 2 years after application both bankruptcy outcomes variables equal 1, whereas if a firm goes bankrupt 3 years after application only *bkrupt_1-4ya* equals 1. We stopped tracking the outcome variable 4 years after application to maintain consistency throughout our dataset, since our sample includes firms that applied for funding in 2008 where only 4 years have elapsed at time of data gathering in October 2012.

Hypothesis 2 studies the effect of public-private funding on employment. We employ the absolute delta between a firm's number of employees for each subsequent year after funding until 4 years after funding and the same number during the year of funding application (*empd_1ya, empd_2ya, empd_3ya* and *empd_4ya*).

Hypothesis 3 explores whether such public-private partnership funding schemes affect firm growth. We employ the firm's bottom line and calculate the yearly percentage of growth in net income relative to the base year of application (*nigr_1ya, nigr_2ya, nigr_3ya* and *nigr_4ya*) for firms in our sample as follows:

(eq. 3) $$nigr_i\ ya = \left(\frac{net\ income_{i\ years\ after\ application}}{net\ income_{application\ year}}\right)^{\frac{1}{i}}.$$

Hypotheses 4 investigate the relationship between public-private funding and the quantity of knowledge produced both in terms of peer-reviewed academic papers and patents. Hence, we use the number of peer-review papers researchers of the firm have published 1-2 years and 3-4 years (*pub_1to2ya* and *pub_3to4ya*) after the year of application. Identically for patents, we find the number of granted patents assigned to the firm filed 1-2 years and 3-4 years (*patg_1to2ya* and *patg_3to4ya*) after the year of application as well as the number of unissued patents filed 1-2 years and 3-4 years (*patf_1to2ya* and *patf_3to4ya*) after the year of application.

Hypotheses 5 study the quality of knowledge produced from public-private partnership projects. We operationalize the impact of publications and patents using the commonly employed measure of forward citations. Consequently, we count the number of citations garnered by all publications 1-2 years and 3-4 years after the year of application (*fwcit_1to2ya* and *fwcit_3to4ya*).

Finally, hypothesis 6 explores the co-evolutionary nature of science and technology in public-private partnership projects. We use the number of peer-reviewed publications where the authors and inventors are affiliated with different institutions, in other words publications where researchers in the firm co-publish with scientists in academia. To see the effect of the public-private partnership funding, we count the number of instances where peer-review publications by a firm are in collaboration with at least one co-author affiliated with an academic institution 1-2 years and 3-4 years after the year of application (*xinst_1to2ya* and *xinst_3to4ya*). We planned to develop a similar measure for patents, but unfortunately affiliation data for inventors did not include the institution for which they work and therefore we could not make any rigorous inferences as to their professional affiliation.

Datasets

As described earlier, our dependent variables fell within three categories – economic variables, patent variables and publication variables – which each require a different data source.

Data on the economic variables was collected at the firm level (e.g. number of employees, net profit etc.). The data source used was BiQ (BiQ Erhvervsinformation in Danish), a Danish database that

includes all registered Danish firms. BiQ is updated daily from the Danish Business Authority which is a governmental database that keeps comprehensive information on all Danish firms. BiQ provides yearly information on each firm from 2004 onwards. The firms in our study all applied for funding from 2005 onwards which made it possible to collect data before and after funding. For each economic variable, data was collected in panel form for each firm-year. In addition to the economic variables, BiQ also offered consistent basic information on the firms such as year of establishment and time of eventual bankruptcy.

The reason for choosing BiQ as data source was the availability of yearly data on a range of key economic variables before and after funding application. Other alternatives to BiQ that exist in Denmark include Statistics Denmark (Danmarks Statistik in Danish), which was the main data source for key information on things like population numbers. Statistics Denmark also keeps information on firms, however this information is only available on an aggregated level in contrast to the relatively more nuanced yearly firm level data from BiQ. In rare instances data was unavailable from BiQ, for example, the number of employees could be missing for a certain year. Thus in order to increase sample size, another Danish governmental data source – The Central Business Register (CVR or Det central virksomhedsregister in Danish) – was used. In only a few other instances, data was obtained from DNATF, which also keeps information on some of the economic variables used.

Data on patent variables was collected at the firm level using a combination of Google patents and USPTO data (Lai, D'Amour, & Fleming, 2009). Firm name was used for searching sometimes with minor adjustments due to Danish letters not found in English. Information on both applied and granted patents was collected annually before and after the funding application.

Publication variables were collected from the Web of Science. We used firm name to search for publications with relevant organizational affiliation, where we extracted the quantity and quality of publications per firm as using the number of publications and the number of citations garnered by these publications as proxies. One additional variable on cross-institutional co-authorship, i.e. papers published in cooperation between firm(s) and universities was also constructed.

Finally, a number of basic variables were obtained from DNATF's database and integrated into the dataset. Variables such as project duration, number of parties and amount of funding were all included as potential control variables for the analyses. The basic variables mainly consisted of information on the specific project/application each firm has been part of (e.g. the amount of funding from DNATF, number of parties, project duration etc.).

Results

This section shows results for the hypotheses we proposed earlier in an effort to empirically and causally bring evidence to the research questions of how does public-private partnership funding affect firm performance and firm innovative performance. Table 3 shows the summary statistics including the mean, standard deviation, minimum and maximum for each dependent variable as well as the treatment variable.

[Insert Table 3 about here]

Effects on firm bankruptcy

Table 4 reports results for the firm's likelihood of going bankrupt for all three sample specifications following equation 1 and controlling for industry and application year fixed effects. For each specification, we tested two outcome variables corresponding to two time periods following funding – 2 years and 4 years after funding application. We find for all three specifications that funded firms are significantly less likely to be bankrupt 4 years after applying for funding (columns 2, 4, and 6) and no significance for firm survival 2 years after (columns 1, 3, and 5). Most importantly in column 6, using the narrow bandwidth of firms close to the funding cutoff our results causally show that funding significantly increases the likelihood of survival.

The second model in Table 4 shows that firms successful in obtaining funding are 1.34 times more likely to survive up to 4 years after receiving funding compared to non-funded firms that went through the same application process while employing the full sample of firms in the second round of

selection. Similarly restricting the sample to small and medium size enterprises, the fourth model shows that funded SMEs are 1.32 times more likely to survive. And finally, even restricting ourselves to the sample just above and below the cutoff and using regression discontinuity on SMEs we find analogous strong results where funded firms are 1.11 times more likely to survive than non-funded ones. These results show that the firms do not immediately feel the effect of funding on survival; however, in the medium time horizon of 4 years after funding the effects are striking. Specifically, hypothesis 1 is confirmed. Therefore our results shed more empirical evidence on the hypothesis that funding for public-private partnerships alleviates capital constraints for a firm and consequently increases the likelihood for a firm to remain in business.

[Insert Table 4 about here]

Effects on firm employment growth

In similar fashion, Table 5 reports our findings on the effect of private-public partnership funding on employment by taking the change in the number of employees since grant application as the outcome variable. Each panel (A, B and C) in the table respectively shows the three sample specifications. In panel A, we find that, for the sample of all firms that applied for DNATF funding, there is no significant difference in the change of number of employees since application between funded and non-funded firms. In panel B with the SME sample, we find the most significant results for employment between 1 to 3 years after funding application. The significance in these results is not surprisingly, since the effect of DNATF funding is greater for SMEs with relatively small R&D budgets compared to companies of all sizes found in the full sample. We can more directly attribute the effects seen in employee number changes to funding for SMEs than for larger companies where many R&D programs may be pursued concurrently. Furthermore, constraining the sample to the one used for regression discontinuity in panel C, we see that the effect is still positive but becomes weakly significant for change in employee number 2 and 3 years after, while it is indistinguishable from zero for 1 year after.

More specifically, in panel B, we find that funded SMEs add an average of approximately 5.0 to 13.0 more employees 1 to 4 years after application than unfunded SMEs; and in panel C for SMEs in the narrow band right above and below the cutoff, funded firms add approximately 10.3 to 12.7 more employees 2 and 3 years after application. Although weakly significant for the regression discontinuity case (which may be partly due to the small sample size), these results still provide evidence for validating hypothesis 2 in the employment growth dimension. Thus, funding for public-private partnerships alleviates capital constraints and enables investment in more risky innovative projects, which may require more personnel or more individuals with unavailable skillsets to be hired into the firm, and consequently weakly increases the number of employees relative to unfunded firms for SMEs.

[Insert Table 5 about here]

Effects on firm profit growth

A third set of analyses we performed pertains to assessing how DNATF funding affects firm growth as exhibited in Table 6. Initially we sought to define growth using the annual percentage change of both the top line and the bottom line of the firm's sales and net income relative to the base year of application. However, due to an excessive amount of missing data in the sales figure for each firm, we decided to drop sales and only define firm growth using the yearly growth of its net income in the years after funding application relative to the application year.

Unlike the first two sets of analyses, we find no significant relationship between funding and firm growth, and thus do not find any empirical evidence to confirm hypothesis 3. In fact, all three sample specifications in panels A, B and C representing respectively the full, SMEs and SMEs with regression discontinuity samples show beta coefficients for the treatment variable to not be significantly different from zero. This result can be potentially explained by the fact that the provided funding is for relatively risky and novel projects that take several years to develop in collaboration with academia. Even at the completion of the funded projects the common deliverable is a prototype rather than a fully

commercializable product. Therefore given our time horizon of up to only 4 years in measuring firm growth as an outcome variable, it is perhaps not surprising that we are not seeing a significant effect.

[Insert Table 6 about here]

Effects on quantity of firm innovations

Starting with the fourth set of regressions we shift from investigating the effect of public-private funding on firm performance with economic variables to exploring the effect on firm innovative performance, including productivity in patents and publications, as well as the quality and nature of the publications.

We measure how funding affects a firm's innovative productivity by counting the number of filed and issued patents after application, as well as the number of peer-reviewed publications. Table 7 shows our findings for the number of patents filed and granted respectively in panel A and B, and similarly panel A of Table 8 shows the results for publication count. Again we separate our outcome variables into two time periods after grant – 1-2 years and 3-4 years after.

In panel A of Table 7, we find that for all three sample specifications and for both outcome variable time frames the number of filed patents after funding application is significantly higher for funded firms than for non-funded ones. Specifically, in columns 5 and 6 of the table we find the strongest results for our narrowly defined band of firms near funding cutoff, and thus obtain a positive causal relationship between funding and filing patents where respectively funded firms file on average 6.8 times ($e^{1.918}$) and 10.9 times ($e^{2.396}$) more patents 1-2 years and 3-4 years after funding than unfunded firms. In panel B, we find less consistent results for granted patents. These granted patents are patents filed 1-2 years and 3-4 years after application. In the regression discontinuity case granted patents filed 1-2 years after application are significantly positive (funded firms have on average $e^{2.590} = 13.3$ times more granted patents filed 1-2 years after application), whereas granted patents filed 3-4 years after application exhibit no statistically distinguishable effect from zero. These results make sense because granted patents usually

take some time to be issued, therefore patents filed right after funding application have higher probably of being processed and issued. Thus, we find empirical evidence to confirm hypothesis 4a.

[Insert Table 7 about here]

Similarly we show results for the effect of public-private partnership funding on the count of peer-reviewed publications in panel A of Table 8. Again we find strong and significant results for all three sample specifications. However, it is interesting to note that for the regression discontinuity approach in columns 5 and 6, only the latter time frame of publishing 3-4 years after is strongly significant whereas the earlier time frame is only weakly significant. Interpreting these results, this finding may be explained by the cycle time of peer-reviewed publishing -- it might take several months to a few years to move a paper from initial submission to final publishing alone. These last two models show that funded SMEs within the narrow range close to the funding cutoff publish respectively 3.4 ($e^{1.223}$) and 7.8 ($e^{2.056}$) more times than those not receiving funding. Consequently, we also empirically validate hypothesis 4b.

[Insert Table 8 about here]

Effects on quality of firm innovations

Aside from assessing the quantity of innovative productivity, we also explore their quality. We employ a commonly used measure of citations to operationalize quality for peer-reviewed papers. These results are shown in an analogous setup in panel B of Table 8 with all three sample specifications. Again we find strikingly strong positive results for the effect of funding on innovative quality. Interestingly, for SMEs we obtain a similar pattern with the two time frames of 1-2 years and 3-4 years after application as when quantity of publication is the outcome variable. The coefficient for the treatment variable is statistically insignificant for the former (columns 3 and 5) but significant for the latter time frame (columns 4 and 6).

Specifically, the sample of all SMEs firms funded have 15.7 times ($e^{2.755}$) more citations for their peer-reviewed publications than unfunded firms, while for the sample of SMEs firms used in the

regression discontinuity design funded ones have a whooping 38.1 times ($e^{3.640}$) more citations. Thus, we find strong evidence for hypothesis 5b.

Effects on nature of firm innovations

The last set of analyses investigates the public-private nature of the funded partnership. Panel C of Table 8 shows whether participation in such cross-instructional projects changes the nature of the innovation produced, and sheds light on collaborative behavior. Our outcome variables are defined as the number of papers published 1-2 years and 3-4 years after application in which co-authors are affiliated with different institutions. For a publication to count as cross-institutional at least one author needs to be from academia while another one from a firm. Results for the first two sample specifications show strong and positively significant tendencies to collaborate cross-institutionally for funded firms relative to unfunded firms. The regression discontinuity method exhibits the same trend of showing positive statistical significance only for the time frame of 3-4 years after application, where funded firms have 6.1 times ($e^{1.814}$) more cross-institutional collaborative papers than unfunded ones, thus providing evidence for hypothesis 6.

Discussion

Implications for the literature

Aside from providing empirical evidence on the effect of a novel source of governmental funding to public-private partnerships on firm performance and innovative performance, this paper also informs the entrepreneurial finance literature on the interplay between the institutions of science and technology. To the best of our knowledge this paper is the first to causally show the effect of such funding sources using a regression discontinuity setup at the level of the firm, thus informing not only policymakers but also managers. To summarize our results we observe compelling evidence that public-private partnership funding affects firm performance especially in the mid-term range of 3-4 years after funding. Using regression discontinuity and its corresponding subsample of small and medium enterprises just above and

below the funding cutoff, we find that receiving funding for public-private partnerships alleviates financial constraints and helps firms in staying more financially viable by significantly decreasing the likelihood of bankruptcy by up to 1.11 times 4 years after funding application, and increasing the average number of headcount by 10.3 and 12.7 more employees respectively 2 and 3 years after application. From the perspective of innovative performance, firms that receive funding have 13.3 times more granted patents and 7.8 times more peer-reviewed publications, but the effect of funding is mostly felt on quality of innovation where peer-reviewed citations for funded firms are 38.1 more than unfunded firms. Finally, public-private partnership funding also alters the nature of knowledge produced as well as the collaborative behavior of scientists, with those firms that receive funding collaborating 6.1 times more frequently with colleagues in academia.

With regard to the literature on the impact of funding on firm performance, our results provide empirical evidence that this novel type of funding in the form of public-private partnerships indeed alleviates capital constraints which in turn not only increases the financial viability of a firm by increasing its likelihood of survival, but this model also leads to increases in firm headcount. These effects are observed in the mid-term range of the firm since funding is directed towards specific innovative projects that take several years to develop and market. By implementing such funding programs, governments are able to incentivize firms to take on more basic science R&D projects, as evidenced by the significantly higher numbers of peer-reviewed papers and patents published by funded firms. Thus enhancing a private firm's ability to not only monitor the scientific landscape, but also build basic research capabilities that enable faster and more efficient recognition of spillover opportunities into more applied activities.

By investigating the quality and nature of innovative outputs, we contribute to the literature on the interplay of science and technology. The partnership structure of requiring academics to work in collaboration with scientists in private firms suggests that science and technology develop concurrently instead of via waterfall model proposed in earlier works (Freeman, 1992; Mansfield, 1995). The setup also displays a novel model of interaction between the realms of science and technology that strays away from the conventional belief of dedicated gatekeepers that straddle both institutions (Cockburn &

Henderson, 1998; Murray, 2004). Instead of having single actors transfer knowledge back and forth between independent silos of science and technology, the setup we studied temporally breaks down the boundaries between the two institutions and enables teams of individuals from both sides to work together alongside one another. Thus, we see a predominant number of peer-reviewed papers with cross-institutional authorship for funded firms. Finally, we observe higher quality papers from funded firms, which provide further support of the role of science as a map that helps in producing more impactful research.

Implication for practitioners and policymakers

The translation of basic scientific research results into commercialized technology outputs from private firms with the concomitant benefits to employment and economic growth is a goal shared by many policy makers and business leaders. The results of the analysis reported here highlight the effectiveness of a uniquely effective funding and intervention model. By specifically asking potential public and private sector partners to come forward and go through an application screening process followed by a collaboration model that places a heavy emphasis on cross-boundary work, the organization under study is able to reap impressively higher returns over an intermediate term in job growth, innovative output, and cross-boundary collaboration that likely will contribute to a virtuous cycle of enhance future outputs.

From a policy standpoint, by providing public-private partnership funding schemes governments are able to incentivize firms to take on more basic science R&D. This potentially helps with the free-rider problem in appropriability, the lack of economic incentives for private firms to undertake such projects due to the inability to capture all the benefits from such basic research (Nelson, 1959). As a way to help companies to remain competitive, governments can view this approach as a potentially powerful policy tool.

Limits and weaknesses

Despite showing compelling and causal outcomes that public-private partnership funding can have on firm performance, this paper still suffers from several limitations and weaknesses. Thus the interpretation of our results should be read with care. For instance, we are unable to address the most important question for practitioners, how partnerships in which team members come from very different institutional roots can be effective managed. In effect, this paper shows the relationship between input – funding, and output – firm performance – without delving inside what remains a "black box." Preliminary qualitative interviews (n = 12) with project managers of these public-private partnership projects indicate that one of the biggest challenges is getting individuals from different institutions to align their goals, understand each other and collaborate effectively.

From a policy standpoint, this paper has difficulty teasing apart the effect of providing funding from the novel intervention model specific to DNATF. As explained in the earlier Setting section, DNATF intervenes in 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. 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 through active follow-up, frequently mediating conflicts that arise among funded parties. However, since our sample of firms all consist of DNATF funded projects, we do not possess any source of variation on this intervention dimension.

Finally, since we have studied one specific funding scheme in one specific country, the generalizability of our results may have limitations. However, we have not concentrated on the intricacies and idiosyncrasies specific to our setting, and instead attempted to explore more largely the effect of funding, we strongly believe that the implications of our results can be interpreted more broadly.

Future research

Despite these limitations and weaknesses, we have opened ourselves to several interesting future research topics beyond the research question explored herein of how public-private funding affect firm performance and firm innovative performance. From a management perspective, understanding the

challenges of managing conflict inside partnerships that are essentially virtual companies with multiple cross-institutional stakeholders is vital. Research can be done to 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 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.

Conclusion

In this paper we have used regression discontinuity to demonstrate that receipt of funding for public-private partnerships alleviates financial constraints and helps firms significantly decrease the likelihood of bankruptcy while substantially increasing the average level of employment. Funded firms are awarded significantly more granted patents and publish more peer-reviewed papers, and the impact of these publications is significantly higher. Finally, public-private partnership funding alters the nature of knowledge produced as well as the collaborative behavior of scientists with significantly higher level of citations and more cross-institutional co-authored publications.

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

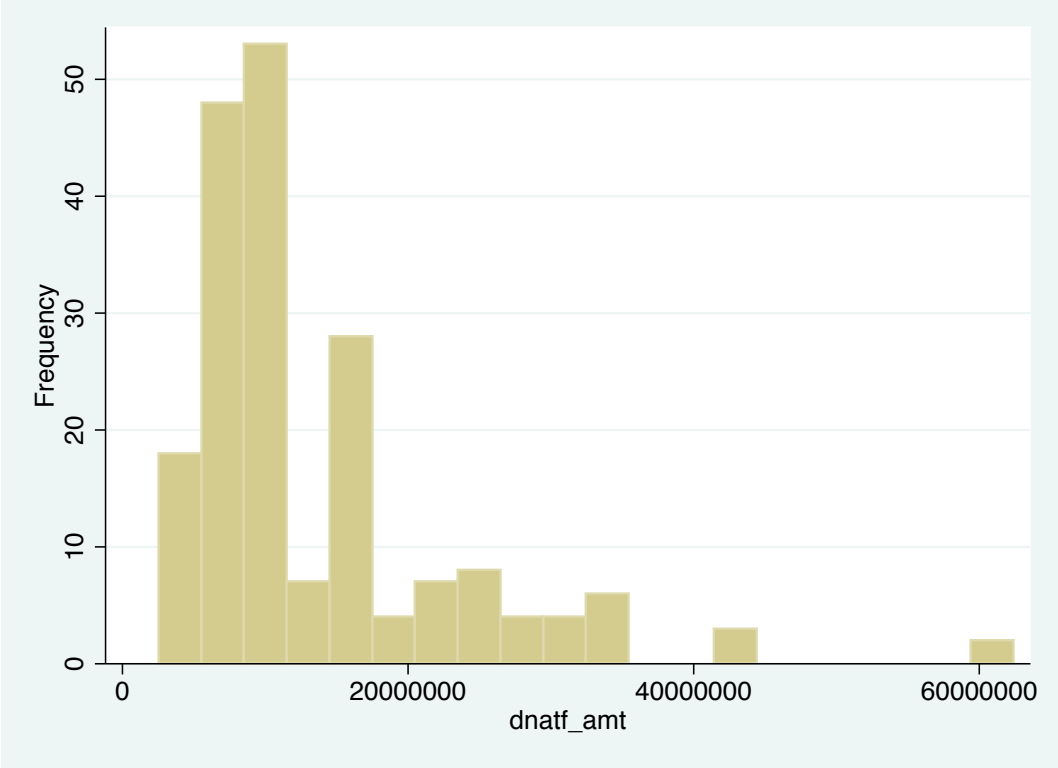


Table 1 – DNATF funding selection

Normalized score lower limit [	Normalized score upper limit)	Funded (%)	Number of applications	Applications (%)	Cumulative applications (%)
-8	-6	0.0%	6	5.2%	5.2%
-6	-4	0.0%	5	4.3%	9.6%
-4	-2	0.0%	19	16.5%	26.1%
-2	0	22.2%	9	7.8%	33.9%
0	2	37.1%	35	30.4%	64.3%
2	4	33.3%	12	10.4%	74.8%
4	6	58.3%	12	10.4%	85.2%
6	8	100.0%	9	7.8%	93.0%
8	10	100.0%	8	7.0%	100.0%

Table 2 – Border discontinuity comparison above and below for small and medium enterprises

Characteristic	Below border	Above border	Two-tailed t-test
age	9.468085	9.071429	0.8593
score	1.610195	1.836026	0.653
duration	3.042553	2.928571	0.5394
amount funded by DNATF	1.23E+07	1.13E+07	0.6106
number parties	5.468085	5.857143	0.631
number employees_yr0	21.87805	33.51852	0.2747
avg employee growth	0.6932353	0.1863158	0.4874
employee growth_yr-1	0.0997088	0.1645211	0.5124
net income_yr0	-3297725	-8033840	0.3832
filed patents_yr0	3	1.259259	0.447
granted patents_yr0	2.422222	0.8846154	0.4856
publication_yr0	3.808511	7.5	0.3124
pub citation_yr0	109.3191	170.8214	0.5697
cross-institutional pubs_yr0	2.12766	3.785714	0.4683

Table 3 – Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
funded	205	0.493	0.501	0	1
sme250	193	0.684	0.466	0	1
bkrupt_1-2ya	202	0.025	0.156	0	1
bkrupt_1-4ya	202	0.045	0.207	0	1
empd_1ya	150	-1.473	87.117	-652	512
empd_2ya	134	-6.201	191.929	-1061	997
empd_3ya	133	-3.165	265.034	-1391	1347
empd_4ya	118	-12.568	260.656	-1448	914
nigr_1ya	164	-0.644	7.131	-58.519	24.139
nigr_2ya	124	0.457	1.140	-0.903	6.057
nigr_3ya	121	0.244	0.828	-0.872	4.908
nigr_4ya	97	0.132	0.491	-0.598	2.338
patf_1to2ya	182	0.632	1.584	0	9
patf_3to4ya	182	0.538	1.954	0	18
patg_1to2ya	183	0.432	1.844	0	18
patg_3to4ya	182	0.165	0.627	0	4
pub_1to2ya	197	3.213	9.941	0	71
pub_1to2ya	197	4.228	15.040	0	140
fwcit_1to2ya	197	29.731	199.719	0	2708
fwcit_3to4ya	197	33.020	217.625	0	2708
xinst_1to2ya	197	2.467	7.297	0	48
xinst_1to2ya	197	3.442	12.050	0	111

Table 4 – Survival data

Probit regression models with bankruptcy as indicator outcome variable 2 years and 4 years after receiving funding run on all three sample specifications: full sample after second round selection, SMEs, and SMEs just above and just below funding cutoff.

	Full sample		SME sample		SME RD sample	
	bkrpt_1to2ya	bkrpt_1-4ya	bkrpt_1-2ya	bkrpt_1-4ya	bkrpt_1-2ya	bkrpt_1-4ya
	b/se	b/se	b/se	b/se	b/se	b/se
funded	0	-1.343**	0	-1.320**	0	-1.105*
	(.)	(0.39)	(.)	(0.43)	(.)	(0.50)
constant	-1.379+	-4.682**	-1.437+	-4.427**	-5.400**	-5.121**
	(0.83)	(0.54)	(0.85)	(0.59)	(0.51)	(0.72)
N.Obs	71	179	55	120	26	61
LogLklhd	-16.13	-29.849	-15.016	-27.462	-7.107	-16.669
PseudoR2	0.108	0.163	0.104	0.141	0.236	0.15

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

Table 5 – Employment data

OLS regression models with the absolute change in the number of employees 1 to 4 years after receiving funding as outcome variables run on all three sample specifications: Panel A – full sample after second round selection, Panel B – SMEs, and Panel C – SMEs just above and just below funding cutoff.

Panel A - Full sample	empd_1ya b/se	empd_2ya b/se	empd_3ya b/se	empd_4ya b/se
funded	-0.876	25.721	44.202	33.381
	(19.03)	(43.72)	(63.86)	(49.89)
constant	-36.33	-21.067	44.56	97.549
	(44.17)	(75.03)	(91.69)	(86.80)
N.Obs	149	133	132	117
R2	0.09	0.086	0.112	0.175
ajdR2	0.031	0.02	0.046	0.114

Panel B - SME sample	empd_1ya b/se	empd_2ya b/se	empd_3ya b/se	empd_4ya b/se
funded	4.976**	10.877*	13.010*	9.641+
	(1.86)	(4.48)	(5.04)	(5.73)
constant	-6.368*	-6.301	1.823	3.965
	(2.96)	(7.99)	(9.56)	(10.51)
N.Obs	105	90	88	78
R2	0.118	0.111	0.14	0.171
ajdR2	0.035	0.01	0.04	0.075

Panel C - SME RD sample	empd_1ya b/se	empd_2ya b/se	empd_3ya b/se	empd_4ya b/se
funded	3.437	10.323+	12.686+	4.14
	(2.68)	(5.48)	(6.98)	(7.37)
constant	-4.976	-6.082	-0.184	-2.995
	(3.66)	(7.64)	(8.34)	(9.81)
N.Obs	61	51	48	46
R2	0.09	0.124	0.17	0.056
ajdR2	-0.07	-0.069	-0.026	-0.148

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

Table 6 – Growth data

OLS regression models with the yearly percentage change in net profit 1 to 4 years after receiving funding run as outcome variables on all three sample specifications: Panel A – full sample after second round selection, Panel B – SMEs, and Panel C – SMEs just above and just below funding cutoff.

Panel A - Full sample	nigr_1ya	nigr_2ya	nigr_3ya	nigr_4ya
	b/se	b/se	b/se	b/se
funded	-0.092	-0.086	-0.096	-0.061
	(1.16)	(0.23)	(0.15)	(0.10)
constant	-4.533	-0.122	0.337	0.269
	(4.39)	(0.28)	(0.28)	(0.19)
N.Obs	163	124	120	97
R2	0.067	0.057	0.032	0.11
ajdR2	0.012	-0.017	-0.047	0.03

Panel B - SME sample	nigr_1ya	nigr_2ya	nigr_3ya	nigr_4ya
	b/se	b/se	b/se	b/se
funded	-1.279	0.341	0.084	0.07
	(1.60)	(0.27)	(0.15)	(0.11)
constant	-0.359	-0.136	-0.315	0.22
	(2.22)	(0.32)	(0.21)	(0.16)
N.Obs	109	83	77	65
R2	0.079	0.079	0.144	0.163
ajdR2	-0.005	-0.035	0.029	0.043

Panel C - SME RD sample	nigr_1ya	nigr_2ya	nigr_3ya	nigr_4ya
	b/se	b/se	b/se	b/se
funded	0.81	-0.135	0.038	-0.041
	(1.12)	(0.23)	(0.20)	(0.15)
constant	-3.696	0.345	0.214	0.451*
	(2.89)	(0.34)	(0.32)	(0.22)
N.Obs	62	46	44	37
R2	0.072	0.321	0.202	0.135
ajdR2	-0.088	0.174	0.02	-0.074

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

Table 7 – Patent data

QML Poisson count regression models with unissued patents filed 1-2 years and 3-4 years after receiving funding as outcome variables in Panel A and granted patents filed 1-2 years and 3-4 years after receiving funding as outcome variables in Panel B, run on all three sample specifications: full sample after second round selection, SMEs, and SMEs just above and just below funding cutoff.

Panel A	Full sample		SME sample		SME RD sample	
	patf_1to2ya	patf_3to4ya	patf_1to2ya	patf_3to4ya	patf_1to2ya	patf_3to4ya
	b/se	b/se	b/se	b/se	b/se	b/se
funded	0.802*	1.603**	1.232**	1.617**	1.918*	2.396**
	(0.38)	(0.50)	(0.43)	(0.59)	(0.80)	(0.91)
constant	0.711	-0.364	-0.043	-16.446**	1.975	-18.81
	(0.72)	(0.81)	(1.11)	(0.38)	(1.27)	(.)
N.Obs	181	181	124	124	71	71
Log-Likelihood	-229.89	-192.017	-133.965	-114.148	-67.42	-59.191

Panel B	Full sample		SME sample		SME RD sample	
	patg_1to2ya	patg_3to4ya	patg_1to2ya	patg_3to4ya	patg_1to2ya	patg_3to4ya
	b/se	b/se	b/se	b/se	b/se	b/se
funded	1.444**	1.494**	0.777	1.163+	2.590*	1.006
	(0.55)	(0.57)	(0.60)	(0.61)	(1.23)	(1.61)
constant	-0.07	-1.537	-0.046	-18.211**	1.103	-17.941**
	(0.90)	(1.30)	(1.26)	(1.90)	(1.22)	(1.59)
N.Obs	182	181	123	123	70	70
Log-Likelihood	-186.88	-72.409	-93.062	-40.844	-52.573	-12.62

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

Table 8 – Publication data

QML Poisson count regression models with number of peer-reviewed papers published 1-2 years and 3-4 years after receiving funding as outcome variables in Panel A, the sum of forward citations from peer-reviewed papers published 1-2 years and 3-4 years after receiving funding as outcome variables in Panel B, and number of cross-institutional collaborative peer-reviewed papers published 1-2 years and 3-4 years after receiving funding as outcome variables in Panel C, run on all three sample specifications: full sample after second round selection, SMEs, and SMEs just above and just below funding cutoff.

Panel A	Full sample		SME sample		SME RD sample	
	pub_1to2ya	pub_3to4ya	pub_1to2ya	pub_3to4ya	pub_1to2ya	pub_3to4ya
	b/se	b/se	b/se	b/se	b/se	b/se
funded	1.375**	1.929**	1.139*	1.546**	1.223+	2.056*
	(0.43)	(0.43)	(0.50)	(0.59)	(0.67)	(0.82)
constant	0.303	-0.228	-0.252	-0.618	0.586	-1.851*
	(0.99)	(0.97)	(1.12)	(0.83)	(1.11)	(0.89)
N.Obs	196	196	129	129	74	74
Log-Likelihood	-1034.853	-1257.98	-423.055	-475.399	-241.558	-275.908

Panel B	Full sample		SME sample		SME RD sample	
	fwcit_1to2ya	fwcit_3to4ya	fwcit_1to2ya	fwcit_3to4ya	fwcit_1to2ya	fwcit_3to4ya
	b/se	b/se	b/se	b/se	b/se	b/se
funded	1.429*	2.212**	1.275	2.755**	0.547	3.640**
	(0.57)	(0.85)	(0.78)	(0.91)	(0.86)	(0.95)
constant	1.894	1.35	1.26	-0.936	3.538*	-1.685+
	(1.20)	(1.09)	(1.62)	(0.85)	(1.58)	(1.01)
N.Obs	196	196	129	129	74	74
Log-Likelihood	-10388.576	-12772.348	-7406.086	-8212.965	-3792.922	-4226.178

Panel C	Full sample		SME sample		SME RD sample	
	xinst_1to2ya	xinst_3to4ya	xinst_1to2ya	xinst_3to4ya	xinst_1to2ya	xinst_3to4ya
	b/se	b/se	b/se	b/se	b/se	b/se
funded	1.276**	1.869**	0.997*	1.361*	0.976	1.814*
	(0.43)	(0.42)	(0.49)	(0.57)	(0.62)	(0.80)
constant	0.118	-0.504	-0.168	-1.008	0.706	-1.847*
	(0.98)	(0.94)	(1.15)	(0.79)	(1.20)	(0.90)
N.Obs	196	196	129	129	74	74
Log-Likelihood	-816.962	-1018.267	-337.813	-383.967	-192.688	-226.278

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

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