Four Essays on Resource Acquisition in the Knowledge Economy

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Four Essays on Resource Acquisition in the Knowledge Economy

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Thesis

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Dedicated to my wife Silva and our son Pascal.

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Chapter 1. General Introduction

The locus of innovation and economic growth has moved away from traditional industries such as automobiles and construction that derived their competitive advantage primarily from economies of scale and gains in productivity. Instead, mainly because of advances in information technology technological revolutions in knowledge intensive industries such as the life sciences, electronics, materials and energy conversion are the prime engines of economic growth in the last two decades. The increased reliance on industries deriving gains from technological breakthroughs is often termed the rise of the "knowledge economy". Formally, the knowledge economy "*is an expression coined to describe trends in advanced economies towards greater dependence on knowledge, information and high skill levels, and the increasing need for ready access to all of these by the business and public sectors*" (OECD, 2005).

As implied by the last part of the OECD definition above, academia and industry are major players in the knowledge economy. Universities increase the stock of useful knowledge, train skilled graduates, form networks and stimulate social interaction, increase the capacity of scientific and technological problem-solving, and create new firms through spin-offs or spillover effects (Salter & Martin, 2001). Indeed, a range of studies shows that knowledge created by academic institutions drives economic growth (Arundel & Geuna, 2004; Berman, 1990; Etzkowitz, 1998; Etzkowitz & Leydesdorff, 2000; Hall, Link, & Scott, 2003; Mansfield, 1998). Industry, composed of both large corporations and small and medium-sized enterprises (SMEs), create new knowledge, use academic knowledge as an input and ultimately transform new knowledge into products and services (Roberts, 2001).

What may constrain the contribution of academia and industry in the knowledge economy is resource scarcity.[1] Such resource scarcity is more pronounced for the two actors I focus on in this dissertation, emerging firms and academics.

High-technology start-ups seek funding to fuel their research activities from outside sources, such as governmental subsidies, venture capital and business angels (Audretsch, 2003; Hellmann & Puri, 2002; Shane, 2012). However, the uncertainty surrounding embryonic inventions as well as complex regulatory environments create information asymmetries between these firms and the potential financers which make investment decisions a thorny task (Sahlman, 1990). As a result, the level of investment for emerging firms is often below the social optimum. To illustrate the importance of funding to start-ups, Gartner, Starr, and Bhat (1999) find that a key reason start-ups fail is because they need resources that are far beyond

[1] This is not to imply that other barriers such as personal, organizational or regional characteristics (Madrid-Guijarro, Garcia, & Van Auken, 2009) do not present obstacles.

the capabilities of the entrepreneurs to raise and Audretsch, Weigand, and Weigand (2002) find that over half of the start-ups funded with SBIR[2] funding would not have been launched without SBIR funding.

Likewise, resource scarcity also restrains the productivity of academics. The public generally finances academic research as a means to encourage research that would otherwise be ignored (Cohen, Nelson, & Walsh, 2002; Nelson, 1959). Yet at the same time, there are many other public tasks competing for the same funding. These competing public tasks, such as healthcare or infrastructure, are much more visible to the public (Salter & Martin, 2001). It follows that fund acquisition is an important and difficult task for most academics (Etzkowitz, Webster, Gebhardt, & Terra, 2000). Yet, knowing where possible funding opportunities exist and being able to write competitive research proposals is a form of tacit knowledge that is not easily learned (Feinberg & Price, 2004; Stephan, Veugelers, & Wang, 2017). As a result, and similar to start-ups, academics who fail to acquire funding are less likely to survive in academia (Gerritsen, Plug, & Van der Wiel, 2013) which is illustrated in many examples of academics who are forced out of academia – sometimes even after decades of research - because they are unsuccessful in attracting funding (Rathi, 2017; Ruben, 2017; The Guardian, 2014).

From the abovementioned, it becomes clear that resource acquisition is one of the main drivers for knowledge production in academics and start-ups alike and that the difficulty of resource acquisition is inversely correlated with the available knowledge, competence and experience the parties have in securing resources. This is problematic because funding is the lifeblood of science (Alberts, Kirschner, Tilghman, & Varmus, 2014) and without it knowledge production hinders (Rosenbloom, Ginther, Juhl, & Heppert, 2015). Thus, the aim of this dissertation is to *investigate how start-up firms and researchers in the knowledge economy can acquire resources that allow them to innovate and advance science.*

Informed by the different norms between academia and industry, the starting point in my dissertation is that start-ups and academics may use different tools to secure resources.

First, to improve their performance academic researchers rely heavily on experience and knowledge of academic peers in their department (Stigler, 2003). Collegial behavior manifested in help towards the generation of valuable ideas, feedback and criticism via formal or informal interactions is recognized as a key input for the advancement of one's (academic) career (Laband & Tollison, 2000; Laband & Tollison, 2003). Therefore, in the first two essays in this dissertation we study how academics with little to no experience in attracting research

[2] Small Business Innovation Research program, a governmental funding program for scientists to launch high-technology start-ups).

funding can learn from colleagues with specific knowledge on this subject. We then ask, what are the conditions that magnify the effects that result from knowledge transfer? We address these questions empirically and reveal evidence consistent with a causal link between increases in the funding record of academics who are inexperienced with raising funds and exposure to academics in their department with experience in acquiring funding.

Second, start-ups look for ways to reduce information asymmetries. One way firms can reduce information asymmetries is to use *signals* that that can shine a light on the potential of the firm (Zhang & Wiersema, 2009). In fact, whenever information asymmetries are present, investors tend to rely on signals of this sort before they make investment decisions because separating high-quality start-ups from the 'lemons' is prohibitively difficult (Amit, Glosten, & Muller, 1990c; Davila, Foster, & Gupta, 2003). Indeed, a number of studies demonstrate that signals reduce information asymmetries and improve funding of start-ups (Baum & Silverman, 2004; Cohen & Dean, 2005; Häussler, Harhoff, & Müller, 2012; Hsu, 2007; Janney & Folta, 2003; Mann & Sager, 2007; Mishra, Heide, & Cort, 1998a; Spence, 1978). However, what is difficult to conclude from these empirical studies is what the dynamics are of the value that different signals carry. Is the value of signals equal to all high-technology firms looking for funding? To approach this question, in the last two essays of this dissertation, we study two factors that influence the level of information asymmetry between start-up and venture capital investor, namely, time and distance.

Chapter 2. The Value of Insiders: Evidence from the Effects of NSF Rotators on Early Career Scientists [3]

[3] This chapter is based on:
Hoenen, SJ., Kolympiris, C. (2018) *The value of insiders: evidence from the effects of NSF rotators on early career scientists*. Submitted to Review of Economics and Statistics, MIT Press Journals.

Introduction

Access to superior human capital generates improvements in productivity via knowledge spillovers (Schultz, 1961). Indeed, within knowledge intensive sectors such as academia, performance, measured with impactful publications, is largely driven by access to scientists with insights gained from success and experience within academia (Azoulay, Graff Zivin, & Wang, 2010; Brogaard, Engelberg, & Parsons, 2014; Waldinger, 2010). We report novel evidence that highlights an alternative route: positive spillovers also result from access to academics with insights from temporary experience in government jobs. As an example think of Steven Chu, Professor of Physics at UC Berkeley, who served as the Secretary of Energy from 2009 until mid-2013 before returning to his academic home or Alexis Abramson, professor of mechanical and aerospace engineering at Case Western University who also spent two years as chief scientist at the US Department of Energy before her return to Case Western. Such employment spells infuse mobile academics with insider knowledge on the allocation of resources by the government, the main funder of research endeavors, and can prove valuable when transmitted to colleagues seeking ways to fuel their research capabilities and advance science.

To study the impact of moves in government jobs we explore the link between research fund acquisition of early career scientists and exposure to so called rotators; academics who are seconded to the National Science Foundation (NSF) for typically two years before they return to their academic institution. During their tenure at the NSF, rotators, formally Program Directors, organize and run the peer review process from the very beginning until the very end while often exercising decision power. They become insiders at the NSF as they gain insights on how funding decisions are made, possess tacit knowledge on the potential funding directions and priorities of the agency, and ultimately they can discern a promising proposal. [4]

Departing from the extant literature on research fund acquisition, we focus on early career scientists (Arora & Gambardella, 2005; Feinberg & Price, 2004; Grimpe, 2012; Li, 2017) because advances in science build on early career academics' progress (Oyer, 2006; Petersen, Jung, Yang, & Stanley, 2011) and because without funds, science stalls (Alberts et al., 2014; Rosenbloom et al., 2015).We find that rotators leverage their insights to transmit

4 The literature on knowledge spillovers within academia has highlighted that context matters. For instance, while Borjas and Doran (2012) and Waldinger (2012) find negative and no spillover effects respectively for same department peers of star scientists, Waldinger (2010) and Azoulay et al. (2010) report positive spillovers for doctoral students and collaborators of star scientists. The fact that context matters suggests that it is difficult to extrapolate the results of Hoenen, Kolympiris, and Klein (2017), the only other study that analyzes spillovers from NSF rotators, here. Using different research design, methods and samples this latter work does not zoom in on those who are arguably in the highest need for funds: early career scientists, and does not shed light, as we do, on the dynamics of the potential effect rotators have on their colleagues.

knowledge to their early career colleagues on what to write, how to write and where to send a proposal. As a result, rotators have a causal impact on the funding acquisition records of new hires landing their first faculty position in their department. Newly hired assistant professors who join departments with a returning rotator raise almost twice the amount similar academics in similar departments without a rotator raise (approximately *$200,000* more which is nearly *half* of the average first time grant from the NSF). These increases are due to rotator's colleagues being more likely to secure medium size grants and are realized one and two years after exposure to the rotator.

Our identification strategy is to compare the funding records of new hires landing their first faculty post in departments with and without a rotator; the latter belonging to our treatment group and the rest belonging to our control group(s). The major empirical challenge in this exercise is that superior human capital is not distributed randomly. Rather, endogenous sorting places individuals of high human capital next to each other (Kim, Morse, & Zingales, 2009; Waldinger, 2016). In our application, this would mean that the colleagues of rotators are more equipped than others in raising research funds in the first place. To circumvent this sorting issue we exploit two features of the rotation program and carefully construct three control groups. The first feature is that (timing of) entry into rotation is independent of the needs of colleagues to raise funds. Academics become rotators because they want to learn more about the NSF, not because they recognize emerging colleagues who need advice. The second feature is that the return to the home institution is also exogenous to the needs of colleagues to raise funds. The rotation duties have a fixed end date. Rotators do not return to their institutions because (or when) their colleagues need help. These two features of the program suggest that the allocation of colleagues to the treatment group is largely exogenous to their choices. But, three different sources of endogeneity may still allocate individuals to treatment and control groups non-randomly, which would constitute a threat to identification. We discuss these sources below.

One, initial job placement can be endogenous with job candidates choosing to accept an offer from a department with a rotator because of her presence in that department and the associated *ex-ante* expectation of learning. Along the same lines, labor market conditions differ across years and can have strong impact on which job candidate lands where. We tackle these issues by exploiting time variation: we construct our first dataset including new hires joining the same department at different points in time when labor market conditions vary, the focal colleague had or not left for the NSF and had or not the rotation experience.

Two, if the academic labor market works efficiently the best candidates will land the best positions and the lesser candidates will land the lesser positions (Cole & Cole, 1973). If that holds, success in raising funds may be explained by this matching process with rotators belonging to the better departments. Similarly, difficult to capture heterogeneity among PhD holders may also explain initial job placements. We tackle these issues by crafting a second dataset that includes PhD holders (some landing a job in a department with a rotator and some without a rotator) who had the same PhD advisor, worked in the same science field and graduated about the same year (Kahn & MacGarvie, 2016). Given that advisor standing and graduating institution are the prime determinants of initial job placement (Miller, Click, & Cardinal, 2005; Terviö, 2011) it is no surprise that, as we show in Tables 2 and 3 below, new hires from the same advisor land their first faculty post in departments whose main difference is the presence of a rotator as they are generally of comparable status, academic productivity and research fund acquisition records. Importantly, because selection into advisors is not random (Waldinger, 2010) and because PhD training is largely standardized within doctoral programs (hence both selection and treatment are nearly identical), these new hires are also similar to each other at the time of their first academic appointment in terms of age, gender, measured innate ability and the like.

Three, university-wide policies, tenure track incentives, grant-writing support and other university-specific factors may boost incentives to become a rotator, shape the types of emerging scientists who decide to join a given university and ultimately explain increased grant acquisition rates. This may lead to erroneous conclusions about the impact of rotators as long as they are disproportionally employed at institutions that for the above mentioned reasons are more successful in research funding acquisitions than others. We tackle this issue by constructing our third dataset. This dataset holds university-wide factors constant and allows us to compare the funding records of new hires who joined the same university at approximately the same time but in different, yet comparable, departments having one main difference: some have a rotator as a faculty member and some do not.

Our work is novel on two main fronts. First, we present causal evidence on gaining knowledge by insiders; academics who possess insights gained from experience outside academia. Two, we present detailed longitudinal information on early career scientists who are exposed to funding acquisition knowledge possessed by NSF rotators; an actor in the knowledge economy whose role is crucial (Li & Marrongelle, 2013) but who has received considerably less attention in the literature when compared to the scope and depth of studies on inventors, entrepreneurs, patent examiners and others (e.g. Jensen & Thursby, 2001;

Lampe, 2012; Lemley & Sampat, 2012; Moser, Voena, & Waldinger, 2014; Toivanen & Väänänen, 2012).

Despite the careful construction of the datasets to match new hires in the treatment and control departments in ways that can isolate the potential impact of rotators on funding acquisition records, remaining differences in training, ambitions, career goals and the like may still exist. As such, we include in the analysis a number of control variables meant to account for such factors. The variables include publication and citation records, research funding from sources other than the NSF as well as characteristics of the department the focal academic joins. Further, we perform a battery of robustness checks that allow us to test the sensitivity of our estimates to a number of potential modeling concerns including endogeneity and the way we specify our control groups to reduce heterogeneity among treatment and control groups. For instance, a) we use Coarsened Exact Matching to find similar academics to those that join departments with a rotator, b) we relax, sequentially, the "same graduation year" and the "same advisor" criteria from the factors we consider when specifying our control academics and c) we conduct a difference-in-difference analysis. By and large, these tests reinforce the stability of our estimates.

To pinpoint with precision the mechanism via which the effects of rotators on new hires materializes we conduct numerous exercises we present in section VI that test alternative competing explanations including favoritism and peer effects. To highlight one, to put knowledge transfer under scrutiny we create a helpfulness index based on the intensity of thank you notes in PhD dissertations and we find that early career scientists in departments with the most helpful rotators raise 3 times more than early career scientists in departments with remaining rotators (Laband & Tollison, 2003; Oettl, 2012). Along the same lines, when we artificially place rotators to departments that in reality did not have a rotator, we do not find any association between the purported presence of a rotator in that department and the NSF grant acquisition of her colleagues.

Our results have direct implications for the advancement of science, for the value of mentoring as a form of having access to superior human capital (Blau, Currie, Croson, & Ginther, 2010), for early career academics landing their first faculty post and aspire to succeed in science and for policy makers devising measures to allow such scientists to develop independent research programs (Kaiser, 2017). They are also relevant for university administrators who confront increasing financial pressures, for job market candidates contemplating which job offer to accept and for the organization of institutions and how they advance or hinder scientific progress (Furman & Stern, 2011).

The rotation program at the NSF and how rotators can induce changes in grant acquisition

The National Science Foundation has an annual budget that exceeds 7.5 billion and funds approximately 12,000 proposals every year in all nonmedical scientific fields. These proposals support more than 360,000 scientists, teachers and students employed at close to 2,000 institutions (NSF, 2017). The agency is structured hierarchically: its seven directorates, corresponding to different scientific fields, are split in divisions which are then split to programs. Program Directors (PDs), subject matter experts, run each program. They put together the review panels, they communicate, *ex-ante* and *ex-post* with submitters of funded and non-funded proposals, they review proposals even from programs and directorates outside their own, they make grant allocation decisions, they participate in panels outside their programs and provide input to central strategic planning not only within their program but also across programs and directorates (Li & Marrongelle, 2013). Overall, PDs are an integral part of the NSF and a key input to shaping the direction of science.

Most PDs are permanent NSF employees. But, since the passage of the Intergovernmental Personnel Act in 1970 roughly 1 out of 3 PDs are academics who are seconded at the NSF temporarily (Mervis, 2016a). These academics, called rotators, infuse the agency with new viewpoints as they move to the NSF headquarters. They work full time for the NSF for up to 4 years (most commonly 2) while effectively pausing their academic duties as they are on loan from their university (Mervis, 2013). Indeed, from 2004 to 2014 alone 800 rotators from around 400 academic institutions served at the NSF. Rotators are subject to strict restrictions during and even after their tenure at the NSF to avoid any conflicts of interest or favoritism (e.g. they cannot submit proposals or evaluate proposals of previous collaborators).

As revealed during a handful of discussions we had with former rotators, the main reason academics enter the program is a desire to learn more about the NSF and to generally contribute to the direction of science.[5] These drivers indeed explain why we do not identify specific trends among rotators: besides the fact that all had won grants from the agency in the past, they are employed at universities of varying size, status, location and they are of varying scholarly productivity, leadership activities, methodological approaches and the like. As mentioned above, the fact that the decision to join the rotation program is exogenous to the need of colleagues for help in raising funds alleviates concerns of endogeneity arising from the

[5] The blog entry of Dan Cosley, associate professor at Cornell University, about his rotation experience is a good example of why academics choose to work at the NSF and the types of insights they gain (http://blogs.cornell.edu/danco/2016/09/09/why-im-rotating-at-nsf/)

potential entry into the NSF as a deliberate response to local early career faculty needing advise to raise funds.

During their tenure at the NSF, rotators become insiders at the agency; they evaluate numerous proposals, they observe others' performing similar tasks, they have hands-on knowledge of the largely unobserved factors that shape panel decision making (Bagues, Sylos-Labini, & Zinovyeva, 2017) and they become aware of a) what the NSF prioritizes and b) the areas where the demand for promising proposals exceeds the supply. We expect these unique insights to allow rotators to recognize what a competitive proposal looks like. In turn, because knowledge sharing is stronger among individuals of the same group (department in our application) (Hargreaves Heap & Zizzo, 2009) this insider knowledge can spillover to rotators' colleagues and create an advantage for them in that they possess knowledge that similar others to do not possess. Indeed, evidence on the effects of rotators on later stage academics without NSF grants *ex-ante* supports this expectation (Hoenen et al., 2017).

Specifically for early career scientists, having access to an insider can be instrumental on three main fronts in securing grants. One, rotators can direct colleagues to research areas the NSF prioritizes and are difficult to detect. That is, they can provide hints on what the agency is keen to fund. Two, because grant writing is typically not the focus of doctoral training, rotators can fill the gap and assist with better presenting ideas and generally crafting proposals in ways that communicate the research in more appealing ways. The sheer number of proposals that the NSF receives suggests that communication and framing are important in allowing externals reviews and later on panel members to better appreciate the merits of a given proposal. Three, rotators can address the main obstacle when it comes to initiating a proposal: idea generation (Custer, Loepp, & Martin, 2000). Because rotators possess tacit knowledge on research themes that are more likely to receive funding, they can infuse their early career colleagues with research questions they can pursue. This process resembles academic mentoring, which typically pays off (Blau et al., 2010) and in which fund raising comes up regularly (Feldman, Arean, Marshall, Lovett, & O'Sullivan, 2010).

Data Sources and Empirical Approach

A. The Treatment Group

To construct the datasets that trace the grant acquisition record of new hires in departments with and without a rotator over time we collect and merge new data from multiple sources. We accessed the list of the 240 academics who served as rotators at the NSF under the Intergovernmental Personnel Act (IPA) from 2009 to 2011 via a Freedom of Information (FOI) request directed to the NSF.[6] Following existing works relying on online data retrieval for academics (Amir & Knauff, 2008; Kim et al., 2009; Terviö, 2011), we then visited current and archived university websites from http://archive.org and combined this search with the career info in the Men and Women of Science database to identify faculty members who, as their first faculty position, were hired as assistant professors before, after and the year of the rotator's return to her department. We were able to build comprehensive and detailed career histories for 80 rotators. We then examined the professional history of more than 3,200 seasoned and early stage academics belonging to these 80 departments with a rotator. Of these 3,200 academics we identified 210 academics with comprehensive career history who as their first faculty post, joined 64 departments with a rotator between five years before and two years after the rotator returned from the NSF.

Within the 210 academics in the treatment group we identify three cohorts: a) 55 academics who joined when (or shortly after) the rotator returned from the NSF, b) 66 academics who joined when the rotator was at the NSF and c) 89 academics who joined within two to five years before the rotator had left for the NSF. Having three cohorts helps us to surmount endogeneity and sample selection concerns. It helps us with endogeneity because from these cohorts we can eliminate nearly with absolute certainty the possibility that the new hires *chose* to join the department expecting to learn from a returning rotator for cohort (c): the academics who joined the department before the given scientist left for the NSF. With regards to sample selection, the rotation experience may correlate with increased ability to select job candidates with higher chances to attract research grants in the first place. If that was true, and if rotators participated in selection committees, then the treatment groups would be populated with new hires who, *ex-ante*, were better equipped to win grants. However, the issue cannot hold for cohort (b), those that joined when the returning rotator was at the NSF, and less likely to hold for cohort (a), those that joined at the time of the rotator's return from the NSF. As such, these two cohorts allow us to address the potential for sample selection at hand.[7]

[6] As detailed in the next section, we track grant acquisition 5 years before the departure of the rotator and 5 years after the return. As such, we focus on academics serving at the NSF between 2009 and 2011 mainly because the start of the *ex-ante* period (2004) is recent enough to source comprehensive data from online sources and the end of the *ex-post* period (2016) allows us to observe the *ex-post* period in its entirety. Along the same lines, the fact that we focus on early career academics allows us to collect and organize online data with increased accuracy as scientists of this cohort are generally more apt to keep their online profiles updated.

[7] What could constitute a threat to identification would be the case in which rotation improves the selection criteria and rotators advice on the selection of candidates informally while at the NSF or during short visits at

B. The First Control Group

This first control group allows us to hold department effects fixed and is composed of 25 academics in 14 departments in the sample who joined a department with a rotator but whose tenure at the department did not overlap with the tenure of the rotator. The lack of overlap results either because these academics left the focal department before the rotator returned from the NSF or, in a few cases, because when the rotator's tenure at the NSF ended, she moved to a new university.[8]

C. The Second Control Group

The second control group addresses individual heterogeneity. Using data from the ProQuest Dissertations and Theses database we identified the PhD advisor of the new hires in departments with a rotator and the remaining PhD students whom she/he supervised as main advisor and graduated at the same year of the focal new hire, two years before and two years after. We focus on same-advisor graduates because a) initial job placement is largely explained by the advisor's network and standing in the profession and the graduating department (Long, 1978; Terviö, 2011), b) selection into advisors is not random (Waldinger, 2010) and c) doctoral training is largely standardized among PhD candidates of the same cohort. It follows that because graduates of the same advisor are similar both in the selection (into an advisor) phase and in the PhD training/treatment phase we expect this exercise to allow us to account for individual specific factors that can influence grant acquisition. Specifically, starting with the 210 academics in the treatment group we constructed the professional history of nearly 600 PhD graduates who had the same PhD advisor and graduated within two years of the focal academic's graduation year. Removing those who either left academia, never landed an Assistant Professor position in the US, moved in an academic position outside the US or had no professional history online (CV, LinkedIn, etc.), we populate our second control group with 105 same-advisor academics who landed their first faculty position in 100 different US departments without a rotator.

D. The Third Control Group

The third control group accounts for university specific initiatives that can promote entry into administration roles outside the university, grant funding sessions and tenure track criteria that

their institution. If that was true, the hires around the time of rotation and return from it would be different from other candidates. This is not what we observe.

[8] The relatively small size of the first control group is consistent with the tenure track system in the US where (in) voluntary departures from a given department are not generally common before the end of the tenure clock.

can explain differences in raising funds across different institutions. Retrieving data from university websites and the Men and Women of Science database, we populate this third control group with academics who started their first faculty position as assistant professors at the rotator's university but in a different, yet comparable, department the same year, two years before and two years after the rotator returned from the NSF. We find similar departments as follows. First, the department must belong to the same larger division or school as the department with a rotator. For instance, when the department of the rotator is an Engineering department we limit the search to other departments in the School of Engineering. Second, the control department must be in adjacent intellectual space to the department with a rotator. Following up on the previous example, if the treatment department is Industrial Engineering, within the School of Engineering we choose the department of Civil Engineering and not, for instance, the department of Chemical Engineering. Typically, the title of the department was sufficient to identify similar departments. When not, we chose departments whose faculty members publish in the same journals the faculty members of the rotator departments publish. These selection criteria yield 60 academics from 24 departments in the same university as the department with a rotator who were hired into their first position any time between two years before and two years after the focal academic joined the focal department.

Once the list of names belonging to the treatment and the three control groups was finalized we extracted data from the abovementioned sources, from the bibliographic database SCOPUS and from the NSF grant retrieval website to build a full career history for the academics we study. Leveraging the career history we construct variables describing NSF acquisition records, tenure at the institution, research productivity, yearly academic position and so on.

E. Baseline Estimation

We employ an OLS estimator where the dependent variable is the inflation adjusted amount of research funds from the NSF raised in a given year by a given new hire belonging to either a treatment or a control group. These amounts reflect new grant(s) with the focal academic being the Principal Investigator and not continuations or extensions of existing grants.

Each observation is a person year starting from the year the focal academic joined a given department as her first faculty post in an assistant professor position and ending up to five years after the return of the rotator to the department.[9] On average, we track the yearly

[9] Only 8 of the 210 academics in the treatment group overlapped with the rotator after her return for less than 5 years.

grant acquisition rate for each academic in the treatment group for 8.7 years (up to five of which are after the return from rotation) and for each academic in the three control groups for 7.7 years. Therefore, in line with the importance of early career academics raising research funds early on, we follow them the years leading to the tenure clock running out. To test whether rotators induce changes in the NSF grant acquisition record of their early career colleagues we include variables that take the value of 1 when the focal academic was in the department of the rotator the year the rotator returned from the NSF (*Treatment 0*), the first year since the rotator returned from the NSF (*Treatment 1*) and in a similar fashion up until the fifth year the rotator returned from the NSF (*Treatment 5*).[10] The person-year set up and the associated *Treatment 0 to 5* variables allow us to test the treatment effect of the rotators on their colleagues with precision as we can uncover the duration of the effect and its magnitude over time.

We conduct the analysis on three different datasets. Each dataset includes the treatment group and then, respectively, the first, the second and the third control group.

F. Control Variables

As Tables 1 to 3 below demonstrate, by and large, academics in the treatment and control groups are similar to each other and they belong to similar departments. These similarities suggest that any differences in the grant acquisition records between academics in treatment and control groups *ex-post* can be attributed to the rotator. Still, additional differences may exist. As such, we include a number of control variables in the analysis to account for such differences.

Difficult to quantify or observe factors at the department level may also induce changes in future fund acquisition. These can include visiting faculty who can transmit knowledge on fund-acquisition or shocks such as increased teaching load at time t that can limit the capacity to submit research proposals in time t+1,2, 3 and the like. We control for such effects by adding the variables *Rotator Department -1* up to *Rotator Department-5* in the analysis. The variables take the value of 1 when the person-year observations refer to academics who joined a department from which a rotator originated from one to five years before the rotator's return from the NSF. To illustrate, if the person-year observations refer to academics who, for instance, joined the focal department two years before the return of the rotator, *Rotator Department – 1* and *Rotator Department - 2* assume positive values while *Rotator Department -3, -4* and *-5* assume the value of 0. To account for potential learning effects during post-

10 We opt to use the 5 year window as it matches the typical application submission time for the common 6 year tenure clock for most junior faculty.

graduate studies we include the variable *PostDoc* which measures the number of years the focal new hire was employed in a post-doctoral position before assuming a faculty post. The variables *Assistant Professor* and *Associate Professor* also account for experience and take the value of 1 for person years the focal academic has an Assistant Professor and Associate Professor position respectively, and 0 otherwise (the base category is Professor and is composed of 9 scientists who became professors within our time window). We include the dummy variable *Male* for male academics to account for gender differences in grant acquisition. The time-varying variable *H-index* (lagged by one year) measures the H-5 citation index of the academic in question and controls for the influence of one's existing track record on grant acquisition. The availability of research funds in previous years or from different sources may condition one's NSF funding record in a given year. As such, we include in the analysis the variable *External Funding* which measures the funding amounts from sources different than NSF and the variable *Previous NSF* which measures the sum of NSF funding raised by the focal academic in the 5 years preceding the focal person-year observation.

Further, we incorporate in the analysis explanatory variables reflecting potential influences from the host institution. We include a) the time-varying variable (*Ranking*) which measures the ranking quartile of the focal university to account for potential status effects afforded to academics in higher ranked universities and b) the time-varying *Faculty NSF* variable which measures the sum of NSF funds raised by existing faculty members in the rotator's department before the rotator's return from the NSF to account for learning how to raise NSF funds from existing faculty members other than the rotator. Finally, we include science field and year fixed effects to control a) for differences across scientific fields in the propensity and need to raise funds from the NSF and b) for differences in funding cycles at the agency.

G. Descriptive Statistics

In this section we provide evidence suggesting that our research design allows us to isolate the effect of the rotator as the academics in the treatment and control groups are similar before the return of the rotator and start their Assistant Professor positions in similar departments. We also provide a description of the rotators and explain that the rotators we employ for the analysis are representative of the population of rotators.

In Table 1 we present selected statistics for the academics in the treatment and the 3 control groups. At the start of their faculty post, between 2003 and 2015 (2012 for those in the treatment group), academics in the four groups were similar in many respects including experience, gender distribution, publication records and, importantly, previous funding from the NSF. For instance, 75 percent of scientists in the treatment group had a first author publication before their graduation (following Kahn and MacGarvie (2016) our measure of innate ability), had an H-index of 1.92 and had raised, on average, $28,000 from the NSF as a Principal Investigator when they started their first faculty post. The average corresponding figures for the scientists in the 3 control groups were 70 percent, 2.17 and $27,000. As well, when the rotator was at the NSF, the funding records across scientists in the four groups were similar. Where we do observe a significant difference is on the total amount raised from the NSF in the five years following the return of the rotator (and the equivalent time period for those in control groups). Academics in the treatment groups raise, on average, close to $500,000 while academics in the three control groups raise half of that amount, $250,000. If, as we discuss below in more detail, we can attribute this difference to the rotator, then the effect is substantial. Not only rotators double the amount a given early stage academic raises from the NSF, they are also responsible for roughly half of the first major grant an emerging scientist raises from the agency: based on NSF data we find that the average inflation adjusted NSF grant across directorates from 2006 to 2016 for first time Principal Investigators is $439,000.

But, what could explain the difference in funding records among academics in the treatment and control groups is heterogeneity in the universities and departments the sample scientists belong to. Tables 2 and 3 suggest this is not the case. Departments with a rotator raise $1.1 Million per year from the NSF the period preceding the rotator's return from the NSF (Table 2). Departments without a rotator raise $1.2 Million. Similarly, the status and research productivity indicators in Table 3 paint a similar picture: 55 percent of the universities with a rotator are members of the prestigious Association of American Universities. The corresponding percentage for universities without a rotator is 50 percent. Along the same lines, 23 percent of the departments with a rotator are in the first quartile in the science field specific Shanghai ranking while 26 percent of the departments without a rotator belong to the same quartile. All in all, we do not observe significant differences in terms of funding records and status/productivity indicators between the departments with and without a rotator.

Table 4 describes the rotators in the sample. They are typically mid-career academics with success in raising funds from the NSF and with varying publication and citation records. Not shown in the table, the descriptive statistics of the rotators in the sample are similar to the descriptive statistics of the population of rotators who served at the NSF.

Table 1. Selected statistics for the academics in the treatment and control groups.

	Treatment group				**1st control group**			
	210 academics who, as their first faculty post, joined a department **with a rotator** between the 5 years before and 2 years after the rotator returned.				25 academics who, as their first faculty post, joined a department **with a rotator** but did not overlap with the rotator			
	Average	Standard Deviation	Min	Max	Average	Standard Deviation	Min	Max
Previous NSF funding when the focal academics starts her first faculty post ($m)	0.028	0.115	0.000	0.761	0.045	0.201	0.000	0.120
Average yearly NSF funding from the start of the faculty post until the rotator's return from the NSF ($m)	0.015	0.049	0.000	0.349	0.014	0.108	0.238	0.000
Total NSF funding in the 5 years following the rotator's return from the NSF ($m)	0.494	0.730	0.000	3.420	0.253	0.540	0.000	2.253
Male	0.714	0.453	0.000	1.000	0.683	0.720	0.458	0.000
Years as a Post-Doc	2.181	2.006	0.000	10.000	2.320	1.600	0.000	5.000
H-index at the time the focal academic starts her first faculty post	1.921	2.147	0.000	10.000	2.339	2.556	0.000	9.000
Average Non - NSF Funding per year until the focal academics starts her first faculty post ($m)	0.006	0.054	0.000	0.750	0.002	0.010	0.000	0.050
Career age (Years between PhD graduation and starting her first faculty post)	2.683	1.962	0.000	10.000	2.817	2.400	2.021	0.000
First author publication before PhD graduation	0.751	0.433	0.000	1.000	0.654	0.478	0.000	1.000

For the Treatment group the Rotator Department and Treatment variables take the value of 1 as follows: RotatorDepartment-5: 40 RotatorDepartment-4: 56, RotatorDepartment-3: 65, RotatorDepartment-2: 86, RotatorDepartment-1: 199, Treatment 0: 214 Treatment 1: 206, Treatment 2: 204, Treatment 3: 204, Treatment 4: 202, Treatment 5: 200

Table 1 continued. Selected statistics for the academics in the treatment and control groups.

	2nd control group				**3rd control group**			
	105 academics who, as their first faculty post, joined departments **without a rotator** and had the same advisor and similar graduation year as academics who joined departments with a rotator				60 academics who, as their first faculty post, joined a department **without a rotator** in the rotator's university in a similar department			
	Average	Standard Deviation	Min	Max	Average	Standard Deviation	Min	Max
Previous NSF funding when the focal academics starts her first faculty post ($m)	0.003	0.019	0.000	0.150	0.034	0.181	0.000	1.270
Average yearly NSF funding from the start of the faculty post until the rotator's return from the NSF ($m)	0.014	0.058	0.000	0.401	0.007	0.038	0.000	0.260
Total NSF funding in the 5 years following the rotator's return from the NSF ($m)	0.261	0.717	0.000	5.689	0.238	0.395	0.000	1.675
Male	0.683	0.468	0.000	1.000	0.733	0.446	0.000	1.000
Years as a Post-Doc	2.308	2.252	0.000	9.000	2.650	1.830	0.000	8.000
H-index at the time the focal academic starts her first faculty post	1.587	2.032	0.000	8.000	2.600	2.294	0.000	7.000
Average Non - NSF Funding per year until the focal academics starts her first faculty post ($m)	0.001	0.006	0.000	0.065	0.001	0.003	0.000	0.015
Career age (Years between PhD graduation and starting her first faculty post)	2.817	2.550	0.000	11.000	3.017	2.221	0.000	8.000
First author publication before PhD graduation	0.654	0.478	0.000	1.000	0.783	0.415	0.000	1.000

For the Treatment group the Rotator Department and Treatment variables take the value of 1 as follows: RotatorDepartment-5: 40 RotatorDepartment-4: 56, RotatorDepartment-3: 65, RotatorDepartment-2: 86, RotatorDepartment-1: 199, Treatment 0: 214 Treatment 1: 206, Treatment 2: 204, Treatment 3: 204, Treatment 4: 202, Treatment 5: 200

Table 2. Departments with and without a rotator raise similar amounts from the NSF.

	Average yearly department NSF funding the five year preceding the rotator's return from the NSF	
	Total	Per faculty member
Department with a returning rotator	$ 1,111,788	$ 34,903
Department without a returning rotator	$ 1,220,669	$ 33,467

Table 3. Departments with and without a rotator are of similar status and research productivity.

		Departments with a rotator	Departments without a rotator
Member of the Association of American University		55%	50%
Field specific Shanghai ranking the year the rotator return from the NSF	*First quartile*	23%	26%
	Second quartile	17%	15%

Table 4. Descriptive statistics of the 64 sample rotators who ended their rotation between 2009 and 2011

	Mean	**Std. Dev.**	**Min**	**Max**
Years in rotation	1.625	0.951	1.000	5.000
Male	0.730	0.447	0.000	1.000
Career age at start of rotation	21.500	8.214	8.000	31.000
Publications (5 years ex-ante)	11.627	11.697	0.000	42.000
Citations per paper (5 years ex-ante)	15.667	27.48	0.000	108.08
NSF funding (5 years ex-ante)	$643,205	1,747,756	$0.000	$ 13,086,007

Main Results

Table 5 presents the baseline estimates. We cluster the standard errors at the at the department level. This choice is predicated on the finding that, as in our case, when the treatment is at the department level but the unit of analysis is at the individual level, the estimation needs to employ a White/Huber heteroscedasticity correction for the standard errors (Bertrand, Duflo, & Mullainathan, 2004). Inference, as we find in unreported results, remains nearly identical when we cluster the errors at the scientist level to account for the fact that each scientist enters the analysis more than once.

In Model 1 we use the sample that includes the academics in the treatment group and the academics in the first control group. The coefficients of the *Treatment 1* and *Treatment 2* variables (also plotted in Figure 1) suggest that rotators induce positive and economically meaningful changes in the funding acquisition of their early stage colleagues. The *Treatment 3* coefficient is also statistically significant. But, we interpret such evidence as suggestive because the significance does not hold across specifications, both for the baseline estimates and for selected robustness checks. Overlapping with the rotator one and two years after her return from the NSF leads to an increase in funding that exceeds $200,000. To put this in perspective, as shown in Table 1 above, academics in the treatment groups raise $500,000 in the 5 years following the return of the rotator while in the corresponding period academics in the control groups raise $251,000. At the same time, the average first time grant from the NSF across directorates is $439,000. As such, given the *Treatment 1* and *Treatment 2* estimates, it appears that the rotator treatment effect nearly doubles the fund acquisition record of early career scientists and is responsible for close to half of one's first grant from the agency. Interestingly, the gains from the rotator are stronger in the first two years of overlapping (when, roughly, the tenure track clock is about to run out) and do not extend beyond that time period. As we demonstrate in section VII, the main reason we expect this finding to hold is that within the 5 year window we study the increased workload following the award of a grant limits new grant application submissions in the following years. A complementary explanation, which we do not rule out, is that the value of the knowledge the rotator transmits to her colleagues decays with time as the agency evolves, changes priorities and the like.

In Model 2 we conduct the analysis using the academics on the treatment group and the academics in the second control group. Similar to the results in Model 1, the *Treatment 1* and

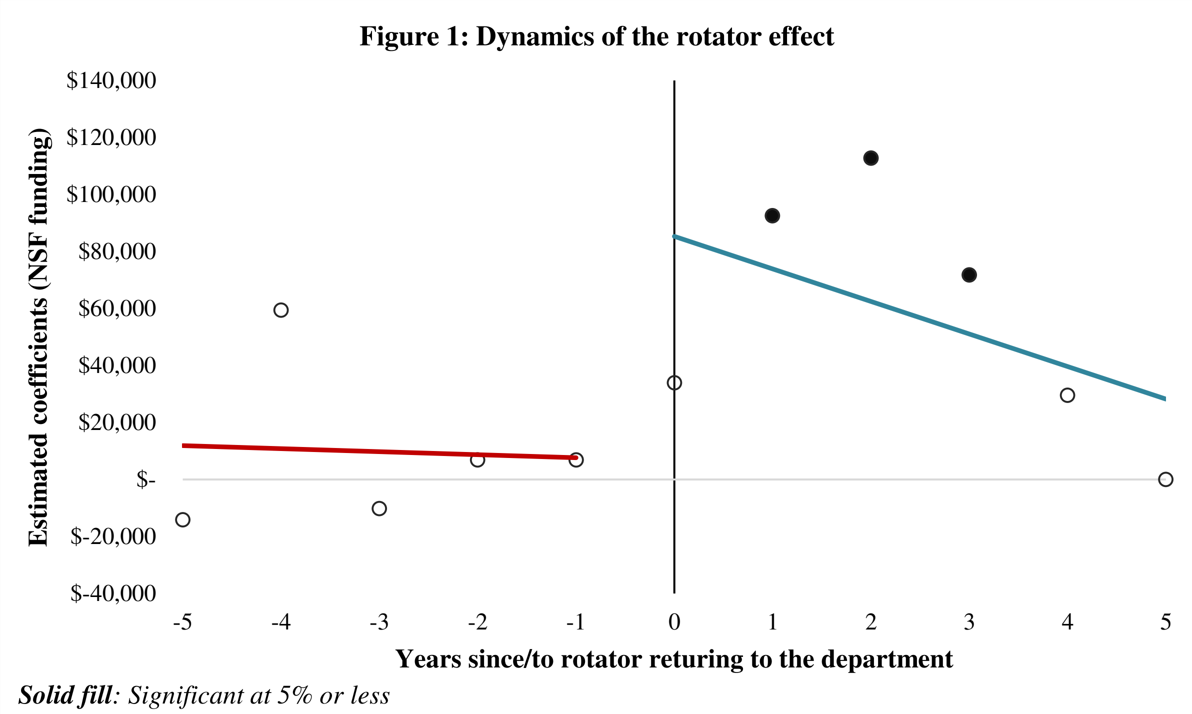
Treatment 2 estimates indicate that indeed overlap with a rotator is beneficial to research funding even after accounting for individual-specific heterogeneity. The reduced magnitude of the *Treatment 1* and *Treatment 2* coefficients in model 2 when compared to the Model 1 coefficients implies that individual-specific factors matter for fund acquisition.

In Model 3 we employ the sample composed of the treatment group and the third control group. The results are qualitatively similar to the results in Model 1 and Model 2. The *Treatment 1* and *Treatment 2* estimates suggest that rotators induce increases in the NSF funding records of their early career colleagues.

Table 5. OLS Baseline Estimates. Dependent Variable is NSF funding in million.

	MODEL 1 Treatment Group & 1st Control Group	MODEL 2 Treatment Group & 2nd Control Group	MODEL 3 Treatment Group & 3rd Control Group
RotatorDepartment t-5	-0.014	-0.010	-0.003
	(0.015)	(0.010)	(0.012)
RotatorDepartment t-4	0.059	0.079	0.099
	(0.040)	(0.045)	(0.055)
RotatorDepartment t-3	-0.010	0.002	0.019
	(0.018)	(0.018)	(0.017)
RotatorDepartment t-2	0.007	0.005	0.029
	(0.027)	(0.028)	(0.027)
RotatorDepartment t-1	0.007	-0.003	0.010
	(0.023)	(0.020)	(0.021)
Treatment 0	0.034	0.037	0.040
	(0.021)	(0.019)	(0.022)
Treatment 1	**0.092*****	**0.058****	**0.070****
	(0.032)	**(0.026)**	**(0.027)**
Treatment 2	**0.113*****	**0.061****	**0.088*****
	(0.036)	**(0.026)**	**(0.024)**
Treatment 3	0.072**	0.034	0.042**
	(0.035)	(0.018)	(0.019)
Treatment 4	0.030	0.007	0.005
	(0.037)	(0.020)	(0.024)
Treatment 5	-0.000	-0.001	-0.004
	(0.033)	(0.025)	(0.026)
PostDoc	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.002)
Assistant Professor	0.017	0.025**	0.011
	(0.016)	(0.012)	(0.013)
Associate Professor	0.009	0.008	-0.007
	(0.015)	(0.012)	(0.013)
Male	-0.001	0.013	0.010
	(0.011)	(0.009)	(0.009)
H-index	-0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)
External Funding ($m)	0.355	0.381**	0.341
	(0.186)	(0.181)	(0.187)
Previous NSF ($m)	0.113***	0.098***	0.122***
	(0.017)	(0.015)	(0.017)
Ranking	-0.007**	-0.007**	-0.007**
	(0.003)	(0.003)	(0.003)
Faculty NSF ($m)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Constant	0.039	0.035	-0.004
	(0.022)	(0.023)	(0.019)
Science field FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	2,152	2,642	2,319
R-squared	0.170	0.156	0.179
R-squared adjusted	0.155	0.144	0.166
Number of Departments	65	158	80

Robust standard errors in parentheses clustered at the department level
*** $p<0.01$, ** $p<0.05$



With regards to control variables, we find that academics with previous NSF funding, in higher ranked universities, perhaps due to the availability of internal grant writing support or status effects, raise more from the NSF. We also document a suggestive positive relationship between non-NSF grants and NSF funding. Importantly, the *Rotator Department* minus 1 to 5 variables are not statistically significant indicating that what drives the estimates is the overlap with the rotator *after* her NSF experience and not unobservable factors that took place in the *ex-ante* period and can influence funding in the *ex-post* period.

Robustness of the Results

To measure the potential rotator effect we include in the analysis, as a subgroup of the 210 academics in the treatment group, 55 new hires who joined a department with a rotator after the rotator returned from the NSF. This modeling choice may plague the estimates if these 55 new hires chose to join the focal department because of the presence of the rotator among the faculty and the expected knowledge transfer from her. To test whether such potential endogeneity indeed biases our estimates in test 1 in Table 6 we omit these new hires from the analysis (showing only the results with the first control group for ease of presentation). The results are qualitative similar to the baseline estimates suggesting that this source of potential endogeneity does not influence our analysis.

We reduce heterogeneity at the scientist level in the second control group based on the expectation that same advisor and graduation year academics who joined departments without a rotator are similar to academics who joined departments with a rotator. In robustness checks 2 and 3 (Table 6) we reduce heterogeneity by identifying similar academics via alternative means. First, we relax the "same graduation year" criterion and run the regression on a sample that includes a) academics who joined departments with a rotator and b) academics who joined a department without a rotator, had the same advisor and graduated 3 to 10 years before the focal academic. Second, we relax the "same advisor" criterion under the idea that the more similar academics might not have the same advisor. Specifically, after we create a pool with all the academics who joined departments without a rotator we identify similar academics from a different advisor using Coarsened Exact Matching[11] and include these similar academics in the sample we analyze together with the treatment group academics. The results are qualitative similar to the baseline estimates and our conclusions remain intact.

[11] We used the following matching criteria: PhD granting university ranking, H-Index at the time of joining the focal department and having at least one first authored publication before PhD graduation.

Table 6. Omit from the treatment group new hires who join the rotator department after the rotator has returned + Relax same advisor and graduation year criteria

VARIABLES	*Test 1* Omit hires who joined the department after the rotator returned	*Test 2* Add academics with the same advisor who graduated 3 to 10 years before the focal academic who joined a department with a rotator	*Test 3* Use Coarsened Exact Matching to populate the control group
RotatorDepartment t-5	-0.010	0.008	-0.009
	(0.015)	(0.012)	(0.069)
RotatorDepartment t-4	0.067	0.081**	0.046
	(0.041)	(0.038)	(0.054)
RotatorDepartment t-3	-0.000	-0.005	0.023
	(0.020)	(0.019)	(0.047)
RotatorDepartment t-2	0.007	0.003	0.036
	(0.029)	(0.023)	(0.036)
RotatorDepartment t-1	0.007	-0.022	0.003
	(0.025)	(0.022)	(0.027)
Treatment 0	0.032	0.025	0.054**
	(0.024)	(0.018)	(0.023)
Treatment 1	**0.098*** **	**0.055** **	**0.064*** **
	(0.037)	**(0.026)**	**(0.021)**
Treatment 2	**0.119** **	**0.072*** **	**0.060*** **
	(0.045)	**(0.024)**	**(0.020)**
Treatment 3	0.084**	0.039**	0.026
	(0.042)	(0.017)	(0.020)
Treatment 4	0.033	0.006	0.003
	(0.042)	(0.020)	(0.019)
Treatment 5	-0.010	0.004	0.001
	(0.046)	(0.024)	(0.019)
PostDoc	-0.003	-0.003	-0.004
	(0.003)	(0.002)	(0.003)
Assistant Professor	0.010	0.030***	0.013
	(0.017)	(0.010)	(0.019)
Associate Professor	0.006	0.016	-0.008
	(0.015)	(0.011)	(0.021)
Male	0.002	0.012	0.004
	(0.014)	(0.008)	(0.010)
H-index	-0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)
External Funding ($m)	0.395**	0.338	-0.038
	(0.176)	(0.186)	(0.055)
Previous NSF ($m)	0.111***	0.096***	0.104***
	(0.018)	(0.013)	(0.009)
Ranking	-0.006	-0.006**	-0.005
	(0.003)	(0.002)	(0.003)
Faculty NSF ($m)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Constant	0.034	-0.019	-0.022
	(0.022)	(0.015)	(0.045)
Science field FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	1,800	3,181	2,654
R-squared	0.197	0.138	0.094
R-squared adjusted	0.179	0.127	0.0813
Number of Departments	180	193	66

Robust standard errors in parentheses clustered at the department level
*** p<0.01, ** p<0.05

Along the same lines, if unobserved factors in raising funds are not captured by our research design to compare new hires from the same university, advisor and graduation year – if for instance inherent ability in raising funds is not distributed normally among the population - it would be difficult to interpret our estimates as causal. Indeed, in test 4 in Table 7 we employ a difference-in-difference specification under which early career scientists from different universities, advisor and graduation year enter the analysis either in treatment or control groups. Those who joined a department with a returning rotator *before* her return from the NSF belong to the treatment group and those who joined departments without a rotator are the control group. The dependent variable is the average NSF funds raised by the focal individual in the three years before the return of the rotator (*ex-ante* period) or of the three years after the return of the rotator to the department (*ex-post* period). The allocation of scientists to treatment and control groups should be quasi-random as we do not expect the majority of academics who joined a department with a rotator before her return to choose to do so because of her presence. Indeed, we include a variable that measures the number of years in the focal department to account for potential selection effects. The statistically significant positive interaction of the *ex-post* and *treatment group* variables is in line with the argument that we are unraveling causal effects.[12]

[12] We have also tested for the influence of outlier observations and found no evidence that they impact the estimates materially.

Table 7. Robustness Check 4. Difference-in-difference estimation.

Variable	Coefficient
After	0.032
	(0.022)
Treatment	-0.010
	(0.020)
After * Treatment	**0.070****
	(0.030)
PostDoc	-0.010**
	(0.005)
Assistant Professor	0.018
	(0.024)
Associate Professor	-0.015
	(0.036)
Male	-0.004
	(0.022)
H-index	0.002
	(0.001)
External Funding ($m)	0.012
	(0.048)
Previous NSF ($m)	0.296***
	(0.108)
Ranking	-0.009
	(0.006)
Faculty NSF ($m)	0.000
	(0.001)
Constant	0.121**
	(0.061)
Science field FE	YES
Year FE	YES
Observations	426
R-squared	0.185
R-Squared Adjusted	0.132
Number of Departments	141

Robust standard errors in parentheses clustered at the department level
*** p<0.01, ** p<0.05

The Mechanism Driving the Results

In this section we explore whether the findings we reveal are driven by favoritism, knowledge transfer from the rotator or other means. When applicable, we present only the estimates using the first control group for brevity as we expect this control group to more closely approximate the counterfactual. The results, available upon request, are qualitatively similar when employing the remaining two control groups.

In the first two tests we put the knowledge transfer mechanism under scrutiny. The first test starts with the premise that if the mechanism underpinning the results is knowledge transfer from the rotator including tips on how to frame a proposal and to which program to submit, then we would expect more helpful rotators to induce more pronounced changes in the funding acquisitions of their emerging colleagues. Similar to Laband and Tollison (2003) and Oettl (2012) and based on the intensity of the thank-you notes in acknowledgements in Ph.D. dissertations supervised by each rotator, we construct a helpfulness index using the sentiment analysis algorithm of Rinker (2013) and the Hu and Liu (2004) weighted sentiment dictionary. Higher values of the index correspond to more helpful rotators. Indeed, early career scientists in departments with rotators in the top 10 percentile of the helpfulness score raise, on average, \$1,135,346 in the 5 years following the return of the rotator. The corresponding figure for early career scientists in remaining departments is \$683,721. The t-test comparing the two figures is statistically significant at the 5 percent level.

For the second test on whether knowledge transfer is the mechanism, we follow Brogaard et al. (2014), in Table 8, to include “false” rotator appointments. We conduct two exercises. In the first one, within departments with a rotator, we randomly pick a year between 2006 and 2011 which we define as the year the rotator supposedly came back from the NSF. Accordingly, for this exercise the *Treatment* variables are by design false (except when the random return year overlaps with the true return year). In the second exercise, we artificially treat the same advisor and graduation year academics who in reality overlapped with a rotator as landing a job in a department without a rotator. Equivalently, we treat the same advisor and graduation year academics who did not overlap with a rotator in reality as if they did. For both exercises, if knowledge transmission is the causal mechanism, the *Treatment* variables should be statistically insignificant. This is what we find.

Table 8. False rotator appointments.

	Random appointment of rotator's return	Random appointment of rotator department
RotatorDepartment t-5	-0.022	-0.002
	(0.018)	(0.025)
RotatorDepartment t-4	0.016	0.292
	(0.031)	(0.265)
RotatorDepartment t-3	0.020	-0.071**
	(0.035)	(0.032)
RotatorDepartment t-2	-0.013	0.062
	(0.020)	(0.064)
RotatorDepartment t-1	-0.001	0.024
	(0.022)	(0.033)
Treatment 0	0.027	-0.023
	(0.027)	(0.029)
Treatment 1	**0.007**	**-0.031**
	(0.026)	**(0.039)**
Treatment 2	**-0.006**	**-0.013**
	(0.023)	**(0.026)**
Treatment 3	0.039	-0.013
	(0.031)	(0.020)
Treatment 4	0.032	-0.007
	(0.030)	(0.014)
Treatment 5	-0.042**	0.001
	(0.020)	(0.021)
PostDoc	-0.003	-0.002
	(0.002)	(0.002)
Assistant Professor	0.021	0.033***
	(0.017)	(0.011)
Associate Professor	0.012	0.016
	(0.013)	(0.013)
Male	-0.001	0.012
	(0.011)	(0.008)
H-index	-0.000	0.001
	(0.001)	(0.001)
External Funding ($m)	0.360	0.388**
	(0.184)	(0.183)
Previous NSF ($m)	0.113***	0.099***
	(0.016)	(0.015)
Ranking	-0.007**	-0.007**
	(0.003)	(0.003)
Faculty NSF ($m)	0.000	0.000
	(0.000)	(0.000)
Constant	0.039	0.035
	(0.021)	(0.022)
Science field FE	YES	YES
Year FE	YES	YES
Observations	2,152	2,642
R-squared	0.170	0.176
R-squared adjusted	0.155	0.141
Number of Departments	65	158

Robust standard errors in parentheses clustered at the department level
*** p<0.01, ** p<0.05, * p<0.1

While the tests above indicate that knowledge transfer from the rotator, the estimates could also be driven by knowledge transfer from co-authors or co-investigators who had success in raising funds from the NSF. To test for such potential mechanisms we conduct two tests. In the first test in Table 9 we omit from the analysis scientists whose more recent frequent co-authors experienced improvement in their *ex-post* NSF funding record. Specifically, we omit from the analysis academics whose at least 1 of the 3 most frequent co-authors gained more NSF funding in the previous three years than the sample average. In the second test we omit from the analysis scientists whose co-investigator in the focal grant had recent success with the NSF. That is, after a focal academic's Co-I is awarded an NSF grant as PI, all subsequent person-year observations of this focal academic are omitted. The results from both tests suggest that neither co-authors nor co-investigator account for the findings we reveal.

Another mechanism consistent with the results would be favoritism. Presence of a former rotator in a given department may induce increased visibility of the department. This visibility may cause favoritism for the applications submitted by the rotator's colleagues (if, for instance, successor rotators are more lenient towards the returned rotator's colleagues). We conducted several tests that lead us to discount such possibility. First, under favoritism we would expect to observe growth in funding among those colleagues that have an established funding record with the NSF. In unreported results, we find that this does not hold. Second, under favoritism the grants of rotator's colleagues would be of lower quality than other NSF grants. Table 10 demonstrates that the number of publications and citations coming out of rotator colleagues' grants are not statistically different than the number of publications and citations coming out of 2009 to 2011 grants awarded to investigators that do not belong to departments with a rotator. Third, though this was not part of our research design, none of the academics we analyze submitted a funded proposal in the *ex-post* period jointly with the rotator and, four, none of the rotators co-authored a publication with the sample academics *ex-ante* or *ex-post,* which addresses the possibility of "ghost" co-authorship in the funded proposals.

Table 9. Testing knowledge transfer from co-authors and co-investigators who had success in raising funds from the NSF.

	Omit co-authors	Omit co-investigators
RotatorDepartment t-5	-0.031	-0.025
	(0.016)	(0.014)
RotatorDepartment t-4	0.021	0.024
	(0.028)	(0.026)
RotatorDepartment t-3	-0.019	-0.005
	(0.020)	(0.017)
RotatorDepartment t-2	-0.015	-0.009
	(0.032)	(0.030)
RotatorDepartment t-1	-0.013	-0.016
	(0.020)	(0.019)
Treatment 0	0.028	0.028
	(0.020)	(0.018)
Treatment 1	**0.090****	**0.067*****
	(0.044)	**(0.025)**
Treatment 2	**0.135*****	**0.081****
	(0.034)	(0.033)
Treatment 3	0.039	0.046
	(0.031)	(0.032)
Treatment 4	0.007	0.016
	(0.032)	(0.026)
Treatment 5	-0.015	0.021
	(0.035)	(0.016)
PostDoc	-0.003	-0.002
	(0.003)	(0.002)
Assistant Professor	0.018	0.017
	(0.017)	(0.015)
Associate Professor	0.005	0.009
	(0.017)	(0.015)
Male	-0.001	-0.011
	(0.012)	(0.012)
H-index	-0.000	-0.000
	(0.001)	(0.001)
External Funding ($m)	-0.070**	-0.031
	(0.034)	(0.029)
Previous NSF ($m)	0.113***	0.131***
	(0.015)	(0.024)
Ranking	-0.002	-0.005
	(0.003)	(0.003)
Faculty NSF ($m)	0.000	0.000
	(0.000)	(0.000)
Constant	0.025	0.001
	(0.026)	(0.017)
Science field FE	YES	YES
Year FE	YES	YES
Observations	1,784	1,843
R-squared	0.112	0.100
R-squared adjusted	0.0930	0.0808
Number of Departments	65	65

Robust standard errors in parentheses clustered at department level
*** p<0.01, ** p<0.05

Table 10. Grants of scientists in treatment and control groups yield similar outcomes

	2009 to 2011 grants of scientists in departments *with* a rotator		2009 to 2011 grants of scientists in departments *without* a rotator		
Variable	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**	**Two-sides t-test**
Publications	6.385	0.854	6.667	1.375	0.859
Citations	322.517	83.296	281.462	112.260	0.781

The results could also be driven by scientists in the treatment departments working on "hot topics" which typically attract more funds. To test for such possibility we conducted the following exercise. First, we counted the number of articles in the SCOPUS database that include in their list of keywords the 3 most occurring keywords for articles published in 2010 by all 400 academics in the sample. Then, we counted the number of articles in SCOPUS that 5 years later, in 2014 included the same keywords. On average, the number of articles that include in their list of keywords the 284 unique keywords from articles published by scientists in departments without a rotator increased by 27.7 percent. The corresponding increase for the 470 unique keywords from articles of scientists in departments with a rotator was 23.7 percent. The t-test comparing these two numbers was 0.8734 and it was statistically insignificant. Accordingly, academics in departments with and without a rotator appear to work on topics that increase in popularity in parallel.

Similarly, the fact that the NSF picks a given scientist to be a rotator may indicate that the scientist's research area is gaining traction and her department is more active in that area when compared to other departments. The following lead us to discount this as a likely driver of the findings: a) as shown above the control and treatment departments are similar to each other and their research topics grow in a similar fashion in popularity, b) the analysis includes fixed effects for science field and c) rotators, are rarely headhunted by the NSF – they are typically self-nominated and decide to apply for a rotator position mostly because they want to learn more about the NSF and contribute to the growth of science.

Supplementary analysis

In this section we elucidate further the driver of our findings by exploring whether the estimates are driven by an increase in the applications submitted by the rotator's colleagues upon her return or whether the applications submitted are of higher quality or/and are better targeted and as such they are more likely to be successful. Because the NSF does not release rejected applications we cannot address the question directly. However, two empirical exercises we describe below suggest that the driver, for the largest part, is not an increased number of applications but an improvement in the quality of the submitted applications.

One, in unreported results we econometrically find that rotators do not have an effect on the number of awarded grants. If more applications correlate with more awarded grants, this finding implies that the rotator effect stems from direction, feedback and the like on better, more carefully targeted proposals. Two, as shown in Table 11, the probability of winning a grant is significantly higher for academics in the treatment group when compared to academics in the first control group. This is supportive of our expectation because better, more carefully targeted proposals should be more likely to be funded. The magnitude of the effects is also informative. The increase in probability for those in the treatment group is considerable for small to medium size grants (84 and 73 percent more likely for grants above \$50,000 and \$250,000 respectively), wanes for larger grants (23 percent for grants above \$500,000) and is non-existent for grants above 1 million. This finding is consistent with the \$200,000 difference in fund acquisition between academics in the treatment and control groups we report in the baseline estimates.

In the last set of supplementary analyses we inform the mechanism driving the results by shedding light on why we observe an effect in *Treatment 1* and *Treatment 2* but not in later treatment years. We consider two main potential explanations. One, in line with the above discussion that an increase in the number of applications to the NSF does not drive the results, it is possible that once the focal academic raises a grant in say treatment year 2, she devotes time in conducting the research of that grant instead of submitting additional grant applications. To test this proposition we start with the premise that more grants correlate with more applications. Then, in Table 12 we limit the analysis to the top 3 directorates in terms of the number of grants awarded from 2006 to 2016 (i.e. engineering, computer science, math and physics), hence the need for a continuous flow of grants is larger. If the lack of applications following the award of a grant is driving the results then among fields of this kind we would expect an effect in the later Treatment years. This is not what we observe. Two, it is possible that the rotator effect wanes over time in that the insights and knowledge that a rotator gains are not updated as NSF progresses, likely changes focus and priorities etc. The figures of Table 13 do not dismiss such possibility. The longer the rotator has been away from the NSF, the less new hires in their first year of overlap with the rotator gain. To illustrate, if the rotator returned at year t, hires who joined the department at t-1 and at t, hence interacted with the rotator when the NSF experience is recent, raise, on average, \$135,467 and \$130,252 at t and t+1 respectively. On the other hand, those who joined the department in t+1 raise \$70,144 in t+2.

All in all, the tests we devise to understand why we do not observe an effect past *Treatment 2* imply that 2 forces are at play: a) increased workload after the award of a grant which limits the number of new applications and b) diminishing applicability of the insights the rotator conveys as the NSF changes over time. Empirically, we cannot separate the two mainly because the NSF does not provide access to rejected applications and it is prohibitively difficult to measure with accuracy whether the relevance of the rotator's insights indeed diminishes over time. Anecdotally, our discussion with a handful of rotators, suggest that the decrease in the number of applications is the stronger of the two forces but we do expect knowledge decay from the rotator to also play a role.

Table 11. Change in probability of securing an NSF grant after the rotator returns.

	Grant larger than $50,000		Grant larger than $250,000		Grant larger than $500,000		Grant larger than $1,000,000
Year of rotator return	0.167	**	0.157	**	0.05		-0.007
1 year after rotator return	0.214	***	0.198	***	0.116	***	0.018
2 years after rotator return	0.235	**	0.226	***	0.109	***	0.010
3 years after rotator return	0.224	**	0.145	**	0.007		-0.005
4 years after rotator return	0.096		0.035		0.012		-0.003
5 years after rotator return	0.062		0.038		0.003		-0.004

The change in probability is calculated after holding all other variables at their means

Table 12. Limit the analysis to the top 3 directorates in terms of the number of grants awarded from 2005 to 2016.

	Treatment Group & 1st Control Group
RotatorDepartment t-5	-0.028
	(0.026)
RotatorDepartment t-4	0.019
	(0.044)
RotatorDepartment t-3	0.013
	(0.025)
RotatorDepartment t-2	0.049
	(0.036)
RotatorDepartment t-1	-0.015
	(0.036)
Treatment 0	0.029
	(0.041)
Treatment 1	**0.139****
	(0.059)
Treatment 2	**0.175****
	(0.075)
Treatment 3	0.118
	(0.106)
Treatment 4	0.089
	(0.091)
Treatment 5	-0.023
	(0.049)
PostDoc	-0.009***
	(0.002)
Assistant Professor	0.029
	(0.030)
Associate Professor	0.001
	(0.029)
Male	-0.006
	(0.025)
H-index	-0.000
	(0.001)
External Funding ($m)	-0.073
	(0.074)
Previous NSF ($m)	0.113***
	(0.021)
Ranking	-0.012**
	(0.006)
Faculty NSF ($m)	-0.000
	(0.000)
Constant	0.097**
	(0.043)
Science field FE	YES
Year FE	YES
Observations	893
R-squared	0.132
R-squared adjusted	0.096
Number of Departments	27

Robust standard errors in parentheses clustered at the department level
*** p<0.01, ** p<0.05

Table 13. The longer the rotator has been away from the NSF, the less new hires in their first year of overlap with the rotator gain.

	Average NSF funding acquired during first three years of overlap with rotator after return from NSF				
Variable	**Tr0**	**Tr1**	**Tr2**	**Tr3**	**Tr4**
Joined 1 year before the rotator returned	**$135,467**	$262,451	$217,168		
Joined the same year the rotator returned	$11,349	**$130,252**	$130,834		
Joined 1 year after the rotator returned		$28,518	**$70,144**	$61,849	
Joined 2 years after the rotator returned			$36,058	$24,383	$78,931

Conclusions

We reveal evidence consistent with a causal link between increases in the NSF funding record of newly hired assistant professors and exposure to academics in their department who return from their tenure at the National Science Foundation as Program Directors (rotators). Tracking the grant acquisition of early stage academics since their first faculty position we find that within a 5 year period newly hired assistant professors who join departments with a returning rotator raise almost twice the amount of research grants similar academics in similar departments without a rotator raise (approximately *$200,000* more which is nearly *half* of the average first time grant from the NSF). These increases are due to rotator's colleagues being more likely to secure medium size grants and are realized one and two years after exposure to the rotator; precisely, then, when early career scientists are at the utmost need for raising research funds that can help them build independent long term research programs and advance science. Via a variety of empirical tests we trace the origins of these improvements to knowledge transfer from the rotator to her colleagues on what to write, how to write and where to send a proposal.

Overall, our research highlights that insiders, individuals with insights of an organization type different than the one they are permanently employed, can generate positive spillovers for their colleagues. These findings speak directly to the literature analyzing the effects of access to high human capital in academia (Azoulay et al., 2010; Borjas & Doran, 2012; Borjas & Doran, 2015; Waldinger, 2010, 2012; Waldinger, 2016) by adding novel evidence on gains from high human capital with insights from experience outside academia. The work is also relevant for the literatures on success in science (Kahn & MacGarvie, 2016; Kelchtermans & Veugelers, 2013) and academic mentoring (Blau et al., 2010). More broadly, the results are informative for the academic labor market. Rotators with recent experience at the NSF appear equipped to set one career's off by inducing significant changes in early fund acquisition. As such, presence of a rotator in a given department may be a decisive factor when choosing among job offers.

Our research is timely and has policy implications. Because science advances when early career scientists build independent careers it is imperative to explore ways they can gain access to resources. Indeed, the difficulties this cohort of academics face in securing resources is concerning (Poirazi, 2017), and it may impede scientific progress and harm overall social welfare (Alberts et al., 2014; Nature_Editorial, 2016). Policy makers have started to react mostly by altering the institutional environment so that it betters the chances of early career scientists raising research funds (Kaiser, 2017). Here, we demonstrate that tapping into existing knowledge held by colleagues' human capital might also be a complementary, less resource-intensive strategy with immediate results which addresses one of the main obstacles early career academics face: lack of experience and insights that put them at a disadvantage as they often compete for the same grants with high status scientists having established funding and publication records.

Along the same lines, the paper speaks directly to the design of the rotation program. Under the premise that home universities gain from the rotation program a recent policy mandates that they cover part of the rotation program bill (Mervis, 2016a). Here, while we do not fully measure the benefits and the costs of the program, we do nevertheless find that home institutions realize gains from returning rotators.

Our analysis, albeit careful, has caveats which render it incomplete and hence subject to improvements. First, we follow previous contributions (e.g Kahn & MacGarvie, 2016) to construct one of our control groups by matching on observable characteristics such as having the same PhD advisor. Success in raising funds may be driven by unobservable factors which we cannot account for. Our expectation, however, is that the unobserved factors correlate, at least to some degree, with the observables. The difference-in-difference analysis we conducted as a robustness check supports this expectation. Second, we focus on early career scientists who land their first faculty position in the US. But, not all PhD holders follow such a career trajectory (Sauermann & Roach, 2016). Accordingly, our analysis is conditional on early career scientists having secured a faculty position in a US research intensive university. We do not see this as a major concern *per se* because our focus is not on who lands a US faculty post in the first place as we compare only similar emerging scientists who followed an academic career in similar institutional environments. Third, the analysis focuses on the US and as such the results may not generalize directly to other countries as the rotation setting is unique to the NSF. This uniqueness of the rotation program at the NSF together with our estimates makes one wonder whether other funding agencies in the US and elsewhere would benefit from a similar setting. This is so because the diffusion of knowledge we document is likely predicated on the design of the NSF to include external academics in its grant review process not only as reviewers but also, and perhaps more importantly, in more central roles as decision makers.

Chapter 3. Learning by Seconding: Evidence from NSF rotators [13]

[13] This chapter is based on:
Hoenen, SJ., Kolympiris, C., Klein, P. (2018) *Learning by Seconding: Evidence from NSF Rotators*. Under revision at Organization Science.

Introduction

Knowledge acquisition is a key source of competitive advantage. How do organizations acquire knowledge? Arrow (1971) provided a classic answer: individuals and groups become more efficient with experience—they learn by doing (see also Romer, 1990; Young, 1991). Organizations develop capabilities over time (Penrose, 1959) as individuals learn and share that knowledge with colleagues. Tacit knowledge diffuses easily among employees of the same organization because they tend to have strong ties, have similar characteristics, and, as such, share a common social identity (Kane, Argote, & Levine, 2005). However, internal knowledge diffusion can be uneven (Dahlander, O'Mahony, & Gann, 2016) and, because knowledge is gained on the job from insiders, it is difficult to incorporate new, non-overlapping knowledge into the organization (Molina-Morales & Martínez-Fernández, 2009).

New knowledge is critical for organizational growth and improvement (Inkpen & Tsang, 2005), and organizations may acquire it by hiring workers from organizations already possessing the relevant knowledge, the phenomenon of learning by hiring (Jain, 2016; Slavova, Fosfuri, & De Castro, 2016). As Simon (1991: 125) notes, an organization learns not only "by the learning of its members," but "by ingesting new members with knowledge the organization didn't previously have." New employees bring reputations, network ties, and tacit knowledge acquired from previous work experience. These employees may also model certain behaviors, including ways of learning, that help current employees learn faster and better (March, 1991; Slavova et al., 2016). However, new employees typically lack (social) ties with existing employees, are often dissimilar to them, and may appear as outsiders, hindering the transfer of tacit knowledge (Gruenfeld, Martorana, & Fan, 2000; Hargreaves Heap & Zizzo, 2009a; Inkpen & Tsang, 2005; Phelps, Heidl, & Wadhwa, 2012), a potential drawback of learning by hiring (Agrawal, McHale, & Oettl, 2017; Szulanski, 2000).

We propose an alternative mechanism for acquiring and incorporating new knowledge without the need to overcome social barriers, what we call *learning by seconding.* Secondment is the practice of sending employees of one organization to short-term assignments in another to learn new practices and procedures, establish new ties, and bring these back to the sending organization (Beyer & Hannah, 2002). Secondment is common among technology companies, law firms, consulting firms, and government agencies. Examples include the US Council of Economic Advisers, composed of academics on short-term leaves from universities, the SEMATECH consortium of scientists in semiconductor firms and the US government (Beyer

& Hannah, 2002), and the Royal Academy of Engineering's Industrial Secondment scheme in the UK.

We combine insights from the literatures of knowledge transfer, employee mobility and social identity to theorize that *learning by seconding* can be a promising mechanism by which organizations can acquire valuable knowledge, network, and similar resources from other organizations. Seconded employees are insiders (the main advantage of learning by doing and what learning by hiring lacks) who can infuse the home organization with new, non-overlapping knowledge (the main advantage of learning by hiring and what learning by doing lacks).

As an employee of the home organization, seconded individuals have ties with non-seconded employees that allow tacit knowledge to transfer within an organization, share similar knowledge bases and a common identity (Reagans, Singh, & Krishnan, 2015; Tortoriello, Reagans, & McEvily, 2012). At the same time, unlike learning by doing, secondments allow the focal individual to fuel her knowledge depository with new knowledge which does not overlap with the knowledge of the non-seconded employees. As such, insiders can influx new, non-overlapping knowledge to the organization. Along the same lines, seconded employees are "boundary spanners"-individuals with ties to multiple organizations (the sending and the receiving organization).

Prior work has established that the presence of boundary spanners increases organizational productivity, partly through effective knowledge transfer (Ancona & Caldwell, 1992; Tortoriello et al., 2012; Tushman & Katz, 1980). To our knowledge, however, no one has looked systematically at the knowledge flows that can result from secondments. We ask the questions, do secondments facilitate knowledge transfer and, if so, what are the mechanisms?

To study secondments we exploit the rotation program at the National Science Foundation (NSF). Under the rotation program, in place since 1970, NSF employs academics, called rotators, who step out of their academic institution for typically 1 to 2 years to lead the review process and exercise decision makings at the agency as Program Directors (PDs). After their secondment these scientists return to their academic homes armed with experience and unique knowledge of the NSF. As a rotator put it during one of our interviews, "I came back knowing how funding decisions were made, and the various ways the institution works. There's so much more that goes into how they're balancing decisions. Knowing this really helped in mentoring junior but also senior faculty."

Besides being a fertile template to study secondments, the rotation program is important in itself. Knowledge flows in and out of government agencies such as the NSF are particularly relevant for scientific research, both at the societal and individual level (Feldman, Desrochers, & Bercovitz, 2014; Stephan, 2012) . Existing studies of government's role in science focus mainly on direct funding (Diamond Jr, 1999; Lichtenberg, 1987; Muscio, Quaglione, & Vallanti, 2013). However, as with other sectors such as energy, transportation, and financial services in which government plays a large role, there are many channels other than direct funding for government action to benefit particular organizations, regions, or industries. Knowledge flows through public-private partnerships are one example (Kivleniece & Quelin, 2012). Seconding academics to government agencies, as the NSF rotator program is doing, represents a not-yet-studied example.

Following convention, we infer knowledge transfer from changes in output which we measure with increases in NSF funding for rotator's colleagues and for comparable academics (Argote & Ingram, 2000). A key means of acquiring new resources such as research funding is through knowledge transfer from new mobile colleagues (Slavova et al., 2016). Mobility in this sense includes not only moving between universities (Slavova et al., 2016) but also taking temporary editorial positions (Brogaard et al., 2014) [14], the (forced) move of academics from one country to another (Borjas & Doran, 2012a; Waldinger, 2010; Waldinger, 2012a), and academic inbreeding where PhD graduates of a focal university are employed as faculty members in the same academic institution without being employed elsewhere in the meantime (Horta, Veloso, & Grediaga, 2010). However, we know surprisingly little about the effects of scientist mobility outside academia such as employment spells in industry or government secondments. These moves are increasingly popular (Geuna, 2015) and could prove important in generating knowledge flows towards colleagues as they can equip the focal mobile academic with unique knowledge and insights from outside her core profession, and hence difficult to

[14] Brogaard et al. (2014) examine journal editor rotations, in which an academic takes a temporary position as a journal editor in addition to regular professorial duties. Unlike NSF rotators, journal editors are not seconded; i.e., they a) typically serve longer terms, b) remain working full-time at their home institutions, and c) do not interact face-to-face with other editorial staff located away from the home institution. Brogaard et al. (2014) look at knowledge flows between editors and their current colleagues during the editor rotation (and find a strong effect—the colleagues publish much more in the editor's journal and the papers are high quality, suggesting knowledge transfer rather than favoritism). We look at knowledge transfer between NSF rotators and former colleagues after they return from rotation. Another relevant literature deals with international assignments of employees among subsidiaries of the same multinational corporation (e.g. Criscuolo, 2005; Lyles & Salk, 1996); because these are internal transfers, however, they do not address non-overlapping knowledge acquisition which is central to our work. Several papers analyze how academics with industry ties impact their colleagues (Bercovitz & Feldman, 2008; Stuart & Ding, 2006) but do not examine changes in the ability to attract research resources and, unlike our interest, do not study academics who pause their home university duties even temporarily.

acquire when mobility is bound to academic circles. And a colleague returning from a stint at a peer or a complementary organization is likely to be viewed as a particularly accessible source of new knowledge.

Our research design takes advantage of the fact that academics within disciplines but across universities are trained in similar ways, have common experiences, and work on similar problems. For this reason, we can compare an NSF rotator's colleagues with academics in the same fields at other universities who do not have a returning rotator in their academic units. As such, our identification strategy features a difference-in-difference estimation in which the dependent variable is the amount of NSF funding for each scientist in academic units (what most universities call departments) with and without a returning rotator. By carefully matching the characteristics of academics with rotator colleagues to those without, we can estimate a treatment effect of bringing an NSF officer back from rotation. Moreover, because rotators typically return to their previous academic institution (hence the decision to return is largely independent to the existing colleagues needing help), we address the endogeneity problem that typically plagues cross-sectional studies of employee mobility (Singh & Agrawal, 2011).

The results suggest that secondments do result in knowledge transfer. We find that scientists exposed to their seconded colleague raise considerably more research funding from the NSF when compared to similar scientists in similar academic units who did not have a rotator as a colleague in the *ex-post* period. Using additional empirical tests and a series of interviews, we trace these improvements in funding records to knowledge transfer from the rotator. We identify three main mechanisms: rotators a) help generate ideas by directing colleagues to areas with significant funding opportunities (i.e. *focusing*), b) assist with *framing* proposals in ways they are appealing to reviewers and c) provide processual knowledge by clarifying the instructions and the process of submitting a proposal (i.e. *formatting*). As with other forms of secondments, acquiring new knowledge that can be transferred back to the originating institution is the main gain of rotation. As such, we expect the three mechanisms for the case at hand to be representative of the more general mechanism of knowledge transfer that underpins secondments.

Our work makes two main contributions. First, we contribute to the literature on knowledge transfer between and within organizations by means of worker mobility. Departing from the current literature we highlight that secondments can address some of the shortcomings of learning by doing and learning hiring while retaining their advantages. Specifically in the context of academic researchers, prior work has shown that scientists who move within academia bring benefits to their colleagues (Borjas & Doran, 2012a; Brogaard et al., 2014;

Horta et al., 2010; Slavova et al., 2016). By examining secondments, we believe we are the first to study the effects of temporary moves *outside* academia, then back to the home institution. This is important as it allows for a better understanding of the origins of knowledge acquisition.

Second, we contribute to the literature on inter and intra organization employee mobility (Almeida & Kogut, 1999; Argote, Ingram, Levine, & Moreland, 2000; Singh & Agrawal, 2011; Song, Almeida, & Wu, 2003; Summers, Humphrey, & Ferris, 2012; Tambe & Hitt, 2013). By analyzing a hybrid case in which the rotator works outside her institution, and partly outside of her profession, and then moves back to the original institution, we offer new evidence on how employee mobility outside one's core profession can induce gains for colleagues that never moved. Specifically, the knowledge and insights rotators gain during their temporary assignments are different than those gained via moves within academia, because the rotators are exposed to complementary, but not overlapping, knowledge bases while on secondment. More generally, we address the lack of work in the knowledge literature at the micro level (Foss, Husted, & Michailova, 2010).

Setting: the NSF Rotation Program

The National Science Foundation supports research in all nonmedical sciences. Each of the seven directorates focuses on a different scientific field: biological sciences, computer and information science, engineering, geosciences, mathematical and physical sciences, social, behavioral, and economic sciences, and education and human resources. The grant process is supervised by Program Directors (PDs), subject-matter experts who oversee the review process. Program directors coordinate with the approximately 40,000 external experts who review proposals, as well as reviewing proposals themselves, chairing review panels, managing program budgets, exercising discretion in making funding decisions, communicating with other PDs, providing formal and informal feedback to applicants, communicating decisions, attending internal and external NSF meetings, and generally navigating the daily internal workings of the NSF (Gorman, 2011; Mccullough, 1994; Muller-Parker, 2007; Stephan, 2012).

To encourage cross-fertilization, maintain quality control, and increase coordination, PDs also sit in panels in directorates other than their own. As such, they are aware of funding opportunities and the state of scientific progress across directorates. Indeed, during our interviews rotators consistently reported that they spent a substantial amount of their time at

NSF on discussing broad issues about various scientific disciplines and how NSF can contribute towards scientific progress.

Since the 1970 passage of the Intergovernmental Personnel Act the NSF has employed academics, called rotators, on loan from their academic institution (rarely from industry) as PDs. These seconded academics serve up to 4 years (typically 1 or 2), working along with permanent NSF PDs (Mervis, 2013). Rotators join the NSF to participate in a rigorous and unbiased review system while bringing in fresh ideas and perspectives to the permanent staff (e.g Duce et al., 2012). Most rotators have previous experience with the NSF, as grant recipients, reviewers, and panel members, and this sparked their interest in the rotation program. Our interview subjects reported a desire to learn more about the NSF and its internal operations, as well as a more general aim of having an impact on the profession, shaping the direction of science, and exercising professional leadership.

In 2016, rotators comprised 28% of the agency's scientific workforce (Mervis, 2016a). During their secondments rotators cannot submit a proposal to the NSF, are subject to restrictions when applying for non-NSF funding, cannot review or process proposals of recent collaborators, and in general are subject to strict rules even after their tenures at NSF are over. These restrictions are designed to avoid conflicts of interests and minimize any chances of favoritism in the review process. From 2004 to 2014 the NSF employed nearly 800 rotators from around 400 academic institutions, mostly as PDs. As we discuss later in the paper rotators come from nearly every academic discipline, have diverse backgrounds, vary in their scholarly records, work at small and big universities of different rankings and status, come from every state, and are of different age and gender.

Literature and Hypotheses

The transfer of knowledge from one unit of an organization to another is a key input to improvements in organizational performance (Chang, Gong, & Peng, 2012). But, the process of knowledge transfer is challenging and often fails (Szulanski, 2000). Its success hinges, in large part, on the properties of the knowledge to be transferred and on the relationship between the sender and the recipient of knowledge (Simon, 1991). Specifically, tacit knowledge is more difficult to be transferred than codified knowledge while similarity and strong social ties between the sender and the receiver of knowledge facilitate knowledge transfer (Phelps et al., 2012).

Not surprisingly, learning by doing is a primary means of diffusing knowledge within organizations: as individuals learn, they are interacting regularly with local colleagues, facilitating the flow of tacit knowledge. Strong ties between group members foster a common social identity in which fellow employees, as insiders, are seen as trustworthy and prone to reciprocity and hence more influential than outsiders (Gruenfeld et al., 2000; Zahra & George, 2002). For sourcing tacit knowledge, people tend to rely on those with unique experiences and insights (Gray & Meister, 2004) but, because knowledge search processes are often confined locally, co-workers possessing unique knowledge often become the key knowledge source (Borgatti & Cross, 2003; Singh, 2005; Stuart & Podolny, 1996). For these reasons, knowledge transfer among individuals in the same group or subunit is typically more effective than that between individuals in different groups or subunits (Cohen & Levinthal, 1990; Tortoriello et al., 2012)

However, while learning by doing facilitates the transfer of tacit knowledge, it is less useful for bringing new, non-overlapping knowledge to the organization. Because new knowledge drives performance improvements (Inkpen & Tsang, 2005), organizations often hire workers from outside (Rosenkopf & Almeida, 2003). This provides workers of the recipient organization the opportunity to integrate outside knowledge to their current context (Allen, 1977), reposition their search processes (Tzabbar, 2009), and develop new capabilities that improve performance (Jain, 2016). Because knowledge is embedded in individuals and individuals often rely on others' experience to learn (Levitt & March, 1988), individuals who move from one context to another can act as knowledge conduits (Argote & Ingram, 2000). However, as noted above, new hires lack social ties with incumbents, are often dissimilar, and therefore do not typically share a common social identity with existing employees, hindering the absorption of new tacit knowledge. Indeed, Agrawal et al. (2017) find that hiring a star employee does not bring noticeable benefits to incumbents. Organizations thus face a trade-off between encouraging internal collaboration, where individuals have a greater ability to learn (from sharing a common social identity), and encouraging external collaboration, where individuals have a greater chance to acquire new, non-overlapping knowledge.

One way to mitigate this trade-off is outward mobility, the practice of sending employees to other organizations while remaining in contact with their former colleagues. Losing valuable employees is generally costly, but does provide potential access to the new firm's knowledge and capabilities, as the outwardly mobile employees will tend to pass information back to their previous coworkers. Importantly, this knowledge is likely to diffuse within the organization because its source is a former insider with ties to other employees sharing a common social identity. Looking at the fashion industry which—like academia—thrives on novelty and creativity, Godart, Shipilov, and Claes (2014) show that moderate levels of outward mobility are associated with higher levels of creativity inside the sending organization. Wang (2015) finds that skilled immigrants returning to their countries transfer organizational practices to the countries of origin.

We argue that secondments represent an even more valuable form of outward mobility because the movement is temporary. The seconded employee goes to the new organization, acquires new knowledge, and then returns for daily, face-to-face interaction with her former colleagues.[15] The NSF rotation program provides an ideal setting for studying the effects of secondments on the sending organization. Specifically, we expect returning rotators to improve their colleagues' ability to secure research funding by transferring to them tacit knowledge about the funding process that can address their lack of experience and judgment (Borgatti & Cross, 2003). Specifically, former rotators can provide a) hints on research areas NSF is keen on funding (what we term *focusing*), b) help with *framing* research proposals in ways that are appealing to reviewers and c) tacit knowledge about the grant process (what we term *formatting*). Hence having a rotator as a colleague should encourage more submissions while also improving the quality of submitted proposals, thus leading to increased funding.

Developing a successful NSF proposal is not easy. As described by Custer et al. (2000), the most frequent challenge is conceptualization and visioning of the project, followed by coordination with collaborators, help from the home institution, budget development, and understanding of NSF guidelines and expectations. Rotators can exploit their NSF experience and address all these challenges. Because rotators have hands-on experience with numerous proposals and applicants from different institutions, they can transmit tacit knowledge on designing and producing a successful application (Muller-Parker, 2007). Indeed, as mentioned above, providing leadership is a prime reason for a given academic to become a rotator. We expect this motivation to prompt rotators to be particularly interested in helping their colleagues upon returning.

As an example of focusing, one rotator explained to us that rotators "demystify NSF . . . and generally open the door to opportunities that are outside one's radar." Another told us he "learned valuable lessons about how NSF communicates intentions about funding priorities."

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[15] Importantly, while ties between employees ameliorate competitive concerns about sharing knowledge, moves between competing groups within the same organization may exacerbate such concerns (Kachra and White 2008). Secondments are plausibly advantageous in that instance as well because the seconded employee does not move from a competing unit within an organization into another.

Referring to the mechanism of framing, another rotator said: “I talked to many colleagues, even when they were outside my field, on general aspects regarding what makes a strong proposal at the NSF.” Another described framing and formatting: “People would show me proposals, say “can you tell me what you think? I would say ‘well, maybe you should aim it a little different or maybe you should pick a different program’. I also gave some talks and alerted people to particular programs.”

Faculty with a rotator colleague can increase their odds of getting funding both by writing better proposals and by submitting more proposals. Indeed, obtaining funding is the most frequent topic of discussion in mentoring relationships (Feldman et al., 2010), and such mentoring tends to pays of in terms of increasing funding success rates (Blau et al., 2010). While the relationship and transmission of knowledge from rotators to colleagues is not necessarily a mentor-mentee relationship, there are parallels and as such the abovementioned results strengthen our theoretical expectations. Thus, we advance the following hypothesis:

Hypothesis 1. *Faculty members in academic units with a seconded returning rotator will improve their NSF grant acquisition record after the rotator returns from the NSF, compared to similar academics without a rotator colleague.*

We expect the relational properties between the sender and the recipient of knowledge about NSF grants to influence the effect of the rotator on the funding records of colleagues (Argote & Ingram, 2000; Singh & Agrawal, 2011). Relational properties should influence how various colleagues of a returning rotator perceive the rotator’s experience, accessibility, and specialized expertise.

As noted above, strong ties between the sender and the receiver improve the transfer of tacit knowledge (Levin & Cross, 2004; Simonin, 1999). Moreover, strong ties are more likely to develop when the two parties interact over time, as longer relationships help form social cohesion and a common social identity (Kane et al., 2005). Individuals with longer tenure at an organization are more deeply embedded and tend to develop better communication channels with colleagues (Gruenfeld, Mannix, Williams, & Neale, 1996; McFadyen & Cannella, 2004; Paruchuri, Nerkar, & Hambrick, 2006). Those with longer tenure in an institution are also more familiar with organizational routines and practices (Gruenfeld et al., 1996). In sum, individuals with longer tenure are more likely to be approached for advice that is focused to the focal environment because they share a common identity with their colleagues, have developed communication channels with them, and are *a priori* expected to provide content-specific feedback. This leads to the following hypothesis:

Hypothesis 2a. *The effect of the seconded rotator on the grant acquisition record of her colleagues is positively moderated by her tenure in her academic unit.*

A second relational property that should influence knowledge transfer between the rotator and her colleagues is similarity. Even within an academic field there is substantial variation in the specific topics and problems researchers study, the theories and methods they consider appropriate, the journals and communities in which they disseminate their work, and so on (Cole & Cole, 1972). Researchers also differ by scientific skill and research productivity: those who are highly productive and whose work is influential will enjoy a strong scholarly reputation, while others will be less well established in their specific fields or in the profession as a whole. Both similarity in the specific knowledge base and similarity in research productivity or impact should affect the quantity and quality of knowledge transfer.

As noted above, knowledge transfer is costly both for sender and receiver. The sender must devote time and effort to helping the recipient to understand (Reagans & McEvily, 2003), and the recipient must integrate the new knowledge into his knowledge depository. When these costs are lower, senders are more likely to invest time in transmitting knowledge and recipients are more likely to approach senders for help. Importantly, a common knowledge base makes knowledge transfer easier (Black, Carlile, & Repenning, 2004; Reagans & McEvily, 2003), so we expect the effectiveness of knowledge transfer between rotators and their academic colleagues to be greater among those working on similar research topics and potentially using similar methods.

Similarity in scientific productivity, influence, and reputation between sender and receiver can also lower the cost of knowledge transfer. More productive individuals have more and newer knowledge and, hence, have more to transmit (Azoulay et al., 2010; Chan, Li, & Pierce, 2014; Lacetera, Cockburn, & Henderson, 2004; Mas & Moretti, 2009). Accordingly, they are more likely to be approached for help. But, they respond differently to different requests (Thomas-Hunt, Ogden, & Neale, 2003). Highly accomplished researchers are more likely to connect with other scholars with similar research experience, impact, and reputation who can assimilate the new knowledge (Black et al., 2004; Salomon & Martin, 2008). This implies that knowledge transfer is facilitated by the sender and receiver being similar in research productivity.

Subsequently, we advance the following two hypotheses:

Hypothesis 2b. *The effect of the seconded rotator on the grant acquisition record of a colleague is positively moderated by similarity in knowledge between the rotator and the colleague.*

Hypothesis 2c. *The effect of the seconded rotator on the grant acquisition record of a colleague is positively moderated by similarity in research productivity between the rotator and the colleague.*

Research Design and Estimation

We use a difference-in-differences research design in which the dependent variable is the inflation-adjusted sum of funds raised by each scientist before and after having a rotator as a colleague. We match "treated" academics with a rotator colleague to similar academics without one. We find matches because academics are not randomly assigned to academic units with and without a rotator colleague. The *ex-post* period is the 5 years after the rotator returns to her academic unit and, equivalently, the *ex-ante* period is the 5 years before the rotator started her tenure at NSF.

The research design offers two main advantages. First, selection into rotation is independent of the need of one's colleagues for mentoring on how to raise funds. As already discussed, most academics become rotators because their prior experience at the NSF—serving in discussion panels and communication with the NSF—prompted them to want to learn more about the NSF and its internal operations, not because *ex-ante* they recognize colleagues that need assistance with grant acquisition. Two, where rotators go after the NSF is also independent to existing colleagues. Almost all rotators return to the school where they previously worked. The fact that the return decision is exogenous to the treatment group is important: if the movement of labor to new organizations is endogenous to the anticipated effects of that new labor on existing labor, it is hard to estimate a treatment effect of mobility (Singh & Agrawal, 2011).

To make sure the results measure knowledge transfer rather than reciprocal learning (Manski, 1993), we include only academics who in the *ex-ante* period had no funds from the NSF. These faculty members have limited (or no) experience in attracting grants and this implies that a) they are less likely to share insights specific to NSF funding with each other and

b) they are more likely to gain from the rotator's advice as faculty with established funding records may be of less need (or even desire) for additional help (Laband & Tollison, 2000). Accordingly, focusing on this cohort of scientists we expect to be able to unravel the potential effects that rotators may have on the ability of their colleagues to attract research resources.

To build our control sample we use Coarsened Exact Matching (CEM), a multivariate technique that matches on covariate values not exactly, but based on different strata built on the joint distribution of the matching variables.[16] CEM features a number of desirable statistical properties including the reduction of model dependence, estimation error, and bias (Iacus, King, & Porro, 2011). In our case, CEM allows us to address heterogeneity at both the level of the individual scientist and the level of her academic unit. We also address heterogeneity at the university level (without using CEM). We build different samples which address different forms of heterogeneity. Specifically, in matching scheme 1 we focus on reducing heterogeneity at the academic unit level, identifying academic units in different universities similar to the academic unit of the rotator based on overlap on science field, faculty size, and average H-index across faculty members *ex-ante*.[17] We then populate the sample we analyze with a) the faculty members in the academic unit with a rotator without NSF funding in the *ex-ante* period and b) the faculty members in the matched academic units that have also not attracted funds from NSF *ex-ante*.

In matching scheme 2 we use the same matching criteria but match at the individual level, such that members of the same academic unit with a rotator could be matched with scientists belonging to different academic units. For example, assume that the University of Maryland (with a rotator) has professors X, Y, and Z without NSF funding in the *ex-ante* period. Each professor, in this hypothetical scenario, has a single match; professor X's match

[16] Following Iacus, King, and Porro (2008) our estimation weights the observations according to the size of the stratum they belong. This is required when, as in our application, the number of control and treatment observations within a stratum are not equal (Blackwell, Iacus, King, & Porro, 2009; Iacus et al., 2008). But weighting does not allow us to cluster the standard errors at the observation level. Given that each scientist enters the analysis twice (one in the *ex-ante* period and one in the *ex-post* period) in unreported results we also run the regressions with clustered standard errors at the scientist level without weighting. The results are qualitatively similar to the baseline estimates.

[17] We expect these factors to influence the accumulation of funds for a given academic as, for instance, some science fields tend to attract more research funds than others. As robustness checks, shown in a later section, we match on different characteristics and find qualitatively similar estimates. On a more technical note, as Singh and Agrawal (2011) explain, with CEM a trade-off must be made between the similarity of the matched sample and the number of observations that are matched. CEM divides variables in bins within certain ranges and then populates the bins with observations that fall within these ranges. Matching observations on variables divided in more bins creates smaller samples that are more similar in the chosen characteristics. The opposite, larger bins, match more observations that are then on average less similar to each other. For matching schemes 1, 2 and 3, we were stricter on science field and H-index by enforcing that every science field gets its own bin and dividing the H-index in 12 bins covering 0 to 75 in increments of 6.81. We determine the *FacultySize* bin boundaries at 30 and 60, effectively creating three bins that represent small, medium and large sized academic units.

is at the University of Illinois, professor Y's at the University of Wisconsin, and professor Z's at the University of Florida. Under the individual matching scheme, the matched scientists from Illinois, Wisconsin, and Florida enter the analysis as controls for the three faculty members at Maryland.

Matching scheme 3 combines schemes 1 and 2 to reduce individual-level and academic-unit-level heterogeneity simultaneously. Similar to matching scheme 1, the first step in matching scheme 3 is to identify comparable academic units based on science field, average H-index, and faculty size. Within those units, we then match at the individual academic level. Importantly, the pool of potential controls for a focal faculty member belonging to a rotator group is bound to the faculty members of the matching academic unit revealed in the first step. For instance, if the first stage matching reveals that the with-rotator biochemistry department at the University of Iowa is similar to the without-rotator biochemistry department at the University of Missouri, then the analysis will include as controls only those academics at Missouri who do not have NSF funds and are close matches to academics without NSF funding *ex-ante* in Iowa. If no match is found among the academics in Missouri (or in Missouri and say the University of Illinois if the latter is also identified as a match to Iowa), then the treatment group academics from Iowa are not included in the analysis.

Finally, in matching scheme 4 we address heterogeneity at the university level (without using CEM) to account for institution-specific incentives, norms, and other factors that can a) condition one's fund raising record and b) potentially prompt a given academic to become a rotator. We select controls who are employed at the rotator's university but in a different academic unit. To choose this unit we imposed two criteria. First, the academic unit must be in the same, immediately larger division or school as the treatment unit. Typically, the immediately larger division was, say, the School of Engineering or the School of Public Policy. In few cases, there were subdivisions within these Schools; there we choose controls from those subdivisions. Two, the control unit must be in a broadly similar scientific field to the treatment unit. For example the treatment unit is Industrial Engineering, we choose controls from Civil Engineering and not, say, Chemical Engineering.

To identify rotators we first posed a Freedom of Information (FOI) request to the NSF asking for rotator names and affiliations across all agency directorates from 2004 to 2014. We limit our analysis to academics who served as NSF rotators from 2004 to 2009 so that we can observe changes in funding for their colleagues 5 years before and 5 years after rotation. Next, we visited the website of each rotator's academic unit and sourced the list of faculty members including the rotator. For every faculty member we a) collected data from the latest version of her CV, LinkedIn, and other sources, b) downloaded from the bibliographic database SCOPUS a list of her publications over time including co-authors, citations, keywords, and the like and c) recorded her accumulation of NSF funds using data provided online by the NSF.

Using this information we built a profile of each scientist with a rotator colleague describing her tenure at her institution, research productivity, co-authors, and so on. We sum these profiles to build the profile of each rotator's academic unit. To build the profile of potential control groups we repeat the steps described above for academic units ranked one position higher and one position lower than the rotator's academic unit in the science-field-specific Shanghai ranking.[18] Whenever insufficient information was available for these units (usually occurring when the majority of academics in the unit did not maintain an updated professional history online), we moved to academic units two or three ranking positions up and down. We opted for this "one up, one down" approach under the premise that academic units in similar rankings are, at least in broad strokes, comparable to each other. As a final step, the pool of potential matches upon which we implement CEM contains a) the academics collected via the "one up, one down approach" and b) the scientists belonging to academic units in the rotator's university which we identified as comparable to the rotator's academic unit. For example, assume that the without-rotator Materials Science and Engineering Department at Cornell University is identified as a match to the with-rotator Physics Department also at Cornell University. When creating the pool for potential matches for academic units with a returning rotator at, say, Carnegie Mellon and Harvard then the Materials Science Department at Cornell University enters the pool.[19]

To test H1 we interact the variable *Rotator Group* which takes the value of 1 for scientists belonging to academic units with a rotator and the variable *Ex-Post* which takes the value of 1 for observations corresponding to the *ex-post* period and 0 otherwise. In support of H1 we expect a positive sign for the *Ex-Post* * *Rotator Group* interaction. Following Meyer

[18] For instance, the Texas A&M University's Department of Mathematics, had a rotator returning in 2007. On the Academic Ranking of World Universities, in the field of Natural Sciences and Mathematics in 2007, Texas A&M had a ranking of 43. For this year Georgia Institute of Technology was ranked 42 in Natural Sciences and Mathematics and University of California, Davis was ranked 44. Accordingly, we populate the pool of controls for the Texas A&M Department of Mathematics with academics in the Departments of Mathematics at Georgia Institute of Technology and the University of California, Davis.

[19] For the example at hand, the fact that we match on science field ensures that the without rotator Materials Science Department at Cornell University is matched only with Material Science Departments hosting a rotator in other universities. Relatedly, the pool of potential control scientists does not include academics who could benefit from a rotator directly: none of the potential control scientists had co-authored a publication with the rotator in the past and none had worked in institutions where the focal rotator had worked before her present academic post. This holds because most rotators had worked only for one university and had collaborated primarily with academics who had won grants themselves.

(1995) we test the moderating effects under H2a, H2b, and H2c using three-way interactions of the *Ex-Post * Rotator Group* interaction and variables we construct to measure tenure and similarity.

We measure tenure (*Tenure*) in the institution as the number of years the rotator has been employed at the focal university. We capture knowledge similarity (*Knowledge Similarity*) by recording the number of top-10 keywords of the rotator's *ex-ante* articles that are also among the top-10 keywords of her focal colleague's *ex-ante* articles. We opt for the *ex-ante* articles expecting relationships between colleagues that strengthen knowledge transfer to develop over time. But, because keywords change only slightly over the time period we study we obtain nearly identical estimates when constructing the variable using *ex-post* articles. We measure similarity of research productivity (*Productivity Similarity*) using the absolute value of the difference between the H5-index of the rotator and the H5-index of the focal colleague. The H5-index is a measure of scientific productivity: in the last 5 years, a scientist with an index of h has published h papers, each of which has been cited in other articles h times or more.

In support of H2a, H2b, and H2c we expect positive signs for the three-way interactions Ex-Post * Rotator Group * Tenure, Ex-Post * Rotator Group * Knowledge Similarity, and Ex-Post * Rotator Group * Productivity Similarity. For scientists in the control groups we use the values of the moderators corresponding to academics we estimate to be similar to the rotators. To capture variation in the moderators that is shared among academics in treatment and control groups, and among all observations in the ex-post period, we also include in the analysis interactions between Rotator Group and the moderators and between Ex-Post and the moderators.

In testing our hypotheses we also include explanatory variables that can affect an academic's ability to get NSF funds. To account for the possibility that other funding crowds out NSF funds we measure the amount of non-NSF funds raised in the *ex-post* period by the focal scientist (*OtherFunds*). We also incorporate a dummy variable taking the value 1 if the academic had attracted funds from the NSF before the *ex-ante* period (*NSFBefore*). To account for potential effects of career experience on NSF funding we measure the elapsed years from the receipt of an academic's PhD until the start of the *ex-post* period (*Years*). Along the same lines, we include a variable that takes the value of 1 if the focal scientist is assistant professor at the start of the *ex-post* period, 2 if she is associate professor, and 3 if she is full professor (*Position*). Serving in an administrative position may take up time that could be spent in writing grant proposals, so we include a dummy indicator (*Administrator*) that takes the value of 1 for academics who are department heads, PhD studies coordinators, and similar positions at the start of the *ex-post* period. We also include controls for gender (*Male*), scholarly output (*Publications*), and cumulative citations (*Citations*). The latter two variables are time varying as they assume different values for the *ex-ante* and *ex-post* period when the publications and citations record of the focal academic has changed.[20]

Academics with extended professional networks may benefit more strongly than others by having a rotator colleague as they have access to larger pool of knowledge and relationships. To account for such effects we include a time-varying variable that counts the number of unique co-authors across time for each focal scientist (*Coauthors*). Scientists in higher-ranked universities may be offered more institutional support when crafting their proposals and may receive a status effect from the NSF, so we include the Shanghai ranking quartile of each academic's university on a given year and field of science (*UniversityQuartile*). The size of one's academic unit may also influence the growth of NSF funds as smaller groups may reflect more intense knowledge flows among faculty members due to elevated familiarity, whereas in larger academic unit the pool of potential knowledge sources is typically larger. We include the number of faculty members in the academic unit (*FacultySize*) to control for these effects. Finally, we include year- and science-field-fixed effects to account for changes in funding trends across years and across scientific fields.

Data

To guide the selection of the rotators' academic units we started with the 778 scientists who served as rotators under the Intergovernmental Personnel Act (IPA) program from 2004 to 2014. To fully measure the potential changes in funding for rotators' colleagues in the *ex-post* period we focused on the 203 scientists who worked at the agency from 2004 to 2009 and for a period of up to 2 years (which is the most common length of stay).[21] Using the abovementioned data sources we were able to source comprehensive information and build full professional histories for 50 rotators.

[20] These variables are time-varying which ameliorates concerns of endogeneity arising from the fact that *Citations* and *Publications* are used to construct the *Productivity Similarity* variable. Still, when we omit the variables from the analysis, we reach identical conclusions to the baseline estimates.

[21] 352 academics served as rotators under IPA from 2004 to 2009 with 203 serving up to two years (the minimum stay for this cohort was 8 months). To illustrate why we limit the search to these 203 scientists, for the rotators whose tenure at the agency lasted 4 years we would have to eliminate those that started rotation in 2007, 2008 and 2009 as the *ex-post* period ends after 2016.

We then searched for professional histories of more than 14,000 scientists belonging to a) the 50 academic units with a rotator, b) the approximately 150 academic units ranked one to three positions higher and one to three positions lower than the academic unit with a rotator, and c) the approximately 100 academic units in the same university of the academic unit with a rotator. We succeeded for about a third of these, 5,120, employed at 89 universities reflecting 37 units with a rotator and 160 units without a rotator.[22] Subsequently, we manually read more than 5,000 CVs and went through more than 3,000 LinkedIn pages, 12,000 university and laboratory websites, and 2,000 personal websites. Following this search, we identified 1,515 faculty members in academic units with and without a rotator who met the following criteria: a) their available information was updated and comprehensive enough to build a full professional history (including for instance the PhD graduation date and information on present position), and b) they were in the same academic unit both in the *ex-ante* and in the *ex-post* period. For these 1,515 academics, who compose our original sample, we then downloaded their more than 110,000 articles included in SCOPUS (including different versions of the first name and searching by university) which were cited by close to 3,000,000 articles to build the *Publications, Citations, Knowledge Similarity, Productivity Similarity, and Coauthors* variables.

The distance statistic L1 shows that using CEM has given us control and treatment observations that are more comparable to the original sample than those collected with the one-up, one-down approach. Specifically, the L1 distance between the treatment and control group decreased from 0.754 to 0.629 for matching scheme 1, from 0.641 to 0.619 for matching scheme 2 and from 0.830 to 0.796 for matching scheme 3. Table 1 offers an additional way to check the *ex-ante* comparability of academics in the treatment and control groups. It compares the treatment and control scientists under matching scheme 3, the most restrictive as it addresses heterogeneity both at the scientist and at the academic unit level (descriptive statistics of samples formed with remaining matching schemes are similar).

Overall, we observe only small differences among the academics in the control and treatment groups. These differences are, for the most part, not statistically significant. For instance, the size of the academic unit for treatment and control groups is on average 33.67 and

[22] The main reason we could not collect data on the colleagues of 13 rotators was that these scientists were employed at academic units that did not include professional histories on their websites. Importantly, we did not identify significant differences in terms of publication and citation records, NSF funding, age, position, and gender among the 37 academics we use for the analysis and a) the remaining rotators who also served at the NSF during the same period (2004 to 2009) and b) the 778 rotators included in the list coming out of the FOI request.

33.12 respectively, the number of publications and citations are nearly identical, and so is the presence of females, the tenure of the rotator, and all remaining variables. In sum, the scientists in the control and treatment groups are observationally identical *ex-ante*. Where we do observe significant differences is on the accumulation of NSF funds *ex-post*. Supporting our expectations, academics in groups with a rotator raise on average $201,505 after the rotator returns to her academic unit while academics in groups without a rotator raise on average $69,169 during the same period. Note that these sums reflect new grant(s) raised *ex-post* and not continuations or extensions of existing grants.

Table 1. Descriptive statistics of scientists in rotator and control academic units.

Matching using scheme 3 (match on academic unit and scientist)							
Variable	**# of scientists**	**Mean**	**Standard Deviation**	**# of scientists**	**Mean**	**Standard Deviation**	**Two-sides t-test**
NSF funding (ex-ante)	101	-	-	330	-	-	
NSF funding (ex-post)	101	$201,505	$71,322	330	$69,168	$14,092	-2.84 ***
Knowledge Similarity	101	0.22	0.61	330	0.49	1.41	1.97 **
Productivity Similarity	101	48.01	105.65	330	57.59	99.17	1.60
Tenure	101	17.41	7.72	330	18.81	9.61	1.81
OtherFunds	101	0.15	0.36	330	0.16	0.37	-0.05
NSFBefore	101	0.44	0.50	330	0.36	0.48	-1.81
Years	101	22.65	9.35	330	22.22	9.31	-0.30
Position	101	2.82	0.55	330	2.69	0.56	-2.77 ***
Administrator	101	0.37	0.49	330	0.35	0.48	-1.39
Male	101	0.87	0.34	330	0.86	0.35	-0.22
Publications	101	15.48	15.24	330	15.60	15.68	-0.21
Citations	101	26.51	34.14	330	25.54	35.89	0.34
Coauthors	101	1.35	0.85	330	1.47	1.16	0.31
UniversityQuartile	101	2.44	1.08	330	2.32	1.05	-1.27
FacultySize	101	33.67	18.51	330	33.12	13.87	-0.57

** Significant at 5%. *** Significant at 1%.

As shown in Table 2, the sample includes rotators from all 7 NSF directorates (and 1 rotator from the office of the Director) with the number of rotators from each directorate being roughly proportional to the funding amounts the focal directorate awards over time. For instance, 21.6 percent of the sample rotators are employed at the Directorate for Mathematical and Physical Sciences, while over the time period we study this directorate awarded 21 percent of all NSF grants. Note that this proportionality is also reflected in the funding amount received from each Directorate among the sample academics. Compared to their colleagues (including those with NSF funding *ex-ante*) rotators have similar characteristics such as having received their PhD training from institutions of similar ranking but they differ in two main respects. First, in the *ex-ante* period their publication and citation records are below those of their colleagues (e.g. 8.59 versus 23.18 articles). Interestingly, the corresponding figures before the *ex-ante* period are comparable between rotators and their colleagues, with the rotators having somewhat more articles (i.e. 39.97 versus 32.47).

Table 2. Characteristics of the 37 rotators that enter the analysis and their 247 colleagues.

Variable	Rotator averages	Rotator colleagues averages
NSF funding as PI (5 years ex-ante)	\$714,180.00	\$302,485.00
NSF funding as PI (5 years ex-post)	\$583,357.00	\$293,288.00
Years	23.43	21.05
Male	0.70	0.87
Position	2.92	2.74
Publications (all years before ex-ante)	39.97	32.47
Publications (5 years ex-ante)	8.59	23.18
Publications (5 years ex-post)	20.08	29.95
Citations (all years before ex-ante)	27.00	43.00
Citations (5 years ex-ante)	17.59	22.31
Citations (5 years ex-post)	25.73	34.14
Coauthors (all years before ex-ante)	1.24	1.08
Coauthors (5 years ex-ante)	3.13	1.50
Coauthors (5 years ex-post)	1.24	1.08
Administrator	0.27	0.38
Ph.D. from Ivy League	0.08	0.11
Ph.D. from Association of American Universities	0.78	0.71

9 rotators were employed in the Biological Sciences Directorate, 3 in the Computer and Information Science and Engineering Directorate, 4 in the Education and Human Resources Directorate, 5 in the Engineering Directorate, 4 in the Geosciences Directorate, 8 in the Mathematical and Physical Sciences Directorate, 1 in the Office of the Director and 3 in the Social, Behaviour and Economic Sciences Directorate.

Taken together, these comparisons suggest that rotators, on average, publish less than they usually do just before joining the NSF. On the other hand, their funding from the NSF is considerably higher than the NSF accumulation of their colleagues both in the *ex-ante* period and before. Therefore, as expected, rotators are typically more successful in raising NSF funds than their colleagues. Similarly, as Table 3 demonstrates, NSF rotators are similar to those we identify as "could-be" rotators. For instance, for both cohorts the elapsed time since PhD graduation until the start of the rotation has been 21 years and they are mostly men with H-indices around 9.[23] In line with the discussion above, the main difference is that the NSF funding records of rotators are higher than the funding records of those academics we have identified as comparable to rotators. As shown in robustness test 7 in Table 8 (below), this difference does not impact our estimates in any material way. Not shown in Table 3, the rotators (and the scientists that match them) are employed at both private and public universities of different size and prestige and from nearly every state. In general, we do not identify trends in terms of the type of institution that rotators come from.

[23] The majority of our academics are in the natural sciences, where multiple postdocs are common. On average, having 21 years of experience post PhD corresponds to about 13 years since holding a faculty position (i.e., running one's own lab). Our average faculty member is thus tenured, and about 20% had received NSF funding before the *ex-ante* period (five years before a colleague becomes a rotator). During the *ex-ante* period, when (by construction) none had NSF funding, most had funding from other sources.

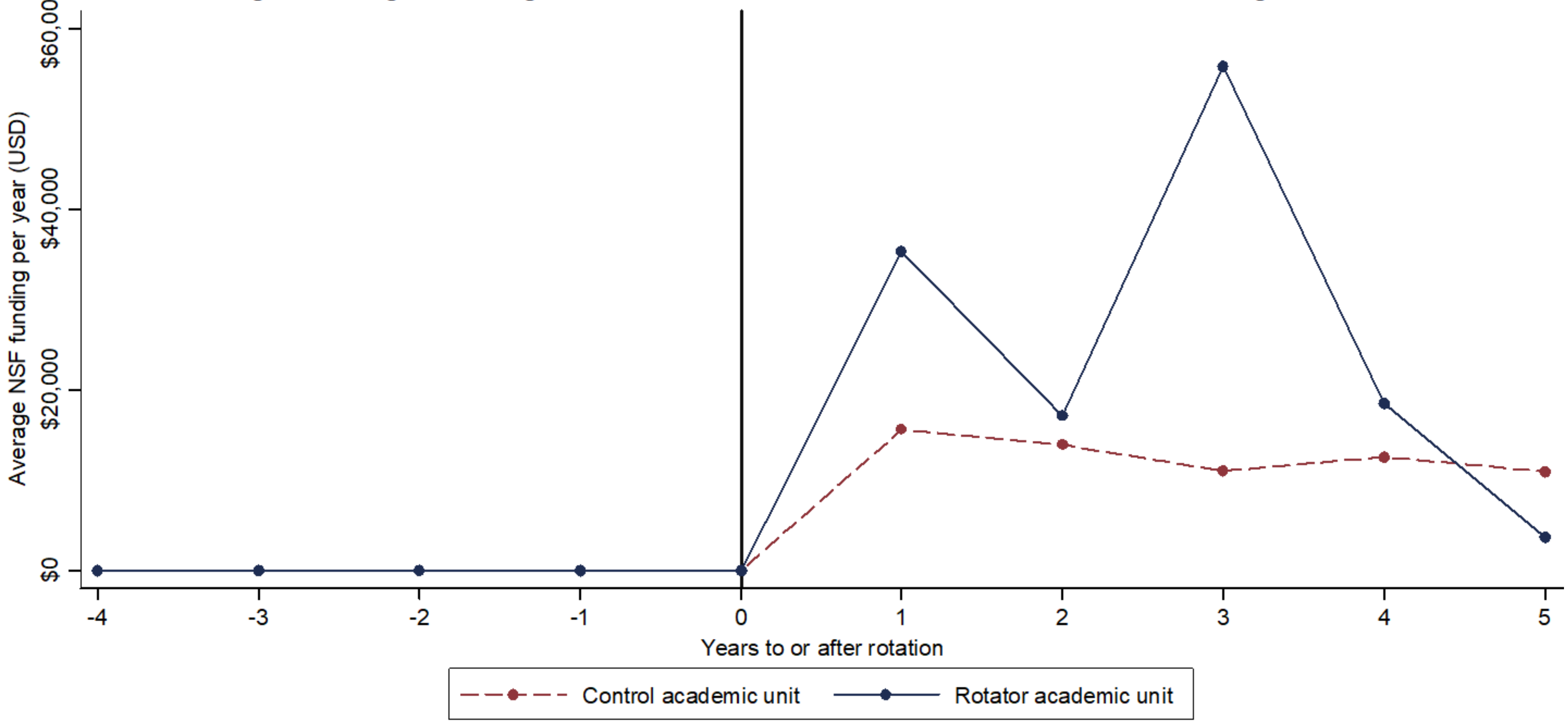
Table 3. Ex-ante characteristics of rotators and academics we identified as 'could-be' rotators.

	37 rotators		148 could-be rotators			
Variable	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**	**Two sides t-test**	
NSF funding as PI (ex-ante)	$714,180	$1,044,847	$436,283	$1,115,223	2.44	**
H5-Index	8.59	5.69	8.44	8.61	0.10	
Years	23.43	8.55	23.69	8.61	-0.16	
Male	0.70	0.46	0.75	0.43	-0.62	
Position	2.92	0.60	2.85	0.67	0.58	
Publications (all years before ex-ante)	39.97	23.49	25.94	31.39	2.54	**
Publications	8.59	5.69	17.16	22.92	-2.25	**
Citations	17.59	15.39	28.01	35.09	-1.76	
Coauthors	3.13	1.88	1.92	1.75	3.37	***

** Significant at 5%. *** Significant at 1%.

Figure 1 plots the average yearly *ex-ante* and *ex-post* funding for rotator colleagues versus scientists employed in the academic units we collected via the one-up, one-down approach. It zooms in on the 431 scientists that did not have NSF grants *ex-ante* (making up our sample), identified using matching scheme 3. While the two groups are similar *ex-ante* (by design), we observe large changes in the *ex-post* period. Figure 1 shows that scientists in the treatment group increase their average funding at a substantially higher rate than scientists in academic units without a rotator. The increase materializes in year 2 and in year 3 after the return of the rotator with year 3 being the pick of the increase.

Figure 1. Average NSF funding for scientists in rotator and control academic units without NSF funding *ex-ante*.



The timing of this increase fits a recurring theme that came up during our interviews: namely, that the rotators helped their colleagues put together their NSF applications in the second and third funding round after their return to their academic unit. In other words, as expected, the rotator effect is pronounced after the rotator has transmitted knowledge for about a year to her colleagues. In line with the interview findings, the decline in funding we observe after year 3 is likely driven by the fact that the majority of academics who were awarded grants in years 2 and 3 did not submit additional applications in years 3 and 4, as they were still working from the earlier grants. Overall, the figure strengthens our expectation of an impact from rotators to their colleagues.

Analysis and Results

Table 4 presents the baseline estimates using matching scheme 3, the one we expect to better capture the counterfactual as it is the most restrictive. The results are qualitatively similar when using the other matching schemes. We present 5 specifications. Specification 1 tests the main effect under H1. Then we include separately the moderators we hypothesize in H2a, H2b, and H2c in specifications 2, 3, and 4. Specification 5 is the full specification including all moderators.

We find strong support for H1 as shown in specification 1. We also fail to reject H2a and H2b while we find only partial support for H2c. The control variables are not statistically significant and do not change the main results when included, likely because of the matching procedures we have followed which, by design, minimize the differences between control and treatment groups.

Table 4. Baseline Estimates under matching scheme 3 (specify as control scientists those that are similar to scientists in the rotator academic unit and belong to academic units that are similar to the academic unit of the rotator). The dependent variable is the sum of funds raised from NSF in the *ex-post* period.

	Specification 1	Specification 2	Specification 3	Specification 4	Specification 5
Ex-Post	61,215.83***	46,076.37	58,341.34**	59,184.90**	39,775.60
	(23,385.57)	(50,700.08)	(24,153.16)	(25,589.33)	(51,907.56)
Rotator Group	-164.24	-22,669.17	145.46	2571.75	-25,889.81
	(33,420.29)	(82,256.64)	(35,038.00)	(37,026.15)	(82,026.47)
Ex-Post * Rotator Group	**138,366.83*** **	**-72,739.79**	**95,064.97**	**167,193.10*** **	**-71,533.25**
	(46,871.95)	**(112,825.91)**	**(49,440.90)**	**(52,642.87)**	**(112,786.37)**
Tenure		-1,131.83			-1,255.12
		(1,758.97)			(1,749.44)
*Ex-Post * Tenure*		824.84			934.05
		(2,362.40)			(2,346.22)
*Tenure * Rotator Group*		1,157.72			1,394.94
		(4,249.59)			(4,283.18)
Tenure * Ex-Post * Rotator group		**12,196.76*** **			**12,484.45*** **
		(5,790.87)			**(5,884.43)**
Knowledge Similarity			-712.30		-437.25
			(13,566.48)		(13,515.37)
*Knowledge Similarity * Ex-Post*			9,734.49		10,121.41
			(18,777.92)		(18,710.96)
*Knowledge Similarity * Rotator Group*			-3,632.05		624.47
			(49,597.33)		(49,700.36)
Knowledge Similarity * Ex-Post * Rotator Group			**237,768.11*** **		**222,621.14*** **
			(78,549.25)		**(78,799.12)**
Productivity Similarity				18.67	38.05
				(141.66)	(140.14)
*Productivity Similarity * Ex-Post*				15.12	-0.26
				(152.02)	(150.38)
*Productivity Similarity * Rotator Group*				-54.49	-27.44
				(310.06)	(309.82)
Productivity Similarity * Ex-Post * Rotator Group				**-689.29**	**-1,117.43*** **
				(521.79)	**(525.84)**
Constant	72,524.20	86,816.42	62,442.90	-72,664.21	78,799.10
	(98,343.94)	(104,360.36)	(97,906.03)	(124,621.59)	(103,940.76)
Controls included	YES	YES	YES	YES	YES
Year FE included	YES	YES	YES	YES	YES
Science field FE included	YES	YES	YES	YES	YES
Observations	862	862	862	862	862
Adjusted R^2	0.048	0.056	0.054	0.047	0.066
F-test	2.67	2.71	2.65	2.41	2.59

Standard errors in parentheses
*** p<0.01, ** p<0.05

Regarding H1, the *Ex-Post * Rotator Group* interaction in specification 1 provides strong support for our theoretical expectation that rotators induce funding improvements for their colleagues. The order of the effect is $138,367. This figure is significant as it demonstrates that rotators have an effect that is economically meaningful: rotator's colleagues with no NSF funding in the *ex-ante* period raise close to $140,000 more than similar scientists in similar academic units who do not have a rotator as a colleague in the *ex-post* period. Given that this increase is attributed to the rotator and not to personal characteristics, time-variant factors, or other reasons we conclude that the gains arising from knowledge transfer are material. To put the figure in perspective, as shown in Table 1, we note that in the *ex-post* period academics without NSF funding *ex-ante* belonging to groups without a rotator, raised, on average, $69,168 from the NSF. These $69,168 can be attributed to a host of factors such as personal improvements and increased effort but they cannot, by definition, be attributed to the rotator. Still, as our estimates reveal the rotator effect leads to an increase that is twice as large as the increase from all the other potential contributing factors combined.

The estimates in specifications 2 and 5 provide support for H2a. The main rotator effect becomes stronger when the rotator has a longer tenure in her academic unit: the *Tenure*Ex-Post*Rotator Group* variable is statistically significant, while the *Ex-Post*Rotator Group* interaction term ceases to be. Indeed, a one-unit increase in the tenure variable corresponds to an increase of the main rotator effect of around $13,000. This is consistent with Dahlander and McFarland (2013) who found that even when not working together (i.e. no co-authorship in our case), same-academic-unit colleagues are exposed to each other (and hence can learn from each other). We also fail to reject H2b. When the rotator shares similar knowledge with her colleague the main effect becomes stronger: in specifications 3 and 5 the interaction of the main effect and the *Knowledge Similarity* variable is positive while the level term of the main effect is no longer statistically significant. On the other hand, based on specifications 4 and 5 we find only partial support for H2c; *Productivity Similarity* has a moderating effect on the impact of the rotator only in specification 5. This likely reflects the fact that researchers with high research productivity, even while unsuccessful in previous grant applications, have accumulated enough knowledge and expertise to be successful going forward, even without the assistance of the rotator.

To make sure our quantitative findings are reasonable we conducted a series of telephone interviews in 2016 with 10 rotators and 15 academics (10 without NSF funding *ex-ante* and 5 with funding) employed in academic units with a rotator. The interviews lasted between 15 and 30 minutes. To select these rotators and rotator colleagues we randomly selected rotators who served at the agency between 2009 and 2012 so that they would all have recent experience and recollection with the NSF and with the *ex-post* period. The interviews focused on three main themes: 1) the rotator's experience with the NSF prior to becoming a rotator, her reason for applying to the position and her thoughts on who becomes a rotator, 2) the experience of being a rotator and her position within the NSF, and 3) how returning to the home institution has affected her and her faculty.

As mentioned above, prior experience with the agency lead academics to apply so that they could learn more about the NSF's internal operations. This is particularly relevant because it ameliorates any endogeneity concerns in the empirical analysis as it demonstrates that selection into a rotation position is exogenous to local colleagues needing help in raising funds. It also informs the managerial implications of our work with regards to the value of secondments versus different forms of knowledge transfer from an external organization such as membership in external committees and government task forces. The scientists at hand had experience with the NSF previously largely by participating in the selection process as an external reviewer. But, such experience did not translate to gains for colleagues. Instead, the secondment in the NSF boosted the colleagues' ability to secure research funding.

All rotators indicated that upon returning to their home institutions, they tried to make their colleagues more knowledgeable about the NSF. Some consulted with the heads of their academic units to identify colleagues working on the NSF's priority issues who could benefit from mentoring. Others assisted faculty members with exploring less-known NSF funding possibilities. Such assistance came from open seminars but also, and more frequently, via one-on-one meetings.

When interviewing rotator colleagues, we refrained from mentioning the rotator but after asking about experience with NSF, we asked if they had ever received help from colleagues with NSF applications. All 5 interviewees who had NSF funds *ex-ante* said they did not receive substantial help from the rotator *ex-post* because they did not need it. The 10 interviewees without NSF funds *ex-ante* identified the rotator as providing valuable assistance in six cases (where, in line with the empirical estimates, there was an overlap in the research topics between the rotator and the focal colleagues). The interviewees mentioned several ways rotators helped them including feedback and direction towards certain funding opportunities. The following is representative of the type of knowledge rotators transfer "[The rotator] organized a day for us to informally talk about opportunities and proposals. He would read the documents we were working on and gave feedback on what could be improved.… [The rotator helped] when trying to figure out what the NSF actually wants to have in a proposal."

Testing the Mechanism and Examining Alternative Explanations

The baseline estimates reported above could reflect not only knowledge transfer, but also political influence—that is, the returning rotator could privately lobby NSF officials on the part of a local colleague, or NSF officials could have an unconscious bias in favor of a former rotator's colleagues. To see if our baseline estimates reflect knowledge transfer rather than influence or bias, we leverage the fact that a few rotators moved to a new academic institution after their tenure at NSF. For those cases, the *ex-ante* and the *ex-post* colleagues are different. As such, under the premise that rotators act as conduits of knowledge transfer, any improvements in funding should occur only to the *ex-post* colleagues. Test 1 compares the funding records of the rotator's new and old colleagues. Given the small sample size and the fact that the *ex-ante* and *ex-post* academic units are not necessarily comparable, we present just descriptive statistics. As seen in Table 5, the new colleagues nearly doubled their average NSF funding from around $55,000 before having a rotator colleague to about $102,000 after. However, the average NSF funding records of the rotator's former academic colleagues remained unchanged, from $108,500 to $107,502. In other words, if rotators are using their NSF connections to help their colleagues, they are not helping the colleagues they worked with before they went to NSF.[24]

[24] We interpret these results with caution as we cannot rule out the case that this handful of rotators changed employment because they did not have strong ties with their former colleagues in the first place or otherwise are different from the other rotators.

Table 5. Test 1. Comparing *ex-ante* and *ex-post* NSF funding for new and old colleagues of rotators who after rotation changed employment.

Variable	Colleagues in original academic institution	Colleagues in new academic institution
Average NSF funding ex-ante	$ 108,500	$ 54,577
Average NSF funding ex-post	$ 107,502	$ 101,747
Number of academics	443	952

If the presence of a rotator in the group in the *ex-post* period coincides with an overall increased focus towards NSF as a funding source at the rotator's academic unit, increased funding records may not reflect learning from the rotator but learning from other faculty members with success in raising funds from the agency. Because the academics we study did not raise NSF funds in the *ex-ante* period, it is hard to imagine that such learning occur previously. Accordingly, the main route such learning could materialize is if those with existing records gained additional NSF knowledge from the rotator, which then, in turn, they transmitted to colleagues with non-existing funding records. To test whether colleagues with existing records gained from the presence of rotators, we conduct the baseline analysis including in the sample only faculty members with one or more NSF grants in the *ex-ante* period.[25] The results, presented as test 2 in Table 6 (which for ease of exposition reports only the variables that test the hypotheses) do not show improvements for those academics, as the *Ex-Post * Rotator Group* interaction is not statistically significant (The inflated size of the coefficients is due to 9 scientists who pulled the regression line upwards as their *ex-ante* accumulation of NSF grants was in the order of 10 million and above.) Hence, it is unlikely that learning from colleagues with existing funding records, present in the same academic unit both in the *ex-ante* and in the *ex-post* period, is driving our findings.

[25] Similarly, improvements in the funding record of those academics without NSF funding *ex-ante*, may also be initiated by the rotator but the full effect is completed once the new recipients of knowledge share their new knowledge with each other. If that holds, the empirical estimates would be attributed to the rotator only partially. In unreported exercises we conducted we did not find support for such mechanism.

Table 6. Testing alternative possible mechanisms.

	Test 2 - Include in the sample only colleagues with NSF grants *ex-ante*		Test 3 - Omit from the sample rotator colleagues whose co-authors raised grants from the NSF recently		Test 4 - Omit from the sample rotator colleagues whose Co-Investigators raised grants from the NSF recently	
	Specification without moderators	Specification with moderators	Specification without moderators	Specification with moderators	Specification without moderators	Specification with moderators
*Ex-Post * Rotator Group*	803,339.52	541,029.73	112,107.48**	-75,767.78	126,356.20***	-29,953.28
	(568,323.44)	(926,502.34)	(48,806.95)	(128,751.72)	(46,295.84)	(112,560.82)
*Tenure * Ex-Post * Rotator group*		-27,562.35		12,852.64**		13,878.78**
		(43,114.01)		(6,798.28)		(5,990.363)
*Knowledge Similarity * Ex-Post * Rotator Group*		1,034,679.23		297,046.56**		106,147.42
		(588,026.63)		(92,428.66)		(86,055.48)
*Productivity Similarity * Ex-Post * Rotator Group*		-998.03		-1,033.40		-1,191.93**
		(6,116.29)		(672.55)		(521.81)
Level terms and two-way interactions	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES
Year fixed effects included	YES	YES	YES	YES	YES	YES
Science field fixed effects included	YES	YES	YES	YES	YES	YES
Observations	627	627	725	725	834	834
F-test	2.04***	5.21***	2.05***	2.57***	2.27***	1.85***
Adj. R^2	0.041	0.051	0.049	0.076	0.038	0.039

Standard errors in parentheses
*** p<0.01, ** p<0.05

Table 7. Test 5. *Ex-post* outcomes of all 2009 NSF awards granted to academics in rotator and control academic units.

	Grants of scientists in academic units with a rotator		Grants of scientists in academic units without a rotator		
Variable	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**	**Two-sides t-test**
Publications	6.04	0.76	6.83	0.75	0.68
Citations	95.17	18.74	96.55	15.26	0.06

Similarly, if the rotator's return to her academic unit coincides with rotator colleagues' co-authors or co-investigators having recent success with NSF funding, then our results might be driven by the co-authors or the co-investigators of the rotator colleagues, not the rotator. To test this we omit from the analysis scientists whose more recent frequent co-authors or co-investigators experienced significant improvement in their *ex-post* NSF funding record. Specifically, we omit from the analysis academics whose at least 1 of the 10 most frequent *ex-post* co-authors or co-investigators raised more than $200,000 from the NSF *ex-post* while their *ex-ante* NSF grant accumulation was below $10,000. The results from this test, presented as tests 3 and 4 in Table 6, are similar to the baseline estimates. As such, these results suggest that the NSF funding increases we reveal are not driven by learning from co-authors or co-investigators.[26]

Because we study increases in funding that take place when the rotator is not in charge of decision making at the NSF and because of the rigorous review system at the agency, we do not expect favoritism to influence our estimates directly. However, it is likely that the rotator's tenure at NSF induces increased visibility of her academic unit. This visibility may cause favoritism for the applications submitted by the rotator's colleagues.

We conducted several tests that lead us to discount such a possibility. First, under favoritism we would expect to observe growth in funding among those colleagues that have an established funding record with NSF. As discussed above, we do not find this. Second, under favoritism the grants of rotator's colleagues would be of lower quality than other NSF grants. Measuring quality with publications and citations and exploiting the Google Scholar option to look up grant numbers and link them to publications, we use awards in 2009 across directorates as our template. Test 4 in Table 7 demonstrates that the number of publications and citations coming out of rotator colleagues' 2009 grants are not statistically different than the number of publications and citations coming out of 2009 grants awarded to investigators that do not belong to rotator groups and we collected via the one-up, one-down approach. Third, though this was not part of our research design, none of the academics we analyze submitted a funded proposal in the *ex-post* period jointly with the rotator and, four, none of the rotators co-authored a publication with the sample academics neither *ex-ante* not *ex-post,* which addresses the possibility of "ghost" co-

[26] The potential influence of the co-investigators is non-existent for the large majority of the sample grants as 80 percent of them do not have a co-investigator. Moreover, we do not find statistically significant differences in the funding levels when breaking down the grants by the number of co-investigators except for 5 grants with 8 co-investigators.

authorship in the funded proposals. Overall, none of our tests suggest that favoritism explains the increase in funding for rotator's colleagues even indirectly.[27]

The increase in funding we document may be driven by four main mechanisms: a) an increase in the number of applications submitted by a given academic, b) applications for larger grants c) work on different proposals that would have worked otherwise and d) submissions of better/more targeted proposals which are more likely to succeed. Because NSF does not provide data on rejected applications on an individual basis we cannot address this directly. But, our interviews did not support mechanism (a). Both rotators and rotator colleagues stressed to us that the amount of time needed to put together a proposal, and the fact that proposals demonstrating ongoing work related to the proposed project have higher chances of success, discourage the submission of multiple applications. Many rotators hinted that most faculty members they interacted with had tried raising funds from the NSF in the past. Said one: "I don't think I had much influence on quantity. Because people were already putting out as much proposals as they could manage, so there wasn't too much room for improvement in that sense." In unreported results we also find econometrically that rotators do not have an effect on the number of awarded grants. Under the premise that more applications correlate with more awarded grants, this reinforces our conclusion that an increase in application does not drive the results. If option (b) above, an increase in the size of grants, is the mechanism at hand: then on average, the grants in our sample would be larger than the population of grants NSF has awarded from 2001 to 2015, in an analysis not disclosed here, we find that this is not the case. While distinguishing quality improvements from project/topic selection is inherently challenging, the fact that the *ex-ante* and *ex-post* keywords of articles published by the focal academics overlap almost perfectly (see discussion above referring to the construction of the *Knowledge Similarity* variable) discounts option (c) above, a switch in topics, as the driver of the results because the scientists appear to be working on similar topics in the two time periods. Therefore, in line with the insights from the interviews we conducted and the mechanisms we expect to be at play as captured by the moderators, the effect of the rotator we document appears to stem from direction, feedback and the like on better, more targeted proposals. As one rotator put it, "…if somebody has submitted their proposal a couple of times and they've

[27] In additional tests (not reported here), we compared the popularity of the keywords in articles authored by academics in treatment and control groups to check whether the former group works on "hot topics" which typically attract more funds. We did not find evidence of this effect.

been unsuccessful, I can call them up and sort of say ‘Why don’t you show me your reviews and see what they’re telling you.”

Speaking mostly to the managerial implications and the generalizability of our work, we also conducted a number of tests to better understand the conditions in which learning by seconding can be more valuable. We first split the sample according to the duration of the secondment to assess whether the length of the secondment influences knowledge transfer. Indeed, longer tenure at the NSF appears to equip the rotator with more knowledge she can transmit back to her colleagues. Then, we investigated whether the nature of the project impacts the value of secondments to the home organization. Specifically, we limited the analysis to a) scientific fields where rejection rates are higher, b) scientific fields that evolve faster and c) scientific fields requiring multidisciplinary approaches. Grant acquisition is potentially more challenging in such fields, hence one would expect the insights of a rotator to matter more. Indeed, the effect of the rotator in cases (b) and (c) above is larger than the rotator effect in the baseline estimates (but not for case (a)). As such, the nature of the project at hand needs to enter the decision making process once a given organization considers seconding one or more of its employees.

Table 8. Testing the robustness of the baseline estimates

	(1) [1]		(2) [1]	
	No Moderators	With moderators	No Moderators	With moderators
*Ex-Post * Rotator Group*	133,213.20***	-57,081.46	111,862.63***	-90,655.29
	(45,854.91)	(97,881.46)	(38,096.03)	(88,622.06)
*Tenure * Ex-Post * Rotator Group*		10,507.94**		13,208.62***
		(5,032.77)		(4,674.49)
*Knowledge Similarity * Ex-Post * Rotator Group*		221,666.00***		200,405.03***
		(72,511.73)		(72,808.04)
*Productivity Similarity * Ex-Post * Rotator Group*		-634.10**		-888.54**
		(310.95)		(360.93)
Level terms and two-way interactions	YES	YES	YES	YES
Control variables	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Science field fixed effects	YES	YES	YES	YES
Observations	1,148	1,148	1,188	1,188
Adj. R^2	0.047	0.065	0.070	0.092
F	2.69***	3.01***	4.41***	4.15***

[1] (1) Adding additional observations from archive.org, (2) academic units matched on departmental NSF funding and individual publications.

** Significant at 5%. *** Significant at 1%. Standard errors in parentheses.

Table 8 Continued. Testing the robustness of the baseline estimates

	(3) [1]		(4) [1]	
	No Moderators	With moderators	No Moderators	With moderators
*Ex-Post * Rotator Group*	143,860.02***	-35,434.54	107,032.60***	-33,308.99
	(33,530.84)	(77,900.36)	(33,284.88)	(78,754.69)
*Tenure * Ex-Post * Rotator Group*		10,718.93***		7,550.95
		(4,129.08)		(3,898.09)
*Knowledge Similarity * Ex-Post * Rotator Group*		220,197.14***		235665.63***
		(60,506.08)		(63,324.90)
*Productivity Similarity * Ex-Post * Rotator Group*		-653.35**		-505.27
		(273.85)		(276.67)
Level terms and two-way interactions	YES	YES	YES	YES
Control variables	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Science field fixed effects	YES	YES	YES	YES
Observations	1,155	1,155	1,438	1,438
Adj. R^2	0.063	0.096	0.051	0.071
F	4.11***	4.30***	3.96***	3.90***

[1] (3) academic units matched on science field and university, (4) Using all academics (without NSF funding ex-ante) as controls without implementing CEM.

** Significant at 5%. *** Significant at 1%. Standard errors in parentheses.

Table 8 Continued. Testing the robustness of the baseline estimates

	(5) [1] No Moderators	(5) [1] With moderators	(6) [1] No Moderators	(6) [1] With moderators
*Ex-Post * Rotator Group*	93,708.35***	-80,341.14	120,546.43**	-68,310.90
	(34,678.24)	(89,377.12)	(46,697.82)	(119,775.44)
*Tenure * Ex-Post * Rotator Group*		11,244.17**		9,834.10
		(4,741.38)		(5,776.02)
*Knowledge Similarity * Ex-Post * Rotator Group*		228,600.45***		185,193.62**
		(70,048.38)		(76,315.53)
*Productivity Similarity * Ex-Post * Rotator Group*		-667.72**		-446.72
		(315.24)		(377.89)
Level terms and two-way interactions	YES	YES	YES	YES
Control variables	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Science field fixed effects	YES	YES	YES	YES
Observations	1,378	1,378	736	736
Adj. R^2	0.064	0.085	0.047	0.060
F	4.79***	3.92***	2.38***	2.24***

[1] (5) Using all academics (without NSF funding *ex-ante*) in academic units ranked one position higher and one position lower than the rotator academic unit as controls, (6) controls chosen based on matched rotator characteristics.

** Significant at 5%. *** Significant at 1%. Standard errors in parentheses.

Table 8 Continued. Testing the robustness of the baseline estimates

	(7) [1] No Moderators	(7) [1] With moderators
*Ex-Post * Rotator Group*	162,584.60***	-71,950.57
	(52,950.21)	(126,841.83)
*Tenure * Ex-Post * Rotator Group*		13,161.13**
		(6,626.85)
*Knowledge Similarity * Ex-Post * Rotator Group*		280,277.84***
		(89,775.23)
*Productivity Similarity * Ex-Post * Rotator Group*		-1,065.40
		(568.43)
Level terms and two-way interactions	YES	YES
Control variables	YES	YES
Year fixed effects	YES	YES
Science field fixed effects	YES	YES
Observations	716	716
Adj. R^2	0.054	0.077
F	2.57***	2.63***

[1] (7) omit from the sample rotators (and their matching groups) whose funding records exceed 2 million dollars.

** Significant at 5%. *** Significant at 1%. Standard errors in parentheses.

Robustness Checks

Table 8 presents several specifications that test the robustness of the baseline estimates. For ease of exposition we report only the variables that test the hypotheses. To identify faculty members who were in the same academic unit at least 5 years before rotation and 5 years after we relied mainly on the current version of university websites. This could result in missing data as rotator colleagues who left the unit after the rotator returned, but before we collected the information, were likely removed from the unit's website. We checked this using archival data from the internet archive (http://archive.org), which preserves obsolete versions of websites, for all 197 academic units in our sample.[28] As shown in test 1 in Table 8, the results from this analysis are similar to the results in the baseline estimates. As such, we conclude that the potential truncation of the data does not come at any material expense.

To reduce the heterogeneity among control and treatment groups we have used CEM for academic units outside the rotator's university and we have found similar academic units in the same university. In robustness checks 2 to 7 in Table 8 we test the findings under alternative ways to reduce heterogeneity. In one approach, used in test 2, we alter the individual-level criteria used as an input to matching scheme 3 to a) the number of *ex-ante* publications and citations for a given scientist, b) the average number of coauthors one has, as a measure of team orientation, and c) funding level of her academic unit *ex-ante* as measure of inclination to submit grants driven by peer effects. Two, in test 3, we use the academic unit level science field and university quartile as matching criteria. Three, in test 4, we use as controls all academics we have collected data for (and have no NSF funding *ex-ante*) without implementing CEM. Four, in test 5, we use as controls the scientists belonging to the academics units ranked one position higher and one position lower than the academic unit with a rotator. Five, in test 6, instead of matching on faculty characteristics to create the control groups we match solely on rotator characteristics. That is, we first find academics that are similar to rotators based on age, gender, previous NSF funding, and h-index. Then, we

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[28] In total, we retrieved 1,253 faculty members from 123 academic units who left their unit between the fifth year after rotation and 2016. For 35 academic units of the original 197 there was no archived faculty webpage and for 39 there was no change in the faculty members list. Additionally, for almost half of the 123 academic units a proximate period (between 6 and 18 months after the fifth year of rotation) was selected as there was no archived version closer to the required date. Of these 1,253 leaving scientists, 229 from 89 academic units had online accessible work history and matched our selection criteria. An issue with accessing archived faculty webpages is the inconsistency between what is reported in CVs and other online sources, which are generally difficult to source for older dates, and what is shown in, often outdated, websites. Relatedly, similar to Ge, Huang, and Png (2016) we do not find evidence that only the most productive scientists maintain updated online CVs, LinkedIn pages, and the like.

include as controls, scientists in their academic units. This exercise relaxes the strict requirements in our baseline estimates under scheme 3 in which we need to identify with precision similar academics in similar academic units and within them discover “could-be rotators”. By and large, the results we obtain are qualitatively similar to the results of the baseline estimates and as such, they further demonstrate the robustness of our findings.[29]

As shown in Table 3 above, the rotators and those academics who match rotators resemble each other in many respects such as having served administrative roles. But, rotators have, on average, higher NSF funding records when compared to the matched group. This difference may bias the estimates of the moderators if rotators and potential rotators are not meaningfully comparable. To test the robustness of our estimates to this potential bias we conducted the analysis using a more comparable set of rotators and potential rotators in terms of funding records. That is, in test 7 in Table 8 we run the baseline specification after we omit from the sample, rotators (and their matching groups) whose funding records exceed 2 million dollars. Once we do so, the average funding records between the two cohorts are more similar: on average, rotators raised $544,558 *ex-ante* while the corresponding figure for potential rotators is $436,283 (see Table 3). The results remain qualitative similar to the baseline estimates and our conclusions remain intact.

Discussion and Conclusion

We draw on the knowledge transfer, employee mobility, and social identity literatures to suggest that organizations can acquire knowledge as a means of competitive advantage by *learning by seconding.*

[29] We observe a few deviations from the baseline estimates in the moderators. We have also checked the assumption of the parallel trend behind the difference-in-difference estimation (Angrist & Pischke, 2008). Following previous works (e.g. David, 2003) we construct a model where the dependent variable is NSF fund acquisition per year, and include dummy variables for the *ex-ante* and the *ex-post* years in the difference-in-differences estimation (excluding the treatment year). The interaction terms between the *ex-ante* year dummies and the treatment unit indicator are not statistically significant, which supports the parallel trends assumption. Relatedly, within a 5 year period (the time frame we employ for the analysis) the incentives to fundraising across institutions may change. This would constitute a threat in the analysis as long as there is an interaction between the group and time period so that changes in incentives, institutional norms and other factors may not influence all groups in the same way. The general homogeneity of the universities and departments in the analysis suggests that this is not an acute concern. Indeed, when we limit our time frame to 2 years, our conclusions remain intact which implies that such potential interaction does not influence our estimation.

To study secondments we exploit the rotation program at the National Science Foundation. Under the rotation program the agency employees, full time, academic scientists for a period of usually 2 years to lead its review process. After we recognize that temporary tenure at the NSF equips seconded scientists with unique knowledge we reveal potentially causal evidence that rotator's colleagues with no NSF funding in the *ex-ante* period raise close to $140,000 more than scientists who do not have a rotator as a colleague in the *ex-post* period. A battery of empirical exercises as well as interviews with rotators and their colleagues suggest that knowledge transfer and not rent seeking from the side of the rotator is the mechanism behind the effects we reveal. Rotators ignite opportunity recognition, assist with framing proposals and provide processual knowledge (i.e. focusing, framing, formatting). We expect mechanisms of this kind to underpin most secondments because one of the main gains of rotation is the acquisition of new knowledge for the seconded employee.

What do these conclusions mean for academic research, for policy as well as for practice? First, they add to the knowledge transfer literature. We provide evidence that organizations can learn not only by learning by doing and learning by hiring but also by *learning by seconding*. We also highlight that contrary to the mechanisms of learning by hiring and learning by doing, learning by seconding is more likely to be effective when the knowledge depositories between the sender and the recipient of knowledge are distant. The evidence we provide is far from conclusive and in fact we expect follow up works to study secondments in more depth. What are the potential drawbacks of secondments? Is learning by seconding a substitute or complement to learning by hiring and learning by doing? These are only some of the inquires our research brings up.

Second, our results speak directly to the literature on the organization of institutions and how they advance or hinder scientific progress (Furman & Stern, 2011a) as they imply that the design of NSF to employ temporarily but full time university scientists underpins the diffusion of knowledge. It is likely that the knowledge transfer we document here would not have materialized with that magnitude had the review process at the agency been designed in a way that did not include temporary employment of external academics in decision making roles. Therefore, a straightforward implication for our analysis is inquiring whether the NSF design has a differential impact than the design of other agencies which employ academics mainly as reviewers.

Third, we touch upon the literature on science mobility by showing that moves outside academia matter. Our results imply that for academics temporary moves outside their core academic duties to serve central roles in different types of institutions can afford benefits to the focal academic's colleagues.

Fourth, we highlight the rotation program as a fertile template for studies on the advancement of science, peer effects, knowledge transfer and diffusion, networking, and other topics. We know how scientists, inventors, entrepreneurs, patent examiners and other actors in the knowledge economy affect the rate that science, innovation and entrepreneurship advances. We contend that the centrality of rotators in the knowledge economy (Li & Marrongelle, 2013) calls for more scholarly attention to this actor as well. As such, we bring rotators to the forefront in this paper.

For management practice and organizations in general, the implications of our research are straightforward: secondments may be a worthwhile endeavor when seeking to infuse a given organization with new knowledge especially in areas of elevated competition in hopes of improvements in productivity, output and the like. Of course, secondments can be expensive but our analysis suggests that different forms of engagement with an external organization such as membership in external committees do not bring the benefits that secondments do. Rotators were acting as reviewers in selection panels before rotation but their colleagues realized gains in research fund acquisition only after rotation. In fact, we also find that longer rotation periods have stronger effects on knowledge transfer. As well, our study is informative for scientists seeking to raise funds as grant acquisitions records are becoming increasingly more central for tenure decisions, gaining academic status, research performance and overall career progression. More generally, our research implies that competition for talent may not be the most effective means to boost productivity for a given organization. Competition for employees with unique knowledge may pay off because these sorts of employees can bring about significant multiplier effects as the benefits from such cohort appear to spill over to other employees.

Specifically for academia, and keeping in mind that most rotators have had a limited number of career moves, if any, an alternative means for universities to create spill-over effects via scientists with unique experience is to promote NSF rotation within existing faculty members. Still, as it also became clear during our interviews, rotation, for the largest part, comes at the expense of one's own, at least short term, research productivity. Therefore, universities must balance the sorts of benefits we document with the decline in academic productivity that rotation tends to entail.

For policy, our estimates are timely because of the increasing concerns that the expenses of the rotation program should not be covered solely by public funds provided to NSF (Mervis, 2016b). Indeed, a recent policy mandates home universities to bear part of the costs (Mervis, 2016a). The basic argument from policy makers is that rotators bring benefits to their home institutions. While our exercise is not meant to provide a cost-benefit analysis, we do document that such benefits in fact exist.

We close by noting that going more deeply into the qualitative approach for the present work could have yielded more insights. These insights could identify with accuracy what type of knowledge rotators convey, when, to whom and how, under which circumstances and so on. We conducted the interviews mainly as a means to better understand the context and to inform our findings. Had we extended the scope of questions and the number of interviewees, we would likely have addressed the questions above in depth. Because our goal here was first to test at a large scale whether secondments indeed transfer knowledge, measure such effect and reveal its origins we leave such refinements for future work. We also note that had the NSF provided access to rejected applications we could directly test what all of our qualitative and quantitative evidence tells us: the effects we reveal are driven by submitting better/more targeted proposals.

Chapter 4. The Diminishing Signaling Value of Patents between Early Rounds of Venture Capital Financing[30]

[30] This chapter is based on:
Hoenen, SJ., Kolympiris C., Schoenmakers W, Kalaitzandonakes N. (2014), *The diminishing signaling value of patents between early rounds of venture capital financing*, Research Policy, Volume 43, Issue 6

Introduction

Patents reflect improvements in innovation and can contribute to the performance of firms and their market value (Bloom & Van Reenen, 2002; Griliches, 1981; Hall, 2004; Hall, Jaffe, & Trajtenberg, 2005). The linkage between patents and firm performance has been attributed largely to monopolistic market rights and future technology options, protection from competitors, and improvements in the negotiating position of patent holders with partners, investors and remaining stakeholders (Blind, Edler, Frietsch, & Schmoch, 2006; Gans, Hsu, & Stern, 2002; Giuri et al., 2007; Harabi, 1995; Helmers & Rogers, 2011; Levitas & Chi, 2010; Silverman & Baum, 2002; Teece, 2000).31

A relatively less studied linkage between patents and firm growth is the value of patents as signals and situations where external investors, such as venture capital firms (VCFs), are attracted to firms with patents. Indeed, there are good theoretical reasons to expect such relationship (Graham, Merges, Samuelson, & Sichelman, 2009; Heeley, Matusik, & Jain, 2007; Long, 2002). For instance, in knowledge intensive industries, the value of emerging firms that seek external finance can be difficult to assess because such firms often lack a track record and they are confronted with technical, scientific and regulatory challenges that are either unknown ex ante or difficult to manage ex post (Harhoff, 2011). Ownership of patents, however, can signal the potential of a firm to external investors through possible future developments with commercial value (Hagedoorn, Link, & Vonortas, 2000; Heeley et al., 2007). Further, because patents confer monopolistic market rights, which can then lead to sustainable competitive advantage, investors may place a market value on these rights, and consequently invest in the firm that possesses them.

To corroborate such theoretical expectations a handful of empirical studies has documented that patents attract prominent VCFs, prompt VCFs to invest faster and generally increase the amounts invested in firms that own them (Audretsch, Bönte, & Mahagaonkar, 2012; Cao & Hsu, 2011; Conti, Thursby, & Rothaermel, 2013; Engel & Keilbach, 2007; Häussler, Harhoff, & Müller,

[31] On a macro level, patents have been associated with increasing national economic growth and the development and diffusion of knowledge (Blind & Jungmittag, 2008; Shapiro & Hassett, 2005).

2009; Hsu & Ziedonis, 2013; Mann & Sager, 2007). [32] In this literature, only few studies tease out the signalling function of patents from the economic function (Cao & Hsu, 2011; Hsu & Ziedonis, 2013). Further, in this body of work the effect of patents on venture capital attraction has mostly been studied as a snap shot in time by focusing, for instance, on the amount of venture capital raised by a target firm over a certain period. As a result, what is largely unknown is whether the signalling value of patents in attracting VCFs diminishes over time as investors and target firms become more acquainted with each other. This question is the point of departure for the present study which contributes to a scant literature that deals with the dynamics of patent signals.[33]

To form our theoretical expectations we reflect upon the main arguments regarding the relationship between patents and venture capital attraction. These arguments focus, in large part, on the reduction of information asymmetries between VCFs and target firms. But, if such asymmetries lessen as VCFs and target firms become more familiar with each other over time, then the value of patents as a signal should also decrease. To study this proposition we leverage the tendency of VCFs to invest in target firms through sequential rounds of financing. Through such rounds, VCFs provide funds to a particular firm after it has met certain milestones that relate, mainly, to technical progress (Gompers, 1995). This sequential structure of VC investments allows us to detect patterns that would otherwise not be apparent. More specifically, each additional round of financing can reduce the information asymmetries between VCFs and the target firm because VCFs gather new information about the firm through monitoring, management and other forms of hands-on involvement with the firms they invest in (Gompers, 1995; Ruhnka & Young, 1987; Wang & Zhou, 2004). Accordingly, the effect of patents on attracting venture capital via a signalling process should diminish through sequential rounds of financing.

To test our theoretical expectations we employ a rich dataset that measures patent activity (granted patents and number of patent applications) from firm birth to the first round of financing and then again from the first round of financing to the second round for more than 580 U.S.-based dedicated biotechnology firms (DBFs) that received funds from VCFs from 2001 to 2011. We focus our attention on the first two rounds of financing because in these rounds information asymmetries between investors and target firms are expected to be more pronounced. Therefore,

[32] There is also evidence linking patents to successful Initial Public Offerings (e.g. Cockburn & MacGarvie, 2009; Heeley et al., 2007).
[33] The present study is also informative for the stream of literature investigating whether venture capital promotes or follows innovation (Hirukawa & Ueda, 2011; Ueda & Hirukawa, 2008).

by concentrating on these rounds we can detect the impact of information asymmetries on the effectiveness of patent activity as a signal. We focus on biotechnology because it is a knowledge intensive industry in which information asymmetries between investors and firms are expected to be significant. Hence, patents as signals could be relevant in this industry (Higgins, Stephan, & Thursby, 2011; Janney & Folta, 2003). Furthermore, patents are popular among biotechnology firms (Fligstein, 1996) and existing evidence suggests that compared to other high technology industries, investors weight patents more heavily in biotechnology when they make investments decisions (Sichelman & Graham, 2010) perhaps because of the strong link between innovation and patents in that industry (Arundel & Kabla, 1998). Biotechnology is also an industry that receives large amounts of (staged) venture capital investments reflecting the risky nature of the industry as well as the potential for high returns (Baum & Silverman, 2004; Gompers & Lerner, 2001). Together, these industry characteristics suggest that if patent activity serves as a signal for investors whose value diminishes over time, evidence of such dynamics should be apparent across biotechnology firms.

For our empirical analysis, we construct models that associate patent activity before and after a round of financing with the amount invested to each firm and we control for regional and VCF-specific characteristics that could influence the level of investment. To separate the function of patents as a signal from their economic value potential, both of which can attract investors and capital, we account for the differential (economic) quality of patents. We also control for the firm growth stage funds are directed to as well as for the reputation of the investors, both of which can influence the amount of capital invested in a firm. To isolate the strength of patents as a signal from other signals firms can employ we include relevant control variables, such as the presence of distinguished scientists on the board of directors.

Our interest in the value of patents as signalling mechanism for capital investments in small firms and specifically on whether such value diminishes over time is motivated by more than academic curiosity. Answers to these questions have important policy implications. The number of patents and patent applications have increased substantially over the years (Kim & Marschke, 2004; Kortum & Lerner, 1999) and so have the costs associated with processing patents. Such issues have prompted questions about the effectiveness of the current patent system and especially with regard to the degree that it puts smaller firms in a disadvantage and thus potentially hinders innovation (Bessen & Meurer, 2008; Jaffe & Lerner, 2004). Assessing whether patents increase private sector investments in small firms and whether such increase is affected by the familiarity between VCFs and target firms, needs to be taken into account when policy makers and other stakeholders consider the effectiveness of the current patent system.

We proceed with the rest of the paper as follows: In section 2 we review the literature on the functions of VCFs and how patents can act as signals and form our hypotheses. In sections 3 and 4 we present our methodology and data. In section 5 we present our results and we conclude in section 6.

How patents can act as signals to investors

In their most common form of arrangement, venture capital firms pool capital from institutional investors such as pension funds and university endowments. VCFs, in turn, use these capital pools to make investments and tie their compensation to the returns of those investments. Because the VCFs manage a rather small share of the funds maintained by institutional investors, the risk exposure of each institutional investor is relatively limited. Accordingly, VCFs can afford to invest in risky ventures that have the potential to yield returns above 25 percent per year so that they maximize their compensation as well as the compensation of the institutional investors (Zider, 1998).

A popular investment target for VCFs is young firms in high technology areas such as biotechnology. These firms offer investors a potential for high returns (Carpenter & Petersen, 2002) but also high risk as they grapple with highly complex scientific problems associated long research cycles and challenging legal environments (DiMasi & Grabowski, 2007; Häussler & Zademach, 2007). Because of such conditions and because of their young age, firms in such sectors may find it difficult to generate current cash flows or establish a record of future cash flows. Accordingly, even when firms in such sectors fully understand their potential, they might still find it difficult to convey it to VCFs. This creates a mismatch in the information possessed by firms and that possessed by VCFs. As a result, the relationship between VCFs and target firms before an investment takes place is commonly prone to information asymmetries (Cumming, 2005; Sahlman, 1990).

To overcome such information asymmetries, firms seeking capital often use signals that partly substitute for the lack of an established record and can portray their potential (Busenitz, Fiet,

& Moesel, 2005; Certo, Daily, & Dalton, 2001; Podolny, 1993, 2010; Zhang & Wiersema, 2009). In fact, whenever information asymmetries are present, VCFs tend to rely on signals of this sort before they make investment decisions (Amit, Glosten, & Muller, 1990a; Higgins & Gulati, 2006) because separating, *a priori*, high-quality start-ups from firms with less potential can be difficult (Davila et al., 2003). Along these lines, a number of studies demonstrate that, in general, signals can reduce information asymmetries (e.g. Cohen & Dean, 2005; Gimmon & Levie, 2010; Higgins et al., 2011; Hsu, 2007; Janney & Folta, 2003; Mishra, Heide, & Cort, 1998).

The next relevant question then is whether patents can effectively act as such a signal. Strong signals are observable and costly to imitate (Cohen & Dean, 2005; Spence, 1973). Additionally, signals which are governed by strong institutions and hence conform to certain institutional standards tend to increase in value (Janney & Folta, 2003). This holds largely because conformity reduces variation across signals and can thus limit the impact that the subjectivity of the receiver can have on the valuation of the signal (Fischer & Reuber, 2007; Perkins & Hendry, 2005). Patents would therefore appear to meet the requirements for a valuable signal because they are easily observable, costly to acquire (Graham et al., 2009) and are governed strictly. For firms in knowledge intensive industries where information asymmetries are typically strong (Chaddad & Reuer, 2009), patents may have increased value for investment decisions (Sichelman & Graham, 2010) because they relate to invention and innovation which in turn can lead to commercial gains (Acs, Anselin, & Varga, 2002; Arundel & Kabla, 1998; Griliches, 1998).

Empirical evidence on whether patents actually serve a signalling function that augments the accumulation of capital for a given firm is scarce as it amounts, as far as we are aware, to two contributions.[34] The first study is by Cao and Hsu (2011) who find that startups with patents were more likely to issue an IPO; the authors demonstrate the signalling function of patents by empirically controlling for a number of remaining factors that can lead to the issuance of an IPO (e.g. growth options of a given firm and technological uncertainty). Nevertheless, Cao and Hsu

[34]The scarcity of research can largely be credited to the inherent difficulties of attributing positive associations of patent activity measures and capital investments solely to signaling. In particular, while some studies report that larger patent portfolios associate with enhanced performance metrics such as the issuance of an IPO and the growth of external financing for a given firm whether such relationships emanate from the signaling value of patents or from the economic value of patents is not entirely clear (Audretsch et al., 2012; Conti et al., 2013; Engel & Keilbach, 2007; Mann & Sager, 2007). A quote from Conti et al. (2013) describes the issue with precision: ...we cannot empirically separate the signaling value of patents from their productive contribution..”. Finally, note that while Häussler et al. (2009) provide evidence of patents serving as signals, they do not study the accumulation of funds and as such it is difficult to extrapolate their findings to our case.

(2011) focus on the impact of patents on the occurrence of an IPO without investigating the impact of patents on intermediary financial milestones a company needs to go through before it issues an IPO. Accordingly, whether patents had a stronger effect in the early financial performance of the firm when compared to the later financial performance as measured by the IPO was not part of the analysis. The second relevant study we identified, by Hsu and Ziedonis (2013) is the most informative with respect to the potential dynamics in the signalling contribution of patents. In their analysis of firm valuations, the authors find that patents are more effective in attracting prominent investors and boosting firm valuations during early investment rounds, which is a finding that supports the expectation that patents act as a signal whose value diminishes over time.[35]

In sum, the evidence on whether the signalling value of patents wanes once investors have a better insight into the value of the firms they injected capital is particularly thin. Hence, it is difficult to infer whether and how the value of patents as signal diminishes once the quality of the firm is assessed more closely by investors.

To answer this question we refer to the literature that examines how VCFs reduce information asymmetries once they have invested in a firm. The starting point of this literature is the basic insight that information asymmetries lead to agency problems (Fama, 1980; Jensen & Meckling, 1976). A major task of VCFs is therefore to reduce agency problems of this sort. A typical mechanism that VCFs use for this purpose is to provide funds in rounds of financing (Neher, 1999; Wang & Zhou, 2004). Under this mechanism, target firms receive funds of a particular round conditional on having received funds in a previous round (and have met certain milestones). Between rounds, VCFs become actively involved in the day-to-day operations of the target firm via consulting and monitoring (Gorman & Sahlman, 1989; Rosenstein, Bruno, Bygrave, & Taylor, 1993). In doing so, VCFs follow the progress of the firms they invest in, evaluate their prospects and generally get more acquainted with their activities and potential. It follows that

[35] In particular, in their analysis of firm valuations, the authors include a dummy variable that takes the value of 1 if the valuation refers to the first or second round of investment and report a positive coefficient for the interaction term of this variable with the patent activity variable; implying thus that patent activity is more effective in boosting firm valuation for early investment rounds. Besides differences in sample size (370 versus 530 firms), period of analysis (1975 to 1999 versus 2001 to 2011), industry focus (semiconductor versus biotechnology) and different measures of patent activity (patent stocks versus applications and granted patents) a fundamental distinction of our work is that we are interested in the transition of the signal value of a patent after the first round of investment has been completed, where we expect information asymmetries between firms and VCFs to greatly diminish. Accordingly, we treat investments in round 1 and round 2 as separate and we do not aggregate them in a composite “early rounds” measure. As a result, we study the dynamics of the signaling value of patents between early rounds of financing while Hsu and Ziedonis (2013) focus on the dynamics between early and later stage financing.

information asymmetries between VCFs and target firms should decrease under these conditions. In environments with reduced information asymmetries the value of signals tends to decrease (Gulati & Higgins, 2003; Higgins & Gulati, 2006). By extension, once a VCF is familiar with the target firm, the effectiveness of patents as signals for attracting additional funds is therefore expected to be limited.

More specifically, it may be reasonable to expect that patents, through signalling effects, can augment the amounts of venture capital raised by firms in their first round of financing. Patents, however, should not be expected to have a significant signalling effect on the amount raised in the second round of financing because the, initially, hidden quality of the firm should now be more apparent to the VCF. Indeed, insofar patents are a quality signal, those acquired after the first round should not materially influence the amount of funds raised in the second round.[36] We expect this to hold because if the unobserved quality of the firm is, in large part, revealed to the VCF, the need for additional signals lessens.[37] Taken together, the foregoing discussion leads to the following hypotheses:

Hypothesis 1: *Patent activity before the first round of financing acts as a signal that increases the amount of funds raised in the first round of financing.*

Hypothesis 2: *Patent activity before the second round of financing does not act as a signal that increases the amount of funds raised in the second round of financing.*

To illustrate our theoretical expectations, Figure 1 presents the dynamic nature of the interaction between VCFs and target firms. This interaction underpins the diminishing signalling value of patent activity and forms the basis of our hypotheses. In the next section, we explain how we go about testing empirically our hypotheses.

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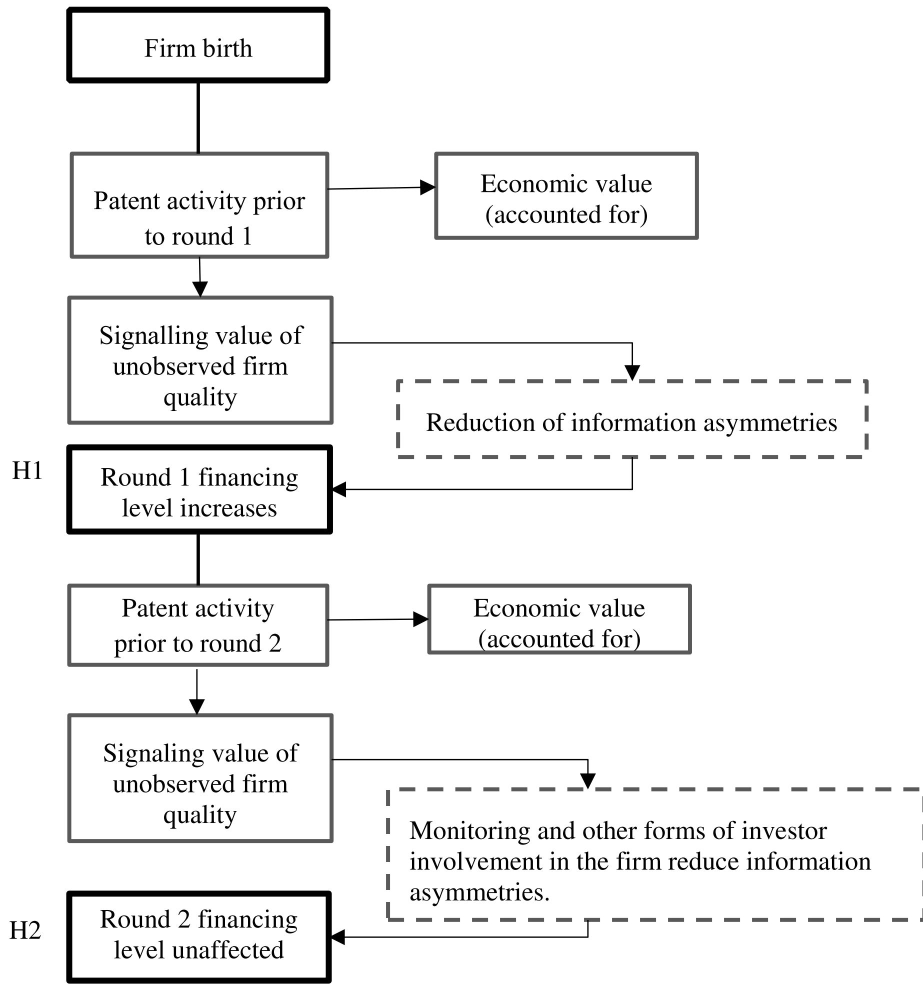
[36] Note that if the quality of the firm changes after the first round, patents after the first round can again act as a quality signal primarily for new investors. For investors that participated in the first round we expect the day to day interactions with the firm to alleviate their need for additional signals. For our sample the large majority of firms received funds from the same sole investor and very few firms received funds from a different set of investors between rounds. As such, we expect our main hypotheses to hold for the vast majority of cases at hand.

[37] Following the same line of reasoning, if patents are valued by VCFs primarily for their implied discounted rents, patents after the first round should be expected to increase the amount of funds for the second round as well.

Figure 1. Theoretical Framework

The signalling effect of intellectual property owned by emerging high technology firms on the attraction of external capital



Methods and Procedures

To empirically test our hypotheses that the signalling value of patents will tend to decline as capital investment in small firms proceeds in sequential rounds, we need to associate the patent activity of a firm with the incremental amount of venture capital it attracts while information asymmetries between investors and the firm diminish over time. We operationalize patent activity with the number of granted patents a firm has received and the number of patent applications it has filled. To test whether the effectiveness of patent activity as a signal declines as a result of reduced information asymmetries we build two empirical models. In the first, the sum of venture capital funds raised by a given firm in the first round of financing when information asymmetries are expected to be stronger is regressed on patent activity. In the second model, the sum of venture capital funds raised by a given firm during the second round of financing at which time information asymmetries are expected to decline, is again regressed on patent activity measures. The dependent variable in each model is the natural log of the total amount of VC funding raised by a given biotechnology firm in round 1 (model 1) or round 2 (model 2). We present the right-hand side variables below.

We include patent activity as an explanatory variable in both models. We separate the number of granted patents from the number of submitted applications because their signalling values might differ in subtle but important ways (Gans, Hsu, & Stern, 2008; Popp, Juhl, & Johnson, 2004). For instance, preparing a patent application is a lengthy and time consuming process which entails the presentation of complex technical issues in a structured format (Häussler et al., 2009). Further, during the correspondence of the applicant with the patent office, the applicant may be prompted to fine-tune the application, become familiar with more strands of relevant research and generally be exposed to situations that can mature the company and help it develop. In fact, mainly because of the harmonized strict requirements that a firm needs to comply with for all of its patent applications, it is conceivable that the patent acquisition process is subject to a learning curve. In turn, emerging firms that have applied for a number of patents may be learning more by being more often involved in the patent acquisition process.[38] Accordingly, the number of patent

[38] As noted, our expectation on the signaling value of applications emanate from a learning-by-doing process and a fine-tuning process. The measure of applications we use (number of applications submitted) is consistent with both processes. It captures the learning-by-doing effects because it measures the intensity a given firm applies for patents. It captures the fine-tuning process because a. the length of time it takes from an application to be granted at the USPTO is extensive (Mabey Jr, 2010), on average two and a half years for our sample patents, and b. between 85 to

applications may have a signalling value in that investors may view firms developing further rather than sitting idle.[39] In contrast, granted patents may signal that firms are well down the path of the learning curve. It is therefore of interest to test whether the pull on capital is sensitive to the different potential signalling value offered by granted patents and experience with patent applications. Indeed empirical evidence indicates that patent applications may have a stronger signalling effect than patents in attracting venture capital faster and at larger volume (Baum & Silverman, 2004; Häussler et al., 2009). For all these reasons, we consider these two forms of patent activity separately in our models.

For the first round of financing we measure the number of patents and patent applications from firm birth until the date of financing and expect positive signs for the corresponding coefficients. Such signs would indicate that patent activity acts as a signal and increases the level of venture capital funds invested in the focal firm (*PatentApp_1* and *PatentGrant_1*). For the second round of financing we maintain our measures of patent activity we use in the first specification and we also add two independent variables that measure the number of granted patents and patent applications filled from the date of the first round of investment until the date of the second round of investment (*PatentApp_2* and *PatentGrant_2*).[40] As discussed in section

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90 percent of applications turn to patents at the USPTO (Quillen & Webster, 2001). As such, the more applications a firm submits the more exposed it becomes to fine-tuning procedures because chances are that before the applications become patents there is extensive communication between the firm and the patent authorities.

[39] While empirical evidence on the drivers of signaling value of the intensity a given firm submits patent applications is scarce, personal correspondence of the authors with Dutch and US-based VCFs attends to this argument. This correspondence also indicated that potential differences in the economic value between applications and granted patents (e.g. applications but not granted patents are open to revisions that could create uncertainty for competitors) does not typically weigh in heavily in investment decisions particularly for VCFs with expertise and experience to approximate beforehand the granted claims of a given application.

[40] To avoid double-counting *PatentApp_1* measures only the number of applications that were not granted patent rights before the first round (for the round 1 regression) or between the first and the second round (for the round 2 regression); that is we exclude applications whose grant we include in the *PatentGrant_1* and *PatentGrant_2* variable. As a consequence, the *PatentApp_1* variable for a given firm can be different across regressions: if an application was applied for before round 1 and it was granted between round 1 and round 2, it is included in the *PatentApp_1* variable in the round 1 regression but not in the *PatentApp_1* variable in the round 2 regression. Overall, the scheme we employ to construct our patent activity variables could materially truncate the *PatentApp_1* variable insofar as a. the elapsed time between the founding of the firm and the receipt of first round funds was extended or b. the elapsed time between financing rounds was extended. But, as we show in Tables 1a and 1b and explain in footnote 25: a. on average, our sample firms received their first round of financing almost 30 months (2.54 years) after their birth and b. the average elapsed time between rounds in our sample is 13 months. Both of those figures are below (or closely approaching) the average 30 months that elapsed between the application and the grant date at the USPTO for the patents in our sample. It follows that from either source of potential truncation, the truncation is minimal. To illustrate, only 17 applications whose patent pendency time was below 13 months were omitted from *PatentApp_1* because they were included in *PatentGrant_2*. Including these applications in the analysis yields qualitatively similar results.

2, *PatentApp_1* and *PatentGrant_1* are included in the analysis of the second round in order to test whether patent activity indeed serves a signalling function; if it conveys a quality signal, then *PatentApp_1* and *PatentGrant_1* should have explanatory power for the funds raised in the first round of financing but not for the second. Along the same lines, under the premise that patent activity serves a signalling function, *PatentApp_2* and *PatentGrant_2* should not augment the amount of funds raised in round 2. If other potential advantages conferred by patents, such as discounted rents, are the prime reasons for the attraction of VCFs to patents, then *PatentApp_2* and *PatentGrant_2* should have significant explanatory power in the amount of funds raised in round 2. Therefore, in line with our hypotheses, we expect the patent activity before the second round of investment to have a diminished influence on the level of venture capital funds received by the focal firm in the second round.

In order to most effectively evaluate whether patents act as a signal that can attract venture capital funds, we need to account for the differential economic value of patents as VCFs will tend to invest in firms with the highest quality of intellectual property and greater future value. That is, we need to tease out the (economic) value of the patent itself from its signalling value. To do so, we follow previous literature (Gambardella, Harhoff, & Verspagen, 2008; Harhoff, Scherer, & Vopel, 2003; Häussler et al., 2009; Trajtenberg, 1990) and we approximate patent economic value with a variable that measures the average number of times a patent has been cited by other patents (i.e. forward citations) (*PatentCiteYear_1*) [41]. Higher citation levels imply superior scientific significance or applicability and are taken to indicate higher quality patents. Indeed, Fischer and

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[41] Our choice to use forward citations as a proxy for patent economic value is based on strong empirical evidence. For instance, recent results suggest that forward citations are reliable predictors of the auction price of patents (Fischer and Leidinger (2013); Sneed and Johnson (2009)). Because in patent auctions the bidders buy only the patent and not the seller firm (or any other type of institutions that holds the patents) this setting is as close as one can get to reliably approximate the economic value of patents. Nevertheless, the small number of studies that have provided these estimates may cast some doubt about their generalizability. Towards this end, an important observation is that the patent value estimates from Fischer and Leidinger (2013) and Sneed and Johnson (2009) are well within the range of patent value estimates reported previously from studies that do not use patent auction data (e.g. Trajtenberg (1990)) and as such they may be measuring both the economic and the signaling value of a given patent. The observation that the patent value estimates from the auction and the non-auction studies are within range is important because a. it implies that even in the non-auction settings what is captured is, for the most part, economic patent value and b. given that forward citations explain a significant part of the patent value derived by non-auction settings (Trajtenberg (1990)), it significantly extends the empirical evidence demonstrating that forward citations capture economic patent value. Finally, in alternative approaches to estimate the economic value of a given patent (i.e. by asking investors the price they would sell their patent had they known its value a priori) the evidence, again, shows that forward citations are the most reliable proxy (Gambardella et al., 2008). Importantly, as robustness check in section 5.2 we present models in which we employ different measures of patent economic value (patent family size) and reach similar conclusions to our baseline models.

Leidinger (2013) and Sneed and Johnson (2009) when they correlate the auction price of patents --- a direct measure of patent economic value --- with the number of forward citations reveal that forward citations are closely associated with the economic value of patents. In the specification of the second round, besides *PatentCiteYear_1* we also include a similar variable that measures the forward citations of patents granted from the date of the first round until the date of the second round (*PatentCiteYear_2*).[42] We expect patents of higher economic value to attract greater amounts of funds in both investment rounds.

The patent activity of a focal firm before the first round of financing is by definition unaffected by the involvement of VCFs in the firm. But, the patent activity before the second round of investment can be influenced by managerial advice under the consulting role that VCFs assume once they invest in a firm. That is, if patent activity after the first round is influenced by the involvement of VCFs in the firm, the empirical model of round 2 could suffer from specification bias. To account for it, in the specification of the second round we include in the lagged dependent variable in level form (i.e. the dependent variable in the first specification, in level form, which is the total amount invested in the first round of investment – *VCF_Investment_1*) (Baum & Silverman, 2004; Jacobson, 1990).[43] Given that conditional on the receipt of funds, the amount per round generally increases with more advanced rounds (Gompers, 1995), we expect a positive sign for this variable.

In return for their investment, VCFs become part owners of the target firm. The size of the amount they invest in order to become part owners depends heavily on two factors: i) the valuation of the firm *ex ante* and ii) the percentage of equity they receive. It follows that we need to account for both of those factors but finding direct measures for such factors is empirically challenging. As such, we use two indicators that can approximate the conceptual variables. Specifically, for both rounds we construct round-specific variables that assume increasing values for investments

[42] Note that the number of forward citations is not a measure that is fully observable by the VCFs when they invest in the firm because VCFs are able to observe only the citations that have been received by the time they invest. Further, more recent patents tend to receive fewer citations compared to older patents mainly due to the effective time a patent may need until it becomes visible. To account for this observation we divide the average number of forward citations for the patents of a given firm by the age of the patent measured in years (citations are measured up to early summer of 2012). Then, we average out the average number of forward citations per firm patent.

[43] Lagged dependent variables are generally more meaningful in panel data structures. While lagged dependent variables in cross sectional data, like in our application, are less regular, they have been used previously (see Hochberg, Ljungqvist, & Lu, 2007 for an example). Nevertheless, in order to test for the empirical relevance of the lagged dependent variable included in our models, in unreported models the estimates from specifications that do not include the lagged variable are largely in line with the main results presented in Table 3 and imply that the inclusion of the lagged dependent variable does not greatly influence our empirical estimates.

directed towards later stages of firm growth (*GrowthStage_1* and *GrowthStage_2*).[44] Generally, the valuation of firms, *ex ante,* increases with the stage of firm growth (Cumming & Dai, 2011) and in this respect these indicators should approximate firm valuation. Importantly, early and later stage investments by VCFs are also typically associated with different equity shares (Beaton, 2010; Kaplan & Strömberg, 2003). As such, the *GrowthStage* indicators should be correlated with the amount of equity secured by VCFs. Given the increased valuation that accompanies firms at later stages of firm growth, we expect a positive sign for the variable at hand. We also construct another indicator to approximate the fraction of equity VCFs receive in exchange for their investments which is based on the finding that VCFs with stronger reputation typically receive larger equity than investors with weaker reputation for the similar investment (Hsu, 2004). As such, we include in both specifications a variable that reflects the Lee et al. (2011) reputation score of the highest ranked funding VCF of the first round of financing (*VCFreputation_1*).[45]

To account for additional signals used by emerging firms that tend to leverage the reputation and previous business history of the team around the firm (Arvanitis & Stucki, 2012; Audretsch & Stephan, 1996; Bonardo, Paleari, & Vismara, 2011; Certo, 2003a; Elitzur & Gavious, 2003; Gompers, Kovner, Lerner, & Scharfstein, 2010; Lee, 2001; Shane, 2000) in both specifications we include a variable that takes the value of 1 if one of the founders of the focal firm is a preeminent member of the academic community[46] and/or has started a firm previously (*FounderSignal*). Along the same lines, once the venture capital investment has been made, the reputation of the investors can also act as a signal since successful investors are presumed to possess skills that allow them to effectively identify firms with economic potential (Casamatta & Haritchabalet, 2007; Sorenson & Stuart, 2001). By extension, we expect the abovementioned variable *VCFreputation_1* in the specification of the second round to also capture effects of this kind. In line with the discussion in section 2, we expect *FounderSignal* to influence the total

[44] Venture capital investments are directed towards different phases of firm growth, with each phase associated with different degrees of risk exposure and potential returns to the investor (Flynn & Forman, 2001). Seed stage funds are typically small amounts directed primarily towards proving a concept. Early stage funds are directed mainly towards product development. Funds directed towards the expansion stage are used, in large part, to boost market entry or strengthen R&D (Jeng & Wells, 2000). There are also funds directed towards later stage financing, such as buy-outs or acquisitions.

[45] As we explain in section 4, in our dataset the investors of round 1 and round 2 are largely the same. As a result, to avoid double-counting, in the specification of the second round we include only the reputation score of the round 1 investors and not the round 2 investors. Nevertheless, even when the reputation of the round 2 investors is included in the analysis, the results remain nearly identical to the baseline estimates.

[46] We code an academic founder as eminent if she holds a distinguished and/or named professorship and/or is a member of the Academy of Sciences and/or has won a Nobel Prize.

amount invested in the first round of financing and this effect to die off for the second round. For *VCFreputation*_1 we expect it to be positively related with the total venture capital amount raised in the second round of financing.

In addition to the signalling effect that funding VCFs can have, their availability of funds can also influence the growth of venture capital funds invested in a given firm. Because such availability is often largely determined by the number of investors that spread the risks of their investments (i.e. by the syndication size) (Lockett & Wright, 2001) as well as by the capital available to the investors (Gupta & Sapienza, 1992; Tian, 2011) we include two variables that measure the number of investors per round as well as their average size in both specifications and expect positive signs for both coefficients (*SyndicateInvestors1, SyndicateInvestors2, SyndicateSize1, SyndicateSize2*). Since in syndicates of VCFs the most proximate VCF is usually the most heavily involved in the day-to-day operation of the target firm (Ferrary, 2010), the last variable we include in the empirical models that relates to the funding VCFs is the distance between the most proximate funding VCF and the target firm (*DistanceClosestVCF*). Spatial proximity between target firms and investors typically eases the monitoring functions of VCFs (Sorenson & Stuart, 2001; Zook, 2005) and can lead to higher investments (Tian, 2011). We therefore expect a negative sign for the coefficient of this variable.

Because agglomeration externalities (e.g. knowledge spillovers and network effects) from different types of organizations often positively influence the performance of high technology firms (Coenen, Moodysson, & Asheim, 2004; Döring & Schnellenbach, 2006; Gittelman, 2007; Kolympiris & Kalaitzandonakes, 2013a, 2013b; Kolympiris, Kalaitzandonakes, & Miller, 2011) we include in both specifications variables that account for such potential influences. The first variable measures the number of universities that perform biotechnology related research and are located in the same MSA as the focal firm (*UniversitiesInMSA*) and we expect a positive sign (Abel & Deitz, 2012; Anselin, Varga, & Acs, 2000; Varga, 2000). As well, we account for potential proximity effects from the presence of VCFs and over-performing DBFs in the vicinity (Beaudry & Breschi, 2003; Gompers, 1995; Shane & Cable, 2002). Following Kolympiris et al. (2011) for each round of financing we construct corresponding variables that measure the density of VCFs and the number of patents granted to biotechnology firms before the focal financing round in 0 to 10 and 10 to 20 miles from the origin firm respectively (*VCFarea_0010_1, VCFarea_1020_1, VCFarea_0010_2, VCFarea_1020_2, PATENTarea_0010_1,* *PATENTarea_1020_1, PATENTarea_0010_2, PATENTarea_1020_2*). We expect positive signs for the corresponding coefficients.

We also measure the age of the focal firm at the round of financing (*Age1, Age2*). We do not form strong priors with regard to the direction the age of firms can move the amount of funds received because VCFs may evaluate positively older firms due to higher experience and survival but they may also view negatively older firms that have not received previous financing. To incorporate in the analysis year-to-year variations such as "hot IPO market" periods (Lowry & Schwert, 2002)[47] that can encourage or discourage venture capital investments at an aggregate level we include in our empirical models a set of year dummies that match with the year in which the investment took place.

With respect to estimation techniques, we employ White's standard errors because the heteroskedasticity tests we conduct (seen in Tables 2 and 3) show evidence of heteroskedasticity. We also test for the possibility that some of the errors in our models might be correlated. This may hold largely because there are often regional factors that are difficult to observe and which can affect the performance of all firms in a region or the capital investments they attract. For instance, such factors may include state subsidies and technical assistance for the development and financing of high technology firms and other such activities.[48] Factors of this sort can therefore cause DBFs of a given state to overperform or underperform jointly. If such influences do exist, the assumption of independence across observations for firms in the same state may be violated (Nichols & Schaffer, 2007; Stimson, 1985). To address this possibility we estimate both specifications with standard errors of firms in the same state modeled as correlated (i.e. clustered at the state level).

[47] On top of the variables described in this section, we further tested the influence of a number of moderation and interaction terms (e.g. the influence of the founder signal on the impact of the firm growth stage variables as a means to control for possible cofounding effects on the valuation of firms by VCFs). These variables did not improve significantly the statistical fit of the empirical models and they were generally not statistically strong. As such, we omit them from the analysis. However, we maintain in the analysis one of the interaction terms we tested for; the interaction between *PatentGrant_1* and *UniversitiesInMSA* in large part because we consider it particularly relevant from a theoretical perspective in that it tests whether the knowledge generation of nearby universities influences the impact of the signaling value of patents.

[48] Additional factors may refer to attitudes towards risky investments or the efficacy of consulting organizations (e.g. the Larta Institute or Foresight S&T) that can assist firms in improving their performance. Such features can expand beyond the geographic boundaries of 10 or 20 miles, which is the geographic boundary for the variables we employ to describe the regional environment. Largely because of the qualitative nature of those features, representing them through associated variables is a task with mounting difficulties and as such we opt for clustering the standard errors at the state level to control for their potential effects. The analysis with the clustered standard errors is conducted by estimates produced with generalized estimating equations which is a method of calculating the standard errors by first estimating the variability within the defined cluster (in our application the state) and then sums across all clusters (Zorn, 2006).

Data Sources and Presentation

To perform our empirical analyses, we began by measuring all venture capital investments toward dedicated biotechnology firms (DBFs) from 2001 up to 2011 using Thomson Reuter's SDC Platinum Database (SDC).[49] We also sourced from SDC the address and founding date of each DBF, the amount invested per round, the firm growth stage each investment was directed to, the date of financing round, the investors per round as well as their address and previous investments. We used this information to construct our dependent variables (*USD_R1* and *USD_R2*) and *Age1, Age2, SyndicateInvestors1, SyndicateInvestors2, SyndicateSize1, SyndicateSize2, DistanceClosestVCF, VCFarea_0010_1, VCFarea_1020_1, VCFarea_0010_2, VCFarea_1020_2, GrowthStage_1, GrowthStage_2.* For *DistanceClosestVCF, VCFarea_0010_1, VCFarea_1020_1, VCFarea_0010_2, VCFarea_1020_2* we needed to calculate the distance between the target firm and investors and the density of VCFs in a region.[50] To do so, we converted the addresses of target firms and VCFs to coordinates at http://batchgeo.com. Subsequently, we plugged these coordinates in the distance formula[51] we employ and constructed the corresponding variables.

For our variables *PatentApp_1, PatentGrant_1, PatentApp_2, PatentGrant_2* we used Google Patents ® which indexes granted patents and patent applications from the United States Patent and Trademark Office (USPTO).[52] We searched for every granted patent and patent application where the focal firm was listed as the applicant/assignee.[53] Using the application and

[49] We focus on this time period because for this period the number of patents and patent applications are available from the United States Patent and Trademark Office (USPTO). Before November 29, 2000 there was no formal obligation for the publication of patent applications from the USPTO. To test the sensitiveness of our empirical estimates to having only observations after 2001 in section 5.2 we present models that include venture capital investments that took place since 1974. In these models we include only the number of granted patents as our measure of patent activity. These results are qualitatively equivalent to the results presented in Tables 2 and 3.

[50] The density of VCFs did not include the funding VCFs of the focal firm.

[51] We employed the general formula of the spherical law of cosines which corrects for Earth's spherical shape: $Distance_{12} = ar\cos(\sin(lat_1).\sin(lat_2)+\cos(lat_1).\cos(lat_2).\cos(long_2-long_1)) \times 3963$

[52] See http://www.uspto.gov/news/pr/2010/10_22.jsp for an official USPTO press release regarding its cooperation with Google Patents ®. In particular, under this agreement USPTO provided all of its patent documents to Google largely because the latter has the technical capacity to provide patent data in bulk. Compared to other popular databases often used in the literature such as Patstat and the NBER database, since the data source is identical (USPTO), the information provided is in large part comparable. For our purposes, the main advantage of Google Patents ® was the ease of retrieving patent counts and applications by using slightly different names of each company without having to search within one file but rather by connecting to the Google Patents® interface.

[53] In a number of cases the name of the applicant/assignee differed across patents as, for instance, "inc." was missing or it was replaced by "inc". To ensure that the validity of our measure was not prone to such issues we double-checked the number of patents using a number of variations of the name of each firm.

granted date we allocated patent activity between rounds. To construct *PatentCiteYear_r1*and *PatentCiteYear_r2* we employed Google Patents ® and counted the number of times each of the patents in our dataset was cited by other patents. Then, for each firm we calculated the average number of citations across all granted patents of the firm. As noted in footnote 12, to account for the tendency of older patents to be cited more heavily, we divided the average number of forward citations for the patents of a given firm by the difference (in years) between early summer of 2012 (when the variable was constructed) and the date that the patent was granted.

To collect biographical information for the academic founders we visited the website of each firm and complemented this search with academic founders' biographies provided at their personal websites. Using these sources, firms whose founder(s) had started a firm previously and/or held a distinguished and/or named professorship and/or were a member of the Academy of Sciences and/or had won a Nobel Prize took the value of 1 in the *FounderSignal* dummy variable.

To build *VCFreputation_1* we first consulted the yearly reputation rankings of VCFs maintained at http://www.timothypollock.com/vc_reputation.htm (Lee et al., 2011). DBFs whose funding VCFs at the time of the financing round were not ranked, were coded as 0. DBFs whose highest ranked VCF was also the highest ranked of all VCFs were coded as 1. To illustrate how we calculated our reputation indicator we provide here an example for which the highest rated VCF was ranked as 250th in the year in question. To construct our index we first divide 250 by 1000 (the total number of ranked VCFs) which yields 0.25 and then we subtract 0.25 from 1 to have 0.75, which is the value of the *VCFreputation_1* variable for this hypothetical example. Along the same lines, if the highest rated VCF was ranked 150th, the value of the *VCFreputation_1* variable would be 0.85. And so on.

To construct *UniversitiesInMSA* we used the list of recipient institutions of biotechnology-related research grants maintained at the website of the National Institutes of Health. We complemented this list with comparable listings from the Association of University Technology Managers and the Chronicles of Higher Education. All three sources had information on the main address of each institution and whenever information was missing we visited the website of each institution to collect the address. The addresses were then assigned to MSAs using the zip code-to MSA list provided by the U.S. Bureau of Economic Analysis.

Finally, to build *PATENTarea_0010_1, PATENTarea_1020_1, PATENTarea_0010_2,* and *PATENTarea_1020_2* we first visited Google Patents ® to measure the yearly total number of patents assigned to each DBF. Then, we summed over the patents that were granted before each round of financing to DBFs within 0 to 10 and 10 to 20 miles from the origin DBF (using the coordinates and the distance formula previously described).

Table 1a. Descriptive Statistics of Selected Variables Used in the Empirical Models for the First Round of Financing

Variable code	OBS	MEAN	MEDIAN	MODE	STD. DEV	MIN.	MAX.
USD_R1	586	7.21	3.56	1.00	11.04	0.00	100.00
PATENTApp_1	586	0.29	0.00	0.00	1.30	0.00	15.00
PATENTGrant_1	586	0.19	0.00	0.00	1.44	0.00	22.00
PATENTCiteYear_1	586	0.06	0.00	0.00	0.44	0.00	6.83
GrowthStage_1	**D:0**	**D:1**	**D:2**	**D:3**	**D:4**		
	12	248	246	78	2		
VCFReputation_1	586	0.0	0.0	0.4	0	0.00	1.00
FounderSignal	119						
SyndicateInvestors_1	586	2.61	2.00	1.00	1.84	1.00	13.00
SyndicateSize_1	586	367.01	75.47	0.00	616.60	0.00	4155.00
DistanceClosestVCF	586	398.49	20.63	0.01	747.92	0.00	3146.00
UniversitiesInMSA	586	9.29	9.00	17.00	8.09	0.00	37.00
VCFarea_0010_1	586	23.34	10.00	1.00	29.36	0.00	103.00
VCFarea_1020_1	586	15.21	5.00	0.00	25.37	0.00	127.00
PATENTArea_0010_1	586	126.55	61.00	0.00	155.87	0.00	531.00
PATENTArea_1020_1	586	69.73	18.00	0.00	115.16	0.00	608.00
AGE1	586	2.54	1.37	0.00	3.12	0.00	27.00

[1]By definition the number of applications needs to be greater or equal to the number of granted patents for a given firm. The reason why the maximum value of granted patents is greater than the maximum value for patent applications is twofold: First, the values refer to different firms. Second, to avoid double-counting PatentApp_1 measures only applications that were not granted patent rights before the first round; that is we exclude applications whose grant we include in the PatentGrant_1 variable. Therefore, the number of granted patents may be greater than the number of applications if for instance the filing and the grant date of the patent are both before the date of the first round.

[2]The variable takes the value of 1 if the investment was categorized as "Seed Stage", 2 if the investment was categorized as "Early Stage", 3 if the investment was categorized as "Expansion Stage", 4 if the investment was categorized "Later Stage", "Buy-Out" or "Acquisition". We code as 0 observations that correspond to other stages, mostly what is reported in our data source as "Pipe". The boxes indicate the number of observations for each round that correspond to each of the 5 categories

[3]The index takes the value of 0 if the participating VCFs are unranked. When participating VCFs are ranked in the the Lee-Pollock-Jin VC Reputation index (Lee, Pollock et al. 2011), the value lies between 1 (when the VCF is rank 1) and 0.001 (when the VCF is the lowest ranked VCF in the list).

[4]In the case of the *FounderSignal* variable the figure measures the number biotechnology firms with the founder matching the said characteristics

Note: 64 observations in 2001, 59 observations in 2002, 52 observations in 2003, 50 observations in 2004, 66 observations in 2005, 74 observations in 2006, 78 observations in 2007, 63 observations in 2008, 33 observations in 2009, 39 observations in 2010 and 8 observations in 2011

Table 1b. Descriptive Statistics of Selected Variables Used in the Empirical Models for the Second Round of Financing

Variable code	OBS	MEAN	MEDIAN	MODE	STD. DEV	MIN.	MAX.
USD_R1	494	6.86	3.10	1.00	11.07	0.00	100.00
USD_R2	494	8.00	4.32	10.00	9.94	0.02	87.00
PATENTApp_1	494	0.18	0.00	0.00	1.10	0.00	13.00
PATENTGrant_1	494	0.12	0.00	0.00	1.03	0.00	20.00
PATENTApp_2	494	0.40	0.00	0.00	1.49	0.00	18.00
PATENTGrant_2	494	0.22	0.00	0.00	1.24	0.00	22.00
PATENTCiteYear_1	494	0.00	0.00	0.44	0.00	0.00	6.83
PATENTCiteYear_2	494	0.08	0.00	0.00	0.56	0.00	9.17
GrowthStage_2	**D:0**	**D:1**	**D:2**	**D:3**	**D:4**		
	30	103	213	148	0		
VCFReputation_1	494	0.37	0.00	0.00	0.45	0.00	1.00
FounderSignal	101						
SyndicateInvestors_2	494	3.01	2.00	1.00	2.19	1.00	15.00
SyndicateSize_2	494	438.17	138.17	0.00	624.23	0.00	3816.43
DistanceClosestVCF	494	345.00	20.42	0.50	686.22	0.00	3146.00
UniversitiesInMSA	494	9.28	8.00	17.00	8.24	0.00	37.00
VCFarea_0010_2	494	24.12	11.00	0.00	30.04	0.00	103.00
VCFarea_1020_2	494	15.51	5.00	0.00	26.61	0.00	127.00
PATENTarea_0010_2	494	133.72	64.00	0.00	162.06	0.00	535.00
PATENTarea_1020_2	494	72.04	21.00	0.00	118.63	0.00	613.00
AGE2	494	3.34	2.41	2.00	3.08	0.00	28.89

[1]By definition the number of applications needs to be greater or equal to the number of granted patents for a given firm. The reason why the maximum value of granted patents is greater than the maximum value for patent applications is twofold: First, the values refer to different firms. Second, to avoid double-counting PatentApp_1 measures only applications that were not granted patent rights between the first and the second round; that is we exclude applications whose grant we include in the PatentGrant_1 and PatentGrant_2 variable. Therefore, the number of granted patents may be greater than the number of applications if for instance the filing and the grant date of the patent are both between the dates of the first and the second round.

[2]The variable takes the value of 1 if the investment was categorized as "Seed Stage", 2 if the investment was categorized as "Early Stage", 3 if the investment was categorized as "Expansion Stage", 4 if the investment was categorized "Later Stage", "Buy-Out" or "Acquisition". We code as 0 observations that correspond to other stages, mostly what is reported in our data source as "Pipe". The boxes indicate the number of observations for each round that correspond to each of the 5 categories

[3]The index takes the value of 0 if the participating VCFs are unranked. When participating VCFs are ranked in the the Lee-Pollock-Jin VC Reputation index (Lee, Pollock et al. 2011), the value lies between 1 (when the VCF is rank 1) and 0.001 (when the VCF is the lowest ranked VCF in the list).

[4]In the case of the *FounderSignal* variable the figure measures the number biotechnology firms with the founder matching the said characteristics

Tables 1a and 1b presents descriptive statistics of the variables used in the empirical models. As described by the modal values of the two dependent variables we use in the analysis, most DBFs in the dataset received $1 million for the first round of financing and $10 million for the second round of financing.[54] Note that the standard deviation is larger than the mean observed value which indicates the wide array of venture capital amounts invested in different firms. Most firms did not have any patent activity before the focal round of financing, but the standard deviation of the observed patenting activity surpasses the average of the observed values and suggests that some firms had a large number of patents and patent applications before the focal round of financing. This is an important observation because it indicates that our sample is composed of firms with varying degrees of patent activity and thus it alleviates concerns of overstressing the significance of patents that might result from the potential tendency of better firms to patent more and better protect their intellectual property assets (Helmers & Rogers, 2011).[55] The majority of the patents granted to firms in our sample did not receive any citations per year.

Most of the firms in the dataset were close to four months (0 years in Table 1a) and two years old when they received first and second round of financing which were mostly directed to the seed and startup stage respectively.[56] The average reputation score for the highest ranked

[54] As seen in Tables 1a and 1b the minimum value for the amount raised for a given firm in our sample is below $10,000, which, especially in biotechnology, is uncommon. We verified this amount with our data source but to ensure that a potential misreporting would not affect our estimates we run the baseline regression omitting the amount at hand and reached almost identical results.

[55] In a similar vein, an alternative explanation could be that larger firms patent more. To check this argument we used LexisNexis Academics, Business Insights: Essentials and Business Source Premier to assess the size distribution, via employee counts, of the DBFs in our dataset at the time they received the focal round of financing. But, employee counts for the specific point in time in which a particular DBF received the venture capital investment were difficult to source. Nevertheless, the statistics for the 196 DBFs that we could find their number of employees at the timing of round 1 indicate that 150 DBFs (or 76.5 percent of the 196 firms) had less than 25 employees. In fact, the standard deviation of the variable in question was below the average, the modal value was 3 and 96 firms had less than 10 employees. In all, these statistics suggest that our sample is relatively homogeneous in terms of firm size. This is a relevant consideration because it implies that the growth of venture capital funds in our sample is not primarily driven by firm size. Further note that we searched for the size of the firms at round 1 because the time span between rounds in the dataset was relatively short implying that firm size between rounds did not change drastically. More specifically, the average time between round 1 and round 2 was 13 months with a standard deviation of 10 months and a modal value of 7 months. Interestingly, this homogeneous distribution in terms of time span between rounds is particularly relevant for the estimates of round 2 because it indicates that the effective time for the reduction of information asymmetries between VCFs and DBFs is relatively similar across firms. As such, potential differences in the reduction of information asymmetries that may result from different time spans between rounds do not appear to raise significant concerns.

[56] Note that the relatively uniform age in which the sample firms receive their first round of financing alleviates concerns that maybe better firms (or/and those that better protect their intellectual property) in the dataset did not

funding VCF in either round was 0.37 which translates to a yearly ranking of 630 out of 1000.[57] One hundred and nineteen firms in the first round dataset had a founder that was coded as conveying a signal of quality (the corresponding value for firms that went to the second round was 101). For half of the firms in either round the closest funding VCF was located within about 20 miles distance from the firm. DBFs received funds mostly from 1 VCF both in the first and the second round of financing and the average number of investors for the first and the second round of financing was 2.6 and 3, respectively. With regard to the size of the investors, on average, they had invested around 367 million before providing first round financing to the firm and 438 million before providing second round financing to the firm.

With respect to the regional environment of the average focal firm, around 9 universities were located in the same MSA, roughly 24 VCFs were located in a 0 to 10 miles radius and approximately 15 VCFs in a 10 to 20 miles radius. Further, in information not reported in Tables 1a and 1b, we note that our dataset draws from both urban and rural areas. Finally, the average DBF in our sample was surrounded by DBFs that in sum had been granted around 200 patents before the focal DBF received funds (approximately 130 patents were granted to firms in a 0 to 10 miles distance and roughly 70 patents were granted to firms in a 10 to 20 miles distance).

Empirical Results

The Impact of Patent Activity on Venture Capital Financing

Tables 2 and 3 present the estimated coefficients for the models described in section 3. First we report the heteroskedasticity robust standard errors and the associated significance levels and in the last two columns of Tables 2 and 3 we report the corresponding information for standard errors clustered at the state level. The statistical inferences from the two sets of standard errors are nearly identical (the coefficients are by definition the same) and hence the models are robust to these alternative specifications.

The fit statistics reported at the bottom of those Tables indicate the joint significance of the variables in the empirical models and suggest that the fitted models have explanatory power.

necessarily receive the most funds during that round but they did receive them faster (Hsu & Ziedonis, 2013 page 772).

[57] 1-(630/1000)=0.37

Finally, the multicollinearity condition index (13.36 and 13.40 for each model) is within limits and do not raise concerns about the presence of multicollinearity (Greene, 2003). Nevertheless, as part of our robustness checks, in section 5.2 we present regressions with only a limited number of regressors where the multicollinearity index is lower and still find qualitatively similar results. Relatedly, the correlation coefficient among the granted patents before round 1 and the granted patents after round 1 is inflated (0.78).[58] Accordingly, the separate impact of each variable in the model of round 2 may be difficult to measure due to such correlation. In section 5.2 we present models where the patent activity measures of round 1 are omitted from the analysis and reach similar conclusion to the baseline estimates of Tables 2 and 3.

[58] This correlation coefficient is inflated by a single firm which has 20 granted patents in round 1 and 22 granted patents in round 2. When we exclude this firm from the sample the correlation coefficient drops drastically to 0.28. As well, excluding this firm from the analysis does not impact the baseline estimates in any material way.

Table 2. Estimated coefficients for the model of the first round of financing. The Dependent Variable is the natural log of the amount of venture capital funds invested by a biotechnology firm for the first round of financing.

Variable code	Coefficient	Heteroskedasticity robust standard errors	Standard errors clustered at the state level
Intercept	12.2816	0.2606 ***	0.4155 ***
PATENTApp_1	0.0773	0.0302 **	0.0289 ***
PATENTGrant_1	-0.0675	0.0534	0.0510
PATENTCiteYear_1	-0.0700	0.0738	0.0858
GrowthStage_1	0.3609	0.0967 ***	0.0761 ***
VCFReputation_1	0.2323	0.1277	0.1648
FounderSignal	0.4516	0.1364 ***	0.1182 ***
SyndicateInvestors_1	0.3876	0.0371 ***	0.0552 ***
SyndicateSize_1	0.0003	0.0001 ***	0.0002
DistanceClosestVCF	0.0004	0.0001 ***	0.0001 ***
UniversitiesInMSA	0.0017	0.0080	0.0101
VCFarea_0010_1	0.0084	0.0023 ***	0.0029 ***
VCFarea_1020_1	0.0029	0.0028	0.0032
PATENTarea_0010_1	0.0008	0.0004 **	0.0004
PATENTarea_1020_1	-0.0002	0.0007	0.0007
AGE1	0.0771	0.0226 ***	0.0225 ***
INTERACTION_1	-0.0051	0.0123	0.0075
Year Fixed Effects	YES	YES	YES
R^2	0.4127		
Adjusted R^2	0.3854		
F-test for overall model significance		15.26 ***	119.57 ***
Multicollinearity Condition Number	13.36		
X^2 for Breusch-Pagan test for heteroskedasticity	13.8 ***		
Number of observations	586		

The ommitted year is 2007

Table 3. Estimated coefficients for the model of the second round of financing. The Dependent Variable is the natural log of the amount of venture capital funds invested by a biotechnology firm for the second round of financing.

Variable code	Coefficient	Heteroskedasticity robust standard errors	Standard errors clustered at the state level
Intercept	13.1081	0.2587 ***	0.2865 ***
PATENTApp_1	0.0262	0.0579	0.0564
PATENTGrant_1	0.0533	0.0951	0.1144
PATENTApp_2	-0.0010	0.0349	0.0266
PATENTGrant_2	0.0083	0.0944	0.1058
PATENTCiteYear_1	-0.1139	0.0836	0.0827
PATENTCiteYear_2	0.0714	0.0506	0.0638
VCF_Investment_1	0.0268	0.0067 ***	0.0070 ***
GrowthStage_2	0.0329	0.0710	0.0582
VCFReputation_1	0.0533	0.1376	0.1306
FounderSignal	0.2414	0.1465	0.1799
SyndicateInvestors_2	0.3310	0.0286 ***	0.0392 ***
SyndicateSize_2	0.0006	0.0001 ***	0.0001 ***
DistanceClosestVCF	0.0002	0.0001 ***	0.0001 **
UniversitiesInMSA	0.0125	0.0077	0.0079
VCFarea_0010_2	0.0013	0.0021	0.0014
VCFarea_1020_2	0.0041	0.0026	0.0029
PATENTarea_0010_2	0.0003	0.0003	0.0003
PATENTarea_1020_2	0.0003	0.0006	0.0006
AGE2	0.0020	0.0212	0.0164
INTERACTION_2	-0.0011	0.0076	0.0086
Year Fixed Effects	YES	YES	YES
R^2	0.4378		
Adjusted R^2	0.4013		
F-test for overall model significance		11.26 ***	341.4 ***
Multicollinearity Condition Number	13.40		
X^2 for Breusch-Pagan test for heteroskedasticity	9.53 ***		
Number of observations	494		

Because the dependent variable is in logarithmic form, the estimated coefficients can be interpreted as semi-elasticities. In line with theoretical expectations, we fail to reject the hypothesis that patents act as a signal that attracts venture capital investments for the first round of investment and have a diminished effect for the second round of investment.[59] In particular, one additional patent application before the first round of financing increases the amount of funds raised by a firm by 7.7 percent. This is a considerable increase especially when considering the 0 modal value for the *PATENTApp_1* variable and suggests that firms without patent activity generally receive significantly less funding from VCFs. To put the magnitude of the estimated coefficient in perspective, when evaluated at the average amount of first round funds observed in the sample (Table 1a) the estimated coefficient indicates that one additional patent application increases venture capital investments by $557,333[60] when the modal value of the first round of financing is $1,000,000. When compared to the direct costs of obtaining a patent, which typically range between $10,000 and $38,000 (Graham et al., 2009; Lemley, 2000), the estimated signalling value of such a patent far surpasses these direct costs. While this comparison is not meant to be a cost-benefit ratio for the acquisition of patents by DBFs, our empirical results strongly suggest that the signalling value of patenting activity is very significant and should be explicitly accounted for when firm strategy and public policy consider the usefulness of patents.

Patent activity does not appear to attract higher amounts of second round venture capital investments, implying that a reduction of information asymmetries between investors and target firms leads to a decrease in the signalling value of patent activity. Notably, patent activity before the first round of financing influences only the first round of financing funds and patent activity after the first round of financing does not influence the amount of funds raised in the second round. These findings are in line with Hypothesis 1 and, importantly, indicate that patent activity carries a significant signalling value that diminishes once the hidden quality of a given firm is better assessed by the investors. Our empirical results also suggest that while patent applications play an important signalling role, the granted patents of a focal firm do not appear to attract additional funds either in the first or in the second round of financing. This result is consistent with previous

[59] Technically, as an anonymous reviewer correctly points out, similar to a large body of empirical literature in a number of domains we cannot accept the hypothesis: by research design while we control for a type I error (wrongly rejecting the null hypothesis) we cannot control for a type II error (wrongly accepting the null hypothesis that patent activity has no effect in the second round).

[60] 0.0773*7.21M (the average amount of first round funds reported in Table 1a)=557,333

findings (Baum & Silverman, 2004; Häussler et al., 2009) and it likely suggests that because patent applications may be stronger in conveying a firm that does not sit idle they are seen more favorably by investors.[61] Interestingly, patents of higher economic value, as proxied by forward patent citations, did not appear to prompt VCFs towards larger investments either in round 1 or in round 2.[62]

The coefficient of the *GrowthStage_1* variable indicates that when the first round of financing occurs at later stages of firm development, the amount invested by VCFs increases considerably. Hence, this indicator seems to capture effectively the elevated financial inflows needed for later stage investments. The coefficient of the *GrowthStage_2* for round 2 financing is not statistically significant, however.

Similar to the diminishing signalling value of patent activity, the founder signal significantly improved only the level of the first round of financing, when information asymmetries are prevalent. The reputation of the first round investors did not influence the level of funding in the second round of investment for the DBFs in our sample. Indeed, most of the firms received funds from a single investor (Tables 1a and 1b), who in most cases was the main investor in the second round as well. As such, our finding may reflect this funding structure in our sample.

Our results on the influence of the syndication of investors are in line with theoretical expectations and recent literature findings (Tian, 2011). In particular, we find that investments by large groups of wealthy syndicated VCFs are associated with higher levels of capital investments in a given firm. In fact, for the second round of financing the characteristics of the funding VCFs are prime determinants of the venture capital funds invested in a given firm. Finally, we find that firms funded by closely located VCFs receive, on average, less per round of financing. One

[61] We note however, that the joint significance test of granted patents and patent applications suggests that patent activity influences the first round of investment but not the second. Therefore, while *per se* granted patents may not exert a significant influence on venture capital attraction, when considered in conjunction with applications, they matter for the first round of investment.

[62] In unreported models where the *GrowthStage* variables are not included in the analysis, the forward citations variable is statistically significant for round 1. Therefore, it appears that VCFs are attracted to patents that may yield higher returns (i.e. higher quality patents) but such effect lessens once calculations about the *ex-ante* valuation of the firm come in place. Note that such finding can be informative for the relevance of forward citations as a measure of economic patent value.

additional mile in the distance between the target firm and the closest investor increases the total amount of financing by approximately 0.03 percent.[63]

The density of VCFs and patents in a 10 mile radius positively influences only the first round level of financing and not the second. We find these results particularly interesting because proximity effects appear to matter when firms are younger and less so when firms are more developed and experienced; a finding that sides with previous evidence that less established firms tend to benefit the most from proximity effects (McCann & Folta, 2011). These results imply that DBFs in early stages of development benefit from proximity effects but as they mature, performance benefits from access to local knowledge are not as pronounced. Finally, the density of universities in an MSA does not appear to influence the accumulation of venture capital funds of DBFs in the region in either round of financing.

Our control variables indicate that older firms receive more funds at the first round of financing and that year to year variations have only limited explanatory power in the amount of venture capital funds raised by firms. Similarly, the interaction term included in the analysis (granted patents * universities in the MSA) was not a statistically significant regressor.

Robustness Checks

To check the robustness of our results we construct a number of additional models whose results we present in Table 4.

Our main estimates rely on a sample of firms that received venture capital investments. But if these firms were more likely to receive funds from other firms in the first place, then our estimates could suffer from selection bias. Along the same lines, for the empirical model of round 2, we focus the analysis on firms that received such funds but if these firms differ from remaining firms, the estimates, again, could be biased. To address these issues we construct two Heckman selection models where for the model of round 1 in the first stage we model the probability that a

[63] This result is shaped, in some part, by the geographic distribution of VCFs and DBFs in our sample. Most of the firms in our sample source funds from VCFs located within walking distance and half of the firms receive funds from VCFs located less than 20 miles away (Tables 1a and 1b). As such, the average distance between target firms and VCFs reported in Tables 1a and 1b (398 and 345 per round) is inflated somewhat by a small number of observations where East/West coast VCFs fund West/East coast DBFs in which typically larger VCFs provided significant amounts of finance to target firms across the country. Consequently, while statistically significant, the effect of the *DistanceClosestVCF* is expected to have a small overall economic effect for the majority of firms in our sample.

firm receives venture capital and in the second stage we conduct the baseline analysis. In the selection model for round 2, we first model the probability that a firm receives second round financing and then analyze the factors that influence the amount it receives in that round. In the set of regressors we include variables such as patents, founder's status and receipt of government grants that have been previously shown to affect the chances of receiving venture capital and to influence the chances a firm receives second round investment (Kaplan & Strömberg, 2004a; Lerner, 1999a; MacMillan, Siegel, & Narasimha, 1986). To source the sample of firms that had not received venture capital funds we relied on proprietary data from InKnowVation reflecting all biotechnology firms that had won grants from the Small Business Innovation Research (SBIR) program from 1983 to 2006.[64] The dataset included firm-specific information such as patents and year of foundation as well as an indicator of whether or not the SBIR winner firms had received venture capital investments, with the majority of those firms not having received funds from VCFs.[65] As shown in Models 1 and 2 of Table 4, the results remain nearly identical in magnitude, sign and statistical significance to our baseline estimates of Tables 2 and 3 and indicate that any potential selection bias does not materially change our estimates.

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[64] The dataset included all life science winners. In order to identify the biotechnology firms we performed a keyword search on the business description of all the firms. The list of biotechnology keywords was constructed after consulting with biotechnology researchers employed at the authors' institutions and included almost 400 keywords with about 100 of them characterizing the vast majority of the firms in the dataset (Kolympiris, Kalaitzandonakes, & Miller, 2014). These keywords included glycosylation, oligo-nucleotide, mutation, antigen, recombinant allergens, biofiltration, glycosylation, Bacillus thuringiensis, polymerase chain reaction (PCR), chondrocyte differentiation, biosynthesis, recombinant enzymes, genetic engineering, stem cells, bioprocessing, genetic, biotic stress, genetic parameters, chimeraplasty, introgression, biomedicine, reverse transcriptase, glycoprotein, directional cloning, western blot, combinatorial biocatalysis, arabidopsis, gene (DNA) sequencing.

[65] Instead of using the age variable in the first stage of the Heckman model we use the year of foundation. We do so because for the age variable to be meaningful in our application we need to model the probability that a firm receives venture capital investment within a specific period of time. However, by definition, such period of time does not exist for firms that did not receive venture capital investments. More to the list of variables we use for the selection equation, we employ only granted patents as our measure of patent activity in the first stage because a number of recipient firms received the award before 2001 and as such the full list of submitted applications is not available from the USPTO (and hence from our data source, InKnowVation). The selection of the remaining variables we employ to construct the first stage of the Heckman model is guided, primarily, by findings of previous literature. To illustrate, for the round 1 selection equation we include the SBIR and the location dummies based on the findings that a. SBIR winners are more likely to attract venture capital funds (Lerner, 1999) and b. that firms located in Massachusetts or California are more likely to attract funds (Lerner, 1999). The relationship of those factors with the amount of venture capital raised in the first round has not been replicated in the existing literature. As such, we consider these factors as relevant for the first and not for the second stage of the Heckman model. Factors for which empirical evidence is scarce but we theorize are relevant for both stages (e.g. *FounderSignal*) are included in both stages. Finally, note that even when different groups of variables are included in the selection equation, the results remain largely unchanged.

Table 4. Model 1. Estimated coefficients from the Heckman Selection Model of the first round of financing. The Dependent Variable is the natural log of the amount of venture capital funds invested by a biotechnology firm for the first round of financing.

Variable code	Coefficient	Standard Errors	
Intercept	12.28935	0.2292	***
PATENTApp_1	0.0880	0.0444	**
PATENTGrant_1	-0.0672	0.0466	
PATENTCiteYear_1	-0.0620	0.1327	
GrowthStage_1	0.4441	0.1396	***
VCFReputation_1	0.0003	0.0001	
FounderSignal	0.3861	0.0329	***
SyndicateInvestors_1	0.2291	0.1408	***
SyndicateSize_1	0.0004	0.0001	***
DistanceClosestVCF	0.0010	0.0081	***
UniversitiesInMSA	0.0082	0.0024	
VCFarea_0010_1	0.0026	0.0030	***
VCFarea_1020_1	0.0008	0.0004	
PATENTarea_0010_1	-0.0002	0.0007	**
PATENTarea_1020_1	0.0822	0.0206	
AGE1	0.3745	0.0834	***
INTERACTION_1	-0.0029	0.0116	
Year Dummy Variables Included	YES		
Heckman First Stage			
Intercept	-125.9853	99.4313	
SBIR	-7.1722	96.0078	
STATE	-0.1698	0.1350	
FounderSignal	0.3076	0.1516	**
PATENTGrants	0.0017	0.0023	
VCFarea_0010_1	0.0102	0.0028	***
VCFarea_1020_1	0.0110	0.0029	***
Founded	0.0659	0.0130	***
Inverse Mills Ratio	-0.1673	0.0952	
Number of Obs	1,680		
Censored Obs	1,094		
Uncensored Obs	586		
Multicollinearity Condition Number, Stage 2	27.27		
Multicollinearity Condition Number, Stage 1	4.21		
Wald Chi^2 (25)	417		

** Significant at 5%. *** Significant at 1%.

Table 4 continued. Model 2. Estimated coefficients from the Heckman Selection Model of the second round of financing. The Dependent Variable is the natural log of the amount of venture capital funds invested by a biotechnology firm for the first round of financing.

Variable code	Coefficient	Standard Errors	
Intercept	13.6456	0.5493	***
PATENTApp_1	0.0315	0.0486	
PATENTGrant_1	0.0513	0.1053	
PATENTApp_2	-0.0012	0.0403	
PATENTGrant_2	0.0154	0.1023	
PATENTCiteYear_1	-0.1105	0.1425	
PATENTCiteYear_2	0.0730	0.1024	
VCF_Investment_1	0.0269	0.0052	***
GrowthStage_2	0.0578	0.0725	
VCFReputation_1	-0.1286	0.2191	
FounderSignal	0.0409	0.2376	
SyndicateInvestors_2	0.3290	0.0273	***
SyndicateSize_2	0.0006	0.0001	***
DistanceClosestVCF	0.0002	0.0001	***
UniversitiesInMSA	0.0133	0.0080	
VCFarea_0010_2	0.0004	0.0024	
VCFarea_1020_2	0.0037	0.0030	
PATENTarea_0010_2	0.0001	0.0004	
PATENTarea_1020_2	0.0002	0.0007	
AGE2	0.0063	0.0204	
INTERACTION_2	-0.0031	0.0101	
Year Dummy Variables Included	YES		
Heckman First Stage			
Intercept	0.1277	0.1095	
STATE	0.2978	0.0899	***
PATENTGrant_1	-0.0583	0.0327	
FounderSignal	0.4220	0.1421	***
GrowthStage_2	-0.2435	0.0546	***
VCFreputation_1	0.5146	0.1099	***
USD_Independent_1	0.0014	0.0024	
Inverse Mills Ratio	-0.4524	0.5755	
Number of Obs	783		
Censored Obs	289		
Uncensored Obs	494		
Multicollinearity Condition Number, Stage 2	13.40		
Multicollinearity Condition Number, Stage 1	6.75		
Wald Chi2 (25)	320 ***		

** Significant at 5%. *** Significant at 1%.

Table 4 continued. Model 3. Estimated coefficients for the model of the first round of financing from 1974 to 2011 without patent applications. The Dependent Variable is the natural log of the amount of venture capital funds invested by a biotechnology firm for the first round of financing.

Variable code	Coefficient		Heteroskedasticity robust standard errors		Standard errors clustered at the state level	
Intercept	11.8688		0.1562	***	0.2305	***
PATENTGrant_1	-0.0505		0.0520		0.0528	
PATENTCiteYear_1	0.0661		0.0810		0.0563	
GrowthStage_1	0.3599		0.0716	***	0.0668	***
VCFReputation_1	0.1455		0.0976		0.1303	
FounderSignal	0.5348		0.1062	***	0.0940	***
SyndicateInvestors_1	0.3599		0.0274	***	0.0322	***
SyndicateSize_1	0.0004		0.0001	***	0.0002	***
DistanceClosestVCF	0.0003		0.0001	***	0.0001	***
UniversitiesInMSA	-0.0002		0.0057		0.0058	
VCFarea_0010_1	0.0088		0.0019	***	0.0016	***
VCFarea_1020_1	0.0025		0.0022		0.0027	
PATENTarea_0010_1	0.0007		0.0003	**	0.0003	**
PATENTarea_1020_1	0.0000		0.0005		0.0005	
AGE1	0.0379		0.0125	***	0.0129	***
INTERACTION_1	0.0032		0.0024		0.0024	
Year Dummy Variables Included			YES			
R^2	0.3924					
Adjusted R^2	0.3708					
F-test for overall model significance			16.97	***	398	***
Multicollinearity Condition Number	12.65					
X^2 for Breusch-Pagan test for heteroskedasticity	11.78	***				
Observations	1,051					

** Significant at 5%. *** Significant at 1%.

Table 4 continued. Model 4. Estimated coefficients for the model of the second round of financing from 1974 to 2011 without patent applications. The Dependent Variable is the natural log of the amount of venture capital funds invested by a biotechnology firm for the second round of financing.

Variable code	Coefficient		Heteroskedasticity robust standard errors		Standard errors clustered at the state level	
Intercept	12.9011		0.1589	***	0.1784	***
PATENTGrant_1	0.0403		0.0423		0.0395	
PATENTGrant_2	0.0237		0.0359		0.0388	
PATENTCiteYear_1	-0.0149		0.0779		0.0280	
PATENTCiteYear_2	-0.0006		0.0266		0.0694	
VCF_Investment_1	0.0294		0.0058	***	0.0052	***
GrowthStage_2	0.0162		0.0490		0.0309	
VCFReputation_1	-0.0584		0.0971		0.1051	
FounderSignal	0.4793		0.1103	***	0.1274	***
SyndicateInvestors_2	0.2440		0.0170	***	0.0185	***
SyndicateSize_2	0.0007		0.0001	***	0.0001	***
DistanceClosestVCF	0.0002		0.0001	***	0.0001	***
UniversitiesInMSA	0.0095		0.0050		0.0041	**
VCFarea_0010_2	0.0036		0.0018	**	0.0009	***
VCFarea_1020_2	0.0044		0.0021	**	0.0029	
PATENTarea_0010_2	0.0002		0.0003		0.0002	
PATENTarea_1020_2	0.0005		0.0005		0.0006	
AGE2	0.0231		0.0117	**	0.0054	
INTERACTION_2	-0.0004		0.0009		0.0010	
Year Dummy Variables Included			YES			
R^2	0.4198					
Adjusted R^2	0.3933					
F-test for overall model significance			15.55	***	412	***
Multicollinearity Condition Number	11.615					
X^2 for Breusch-Pagan test for heteroskedasticity	27.36	***				
Observations	918					

** Significant at 5%. *** Significant at 1%.

Table 4 continued. Model 5. Estimated coefficients for the model of the first round of financing without outliers on patent applications. The Dependent Variable is the natural log of the amount of venture capital funds invested by a biotechnology firm for the first round of financing.

Variable code	Coefficient		Heteroskedasticity robust standard errors		Standard errors clustered at the state level	
Intercept	12.3063		0.2617	***	0.4150	***
PATENTApp_1	0.1515		0.0669	**	0.0428	***
PATENTGrant_1	-0.0710		0.0517		0.0490	
PATENTCiteYear_1	-0.0869		0.0793		0.0866	
GrowthStage_1	0.3608		0.0971	***	0.0766	***
VCFReputation_1	0.2313		0.1287		0.1670	
FounderSignal	0.4621		0.1375	***	0.1133	***
SyndicateInvestors_1	0.3863		0.0371	***	0.0555	***
SyndicateSize_1	0.0003		0.0001	***	0.0002	
DistanceClosestVCF	0.0003		0.0001	***	0.0001	***
UniversitiesInMSA	0.0015		0.0080		0.0101	
VCFarea_0010_1	0.0086		0.0023	***	0.0029	***
VCFarea_1020_1	0.0031		0.0029		0.0032	
PATENTarea_0010_1	0.0008		0.0004	**	0.0004	
PATENTarea_1020_1	-0.0002		0.0007		0.0007	
AGE1	0.0725		0.0231	***	0.0225	***
INTERACTION_1	-0.0055		0.0120		0.0072	
Year Dummy Variables Included			YES			
R^2	0.4144					
Adjusted R^2	0.3842					
F-test for overall model significance			15.09	***	114.78	***
Multicollinearity Condition Number	13.35					
X^2 for Breusch-Pagan test for heteroskedasticity	13.99	***				
Join test of significance PATENTApp_1 & PATENTGrant_1	3.68	***				
Observations	582					

** Significant at 5%. *** Significant at 1%.

Table 4 continued. Model 6. Estimated coefficients for the model of the second round of financing without outliers on patent applications from the first and second round of financing. The Dependent Variable is the natural log of the amount of venture capital funds invested by a biotechnology firm for the second round of financing.

Variable code	Coefficient		Heteroskedasticity robust standard errors		Standard errors clustered at the state level	
Intercept	13.1415		0.2599		0.2922	
PATENTApp_1	0.0640		0.0885		0.0571	
PATENTGrant_1	0.0724		0.1133		0.1303	
PATENTApp_2	0.0348		0.0703		0.0614	
PATENTGrant_2	-0.0122		0.1116		0.1214	
PATENTCiteYear_1	-0.1296		0.0709		0.0718	
PATENTCiteYear_2	0.0678		0.0517		0.0616	
VCF_Investment_1	0.0313		0.0068	***	0.0067	***
GrowthStage_2	0.0274		0.0706		0.0554	
VCFReputation_1	0.0176		0.1369		0.1368	
FounderSignal	0.2235		0.1483		0.1830	
SyndicateInvestors_2	0.3286		0.0292	***	0.0409	***
SyndicateSize_2	0.0006		0.0001	***	0.0001	***
DistanceClosestVCF	0.0002		0.0001	***	0.0001	
UniversitiesInMSA	0.0103		0.0079		0.0075	
VCFarea_0010_2	0.0019		0.0021		0.0014	
VCFarea_1020_2	0.0042		0.0026		0.0030	
PATENTarea_0010_2	0.0002		0.0003		0.0003	
PATENTarea_1020_2	0.0002		0.0006		0.0006	
AGE2	-0.0010		0.0213		0.0161	
INTERACTION_2	-0.0032		0.0091		0.0098	
Year Dummy Variables Included			YES			
R^2	0.4291					
Adjusted R^2	0.3915					
F-test for overall model significance			11.12	***	308	***
Multicollinearity Condition Number	13.33					
X^2 for Breusch-Pagan test for heteroskedasticity	9.5	***				
Join test of significance PATENTApp_2 & PATENTGrant_2	0.35					
Observations	485					

** Significant at 5%. *** Significant at 1%.

Table 4 continued. Model 7. Estimated coefficients for Pooled Regression. The Dependent Variable is the natural log of the amount of venture capital funds invested by a biotechnology firm in the first or second round of financing.

Variable code	Coefficient	Standard Errors	
Intercept	13.5865	0.9747	***
R1_Dummy	-0.2388	0.0718	***
R1_PatentApp	0.0896	0.0329	**
PATENTApp	-0.0459	0.0187	**
R1_PatentGrant	-0.0285	0.0316	
PATENTGrant	-0.0053	0.1143	
PATENTCiteYear	0.0073	0.0657	
GrowthStage	0.0749	0.0760	
SyndicateInvestors	0.3286	0.0265	***
SyndicateSize	0.0004	0.0000	***
VCFarea_0010	0.0503	0.0217	**
VCFarea_1020	0.0180	0.0494	
PATENTarea_0010	-0.0072	0.0016	***
PATENTarea_1020	-0.0022	0.0011	***
AGE	-0.0123	0.0043	**
INTERACTION	-0.0013	0.0043	
Year Dummy Variables Included	YES		
R^2 Within	0.2979		
R^2 Between	0.0988		
R^2 Overall	0.1047		
Rho	0.80		
Multicollinearity Condition Number	42.23		

** Significant at 5%. *** Significant at 1%.

Table 4 continued. Model 8. Estimated coefficients for the model of the second round of financing without patent activity measures of financing round one. The Dependent Variable is the natural log of the amount of venture capital funds invested by a biotechnology firm for the second round of financing.

Variable code	Coefficient		Heteroskedasticity robust standard errors		Standard errors clustered at the state level	
Intercept	13.1200		0.2576	***	0.2839	***
PATENTApp_1	-		-		-	
PATENTGrant_1	-		-		-	
PATENTApp_2	0.0045		0.0348		0.0278	
PATENTGrant_2	0.0459		0.0332		0.0260	
PATENTCiteYear_1	-		-		-	
PATENTCiteYear_2	0.0526		0.0557		0.0278	
VCF_Investment_1	0.0265		0.0066	***	0.0260	***
GrowthStage_2	0.0283		0.0705		0.0586	
VCFReputation_1	0.0530		0.1366		0.1268	
FounderSignal	0.2376		0.1453		0.1714	
SyndicateInvestors_2	0.3332		0.0284	***	0.0384	***
SyndicateSize_2	0.0006		0.0001	***	0.0001	***
DistanceClosestVCF	0.0002		0.0001	***	0.0001	**
UniversitiesInMSA	0.0137		0.0075		0.0080	
VCFarea_0010_2	0.0009		0.0021		0.0014	
VCFarea_1020_2	0.0041		0.0026		0.0029	
PATENTarea_0010_2	0.0003		0.0003		0.0003	
PATENTarea_1020_2	0.0003		0.0006		0.0006	
AGE2	0.0006		0.0211		0.0165	
INTERACTION_2	-0.0027		0.0044		0.0040	
Year Dummy Variables Included			YES			
R^2	0.4340					
Adjusted R^2	0.4013					
F-test for overall model significance			11.74	***	91.47	***
Multicollinearity Condition Number	13.34					
X^2 for Breusch-Pagan test for heteroskedasticity	9.41	***				
Join test of significance PATENTApp_2 & PATENTGrant_2	1.08					
Observations	496					

** Significant at 5%. *** Significant at 1%.

Table 4 continued. Model 9. Estimated coefficients for the model of the second round of financing including only the variables that measure granted patents for the first and second round of investment. The Dependent Variable is the natural log of the amount of venture capital funds invested by a biotechnology firm for the second round of financing.

Variable code	Coefficient		Heteroskedasticity robust standard errors		Standard errors clustered at the state level	
Intercept	13.1035		0.2579	***	0.2814	***
PATENTApp_1	-		-		-	
PATENTGrant_1	0.0568		0.0926		0.1097	
PATENTApp_2	-		-		-	
PATENTGrant_2	0.0045		0.0924		0.1042	
PATENTCiteYear_1	-0.1060		0.0899		0.0873	
PATENTCiteYear_2	0.0696		0.0506		0.0642	
VCF_Investment_1	0.0268		0.0068	***	0.0068	***
GrowthStage_2	0.0344		0.0707		0.0594	
VCFReputation_1	0.0534		0.1376		0.1298	
FounderSignal	0.2372		0.1459		0.1784	
SyndicateInvestors_2	0.3318		0.0275	***	0.0355	***
SyndicateSize_2	0.0006		0.0001	***	0.0001	***
DistanceClosestVCF	0.0002		0.0001	***	0.0001	**
UniversitiesInMSA	0.0122		0.0077		0.0078	
VCFarea_0010_2	0.0012		0.0021		0.0014	
VCFarea_1020_2	0.0041		0.0026		0.0029	
PATENTarea_0010_2	0.0003		0.0003		0.0003	
PATENTarea_1020_2	0.0003		0.0006		0.0006	
AGE2	0.0025		0.0210		0.0163	
INTERACTION_2	-0.0003		0.0070		0.0076	
Year Dummy Variables Included			YES			
R^2	0.4375					
Adjusted R^2	0.4036					
F-test for overall model significance			11.88	***	171.60	***
Multicollinearity Condition Number	13.24					
X^2 for Breusch-Pagan test for heteroskedasticity	9.22	***				
Observations	494					

** Significant at 5%. *** Significant at 1%.

Table 4 continued. Model 10. Estimated coefficients for the model of the first round of financing without the patent activity and citation measures. The Dependent Variable is the natural log of the amount of venture capital funds invested by a biotechnology firm for the first round of financing.

Variable code	Coefficient		Heteroskedasticity robust standard errors		Standard errors clustered at the state level	
Intercept	12.2724		0.2616	***	0.4192	***
PATENTApp_1	-		-		-	
PATENTGrant_1	-		-		-	
PATENTCiteYear_1	-		-		-	
GrowthStage_1	0.3721		0.0972	***	0.0794	***
VCFReputation_1	0.2142		0.1299		0.1667	
FounderSignal	0.4250		0.1366	***	0.1152	***
SyndicateInvestors_1	0.3940		0.0372	***	0.0559	***
SyndicateSize_1	0.0003		0.0001	***	0.0002	
DistanceClosestVCF	0.0003		0.0001	***	0.0001	***
UniversitiesInMSA	0.0028		0.0079		0.0098	
VCFarea_0010_1	0.0085		0.0023	***	0.0028	***
VCFarea_1020_1	0.0030		0.0028		0.0031	
PATENTarea_0010_1	0.0008		0.0004	**	0.0004	
PATENTarea_1020_1	-0.0002		0.0007		0.0007	
AGE1	0.0800		0.0228	***	0.0229	***
INTERACTION_1	-0.0135		0.0119		0.0077	
Year Dummy Variables Included			YES			
R^2	0.4072					
Adjusted R^2	0.3830					
F-test for overall model significance			16.82	***	106.30	***
Multicollinearity Condition Number	13.23					
X^2 for Breusch-Pagan test for heteroskedasticity	12.37	***				
Observations	586					

** Significant at 5%. *** Significant at 1%.

Table 4 continued. Model 11. Estimated coefficients for the model of the second round of financing without the patent activity and citation measures. The Dependent Variable is the natural log of the amount of venture capital funds invested by a biotechnology firm for the second round of financing.

Variable code	Coefficient		Heteroskedasticity robust standard errors		Standard errors clustered at the state level	
Intercept	13.1349		0.2552	***	0.2843	***
PATENTApp_1	-		-		-	
PATENTGrant_1	-		-		-	
PATENTApp_2	-		-		-	
PATENTGrant_2	-		-		-	
PATENTCiteYear_1	-		-		-	
PATENTCiteYear_2	-		-		-	
VCF_Investment_1	0.0266		0.0067	***	0.0067	***
GrowthStage_2	0.0316		0.0702		0.0594	
VCFReputation_1	0.0515		0.1363		0.1266	
FounderSignal	0.2457		0.1448		0.1713	
SyndicateInvestors_2	0.3324		0.0271	***	0.0351	***
SyndicateSize_2	0.0006		0.0001	***	0.0001	***
DistanceClosestVCF	0.0002		0.0001	***	0.0001	**
UniversitiesInMSA	0.0123		0.0074		0.0081	
VCFarea_0010_2	0.0010		0.0021		0.0014	
VCFarea_1020_2	0.0041		0.0026		0.0029	
PATENTarea_0010_2	0.0002		0.0003		0.0002	
PATENTarea_1020_2	0.0003		0.0006		0.0006	
AGE2	0.0034		0.0206		0.0161	
INTERACTION_2	0.0014		0.0038		0.0033	
Year Dummy Variables Included			YES			
R^2	0.4325					
Adjusted R^2	0.4036					
F-test for overall model significance			13.27	***	71.68	***
Multicollinearity Condition Number	13.14					
X^2 for Breusch-Pagan test for heteroskedasticity	9.22	***				
Observations	496					

** Significant at 5%. *** Significant at 1%.

Table 4 continued. Model 12. Estimated coefficients for the model of the first round of financing. The number of forward citations is replaced by the patent family. The Dependent Variable is the natural log of the amount of venture capital funds invested by a biotechnology firm for the first round of financing.

Variable code	Coefficient		Heteroskedasticity robust standard errors		Standard errors clustered at the state level	
Intercept	12.2782		0.2613	***	0.4182	***
PATENTApp_1	0.0753		0.0305	**	0.0289	**
PATENTGrant_1	-0.0717		0.0510		0.0480	
PATENTFamilySize_1	-0.0009		0.0030		0.0030	
GrowthStage_1	0.3610		0.0978	***	0.0759	***
VCFReputation_1	0.2329		0.1280		0.1657	
FounderSignal	0.4552		0.1378	***	0.1206	***
SyndicateInvestors_1	0.3885		0.0371	***	0.0547	***
SyndicateSize_1	0.0003		0.0001	***	0.0002	
DistanceClosestVCF	0.0004		0.0001	***	0.0001	***
UniversitiesInMSA	0.0019		0.0080		0.0101	
VCFarea_0010_1	0.0084		0.0023	***	0.0028	***
VCFarea_1020_1	0.0028		0.0028		0.0032	
PATENTarea_0010_1	0.0008		0.0004	**	0.0004	
PATENTarea_1020_1	-0.0002		0.0007		0.0007	
AGE1	0.0772		0.0226	***	0.0227	***
INTERACTION_1	-0.0048		0.0121		0.0076	
Year Dummy Variables Included			YES			
R^2	0.4124					
Adjusted R^2	0.3851					
F-test for overall model significance			15.18	***	118.88	***
Multicollinearity Condition Number	13.38					
X^2 for Breusch-Pagan test for heteroskedasticity	13.80	***				
Join test of significance PatentApp_1 & PATENTGrant_1	3.68	**				
Number of observations	586					

** Significant at 5%. *** Significant at 1%.

Table 4 continued. Model 13. Estimated coefficients for the model of the second round of financing. The number of forward citations is replaced by the patent family. The Dependent Variable is the natural log of the amount of venture capital funds invested by a biotechnology firm for the second round of financing.

Variable code	Coefficient		Heteroskedasticity robust standard errors		Standard errors clustered at the state level	
Intercept	13.0800		0.2749	***	0.3049	***
PATENTApp_1	0.0130		0.0571		0.0557	
PATENTGrant_1	0.0083		0.1033		0.1194	
PATENTApp_2	0.0086		0.0360		0.0273	
PATENTGrant_2	0.0443		0.1038		0.1101	
PATENTFamilySize_1	0.0053		0.0062		0.0057	
PATENTFamilySize_2	-0.0009		0.0034		0.0033	
VCF_Investment_1	0.0270		0.0069	***	0.0080	***
GrowthStage_2	0.0632		0.0768		0.0760	
VCFReputation_1	0.0723		0.1388		0.1239	
FounderSignal	0.1817		0.1494		0.1774	
SyndicateInvestors_2	0.3147		0.0282	***	0.0389	***
SyndicateSize_2	0.0006		0.0001	***	0.0001	***
DistanceClosestVCF	0.0002		0.0001	***	0.0001	**
UniversitiesInMSA	0.0094		0.0085		0.0115	
VCFarea_0010_2	0.0013		0.0022		0.0017	
VCFarea_1020_2	0.0035		0.0027		0.0033	
PATENTarea_0010_2	0.0002		0.0003		0.0003	
PATENTarea_1020_2	0.0006		0.0006		0.0006	
AGE2	-0.0059		0.0224		0.0174	
INTERACTION_2	-0.0004		0.0078		0.0080	
Year Dummy Variables Included			YES			
R^2	0.4322					
Adjusted R^2	0.3906					
F-test for overall model significance			9.37	***	254	***
Multicollinearity Condition Number	13.67					
X^2 for Breusch-Pagan test for heteroskedasticity	10.19	***				
Join test of significance PatentApp_2 & PATENTGrant_2	0.36					
Number of observations	494					

** Significant at 5%. *** Significant at 1%.

Our analysis uses data from 2001 to 2011 because it is in this period that both granted patents and patent application statistics are available from USPTO (granted patents are available for earlier years). Nevertheless, focusing solely on that period may mask differential effects that took place on earlier periods. Given that our data source on venture capital investments goes back to 1974, in Models 3 and 4 of Table 4 we present the results of empirical specifications that include only granted patents as the measure of patent activity and include observations that reflect investments that took place from 1974 to 2011 inclusive. Importantly, these specifications do not directly test our hypotheses because only one of the two patent activity measures we employ is, by definition, available. The goal of these specifications is to check whether the insignificance of the granted patents variables holds when we extend the period of analysis. Indeed, in accordance with the main results presented in Tables 1 and 2, granted patents have no effect neither on the first round investment level nor on the second round investment level. As well, inferences from the remaining regressors are similar to those in the baseline results.

As seen in Tables 1a and 1b a small cohort of firms had a number of patents and patent applications that surpassed the average patent activity of the firms in the dataset. In Models 5 and 6 we test how these outlier observations impact our baseline results by re-estimating the models of Tables 2 and 3 using data that omits these observations from the analysis.[66] By and large, the results agree with the estimates of Tables 2 and 3 that patent activity carries a signalling value that diminishes once the hidden quality of the DBFs is better approximated by the VCFs. A noteworthy result though is that the coefficient of the *PatentApp_1* variable doubles in magnitude. We find this result particularly interesting because it implies that for firms with average patent activity the signalling value of patent applications is even more pronounced than the corresponding value for emerging DBFs with above average patent activity.

In Model 7 we pooled the data for the first and the second round together to construct a pooled regression model that controls for firm and year fixed effects. The dependent variable in that model is the amount raised in a given investment round and the right-hand side variables are round-specific. Then, we include a dummy variable that takes the value of 1 if the observation corresponds to first round investment and 0 otherwise. To test for the impact of patent activity on venture capital growth we add an interaction term that is the product of the number of patent applications and the dummy variable previously described.[67] The marginal effect of *PatentApp_1*[68] indicates that patent activity is conducive to the increase of funds for the first round and negatively affects the level of the second round funds. This result suggests that unobserved firm-specific time

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[66] Specifically, for the model of round 1 we omitted 4 firms that had more than 10 patent applications before round 1. These same firms were omitted from the analysis of round 2. Additionally, for round 2, we omitted 5 firms that had 10 or more patent applications between the two rounds. Therefore, in total we omitted 9 firms from the analysis. The results remained nearly identical even when we omitted firms with more than 5 patent applications.

[67] We also interact the round 1 dummy with granted patents but the corresponding coefficient is not statistically significant. We do not include that interaction term in the analysis because the multicollinearity index of the model including both interaction terms increases to levels that create inference concerns.

[68] The marginal effect is the first derivative of the amount of funds raised with respect to the number of patent applications. Employing the estimated coefficients, the marginal effect of patent applications can then be calculated as $-0.2388 * D - 0.0459 + 0.0896 * D$ where D equals 1 for observations in the first round and 0 otherwise.

constant features can determine whether the overall trend of patent activity serving a signalling role that diminishes over time holds for a specific firm.

To test the robustness of our estimates to the elevated correlation coefficient between the two variables that measure granted patents between rounds, in Models 8 and 9 we present estimates from i) a model that includes only patent activity measures after round 1 and ii) a model that includes only the two variables that are correlated (*PatentGrant_1* and *PatentGrant_2*). Along the same lines, in models 10 and 11 we test whether the influence of the control variables is sensitive to the inclusion of the patent activity measures by constructing round 1 and round 2 models that include only the control variables. We draw two main conclusions from models 8 to 11. First, the influence of the control variables remains largely unchanged regardless of the inclusion of the patent activity variables. Second, the patent activity variables do not appear to be significantly affected by the correlation in question. Accordingly, we conclude that our main findings in the baseline models are robust.

Finally, to test the sensitivity of our estimates to the (economic) patent value indicator we use in the baseline estimates, in Models 12 and 13 we replace the forward citations variables with variables that measure the average INPADOC[69] family size of each patent owned by the focal firms. Patents in the same patent family typically protect the same (set of) invention(s) in different jurisdictions. Patents that are then part of broad patent families are expected to have a higher economic value as the applicant has chosen to accrue additional costs for protection in multiple jurisdictions (Fischer & Leidinger, 2013; Harhoff et al., 2003; Lanjouw, Pakes, & Putnam, 1998). The results in Models 12 and 13 are nearly identical to the baseline estimates and show that under alternative proxies of economic patent value our main conclusions remain intact.

Conclusion and Discussion

A long stream of research has documented the positive effects that patents bring about to firms. The general consensus is that patents contribute to firm growth and survival because they confer monopolistic market rights, offer protection from competitors and enhance the negotiating position of patent holders. What has received relatively less attention in this literature is that patents can

[69] INPADOC, which stands for International Patent Documentation Center, is a patent information database that is maintained by the European Patent Office and contains cross-referenced data on patents gathered from national patent offices worldwide. The data to construct the variable were obtained from Thomson Innovation.

act as a signal to attract investors and capital. These types of effects are particularly important to emerging firms in knowledge intensive industries where long research cycles, scientific complexities and strict regulatory regimes make the development of a track record for newly established firms difficult. In this context, signals that convey firm potential and quality can be particularly relevant. A handful of empirical studies that have taken up the issue in the past have shown that knowledge intensive firms which hold granted patents or have patent applications are more likely to receive larger venture capital investments faster. Out of these studies only few have demonstrated that the reported results reflect signalling effects and only one has indicated that such signalling effects wane with time. As such, the dynamics of signalling effects have not been investigated in any significant depth, and little is known about whether the signalling function of patents diminishes over time. In this study, we shed new light on the signalling function of patents in attracting investors by examining the strength of the signalling effects of patent activity in sequential rounds of financing for small biotechnology firms. By extension, the overarching contribution of the present study is to be among the first to study the dynamics of signals.

Employing data from more than 580 U.S.-based dedicated biotechnology firms, we examine whether the patent activity (granted patents and patent applications) of small biotechnology firms increases the amount of venture capital funds raised by such firms during their first and second round of financing. Our empirical results strongly corroborate theoretical expectations that patent activity before the first round of financing increases the capital invested in a firm. However, as firms mature and information asymmetries between them and investors decrease, the signalling value of patent activity diminishes and it does not affect the level of funds raised in the second round of financing. We also find that patent applications rather than granted patents have a more significant signalling role. This finding potentially reflects the notion that patent applications offer a stronger signal than patents perhaps because they convey information that young emerging firms are further developing due to the learning curve associated with the patent acquisition process. Investments that are directed towards later firm growth stages are also associated with higher amounts of capital investments. Finally, we find that the amount of venture capital funds raised by small biotech firms is also influenced by certain characteristics of the investors, such as size and syndication, as well as by proximity effects that allow firms to source knowledge from nearby institutions.

Our study has both scholarly and policy implications. For instance, we quantify the signalling value of patent activity and we find that, on average, an additional patent application is associated with an increase of approximately $557,333 in the amount of venture capital funds raised in the first round of financing by small biotech firms. This estimate is generally robust to various model specifications that address potential bias that can result from focusing solely on firms that receive venture capital investments and to alternative empirical designs. Importantly, this $557,333 valuation complements existing studies which estimate the value of patents but do not take into account the value of their signalling effect in attracting capital (Gambardella et al., 2008). The same finding however, has also important policy implications. Concerns have been frequently raised about the current status of the patenting system and about the degree it might hinder innovation, especially by placing young innovative firms at a disadvantage (Kingston, 2001). Our findings, however, suggest that the signalling value of patent activity not only exceeds the typical direct costs of patent acquisition manifold but it can also improve the access of small innovative firms to capital during early stages of financing, exactly when such firms lack a track record and information about their potential is less available. It is therefore clear, that any discussion about the value of patents for small innovative firms and for firm strategy should include such considerations. More specifically, the case can be made that due to the signalling value of patent activity, emerging firms who opt out of using it may be more inclined to reconsider their strategy. Accordingly, if these kinds of firms are fetched back to the patent system they could provide additional income to the patent authorities which could then potentially address common patent system issues such as backlogging of applications via hiring qualified examiners, providing employee bonuses and the like.

Given these policy and firm-specific implications, of direct interest is then the applicability of our results to industries other than biotechnology and to countries other than the US. With regard to applicability to other industries, we generally expect our findings to hold for emerging firms in industries that, like biotechnology, are prone to information asymmetries due to long research or development cycles with uncertain research and commercial outcomes that make quality signals useful. To corroborate these expectations, indeed, there is some limited empirical evidence suggesting that patents are positively associated with increases in venture capital in a number of such industries (Cao & Hsu, 2011) and in some countries outside the US (Baum & Silverman, 2004; Engel & Keilbach, 2007).

There are several ways that our work can be extended. First, in depth analysis of the dynamics of signals, not confined to patents, seems promising especially given the dearth of research on the topic (Higgins et al., 2011). Such research can, for instance, analyze the factors that influence the strength and effectiveness of signals. These factors include transmission mechanisms and the *a priori* credibility of the signal transmitter. Second, a straightforward extension of the present work would be to track the growth of the firms who successfully transmit signals in order to evaluate the long term effects of signalling. Third, a potentially qualitative analysis could directly identify the firm-specific factors that can influence how strong is the overall trend of the diminishing signalling value of patents for a given firm. Fourth, the dynamics of proximity effects on capital investment uncovered in this study may be worth further attention. Proximity effects were found to have a positive impact on the venture capital funds of small biotech firms only during the first round of financing when firms were in the early stages of development. It is therefore possible that knowledge spillovers from agglomeration and associated pecuniary effects may be stronger for smaller firms early in their innovation cycle. Such dynamic effects are not broadly researched in the agglomeration literature and it may be a worthwhile follow-up research topic.

To conclude, we note that our study is not without limitations. For instance, to account for the venture capital funds provided to a firm in exchange of equity in the firm we employ a variable that reflects the firm growth stage that venture capital funds are directed to and a variable that reflects the reputation of the investors. While we expect these variables to indeed be suitable proxies, data limitations do not allow us to use sharper measures such as the actual equity level secured by the investors, which could yield more refined estimates. Along the same lines, assessing proprietary firm-specific information about (unsuccessful) patent applications before 2001 could provide further insights by expanding the time period of the analysis. Finally, based on a large body of empirical work we employ forward citations and patent family size to capture the economic value of patents. However, by design, proxies are imperfect measures. As such, it is possible that the economic value of a given patent is not fully accounted for in our models. Direct inquires to the venture capital firms we study with regard to the economic value they ascribed to the sample patents would address the issue. But, such endeavor is prohibitively difficult in large part because a significant part of the investments we study took place more than a decade ago.

Chapter 5. Geographic Distance between Venture Capitalists and Target Firms and the Value of Quality Signals[70]

[70] This chapter is based on:
Kolympiris, C., Hoenen, SJ., Kalaitzandonakes, N (2017) *Geographic distance between venture capitalists and target firms and the value of quality signals*, Industrial and Corporate Change

Introduction

Signalling theory builds on the premise that signals, defined as purposely sent costly pieces of information, partly reveal unobserved characteristics of the sender to an interested receiver. Credible signals, then, which are too costly to pursue for lesser quality actors, ease transacting by allowing the receiver to place more confidence on the unobserved quality of the sender and thus reduce the negative effects of information asymmetries (Amit et al., 1990a; Connelly, Certo, Ireland, & Reutzel, 2011; Spence, 1973).[71] Precisely because the main function of signals is to increase the confidence receivers place on the senders in the face of information asymmetries, signals should not only be more likely to occur in the presence of high uncertainty (Roberts & Khaire, 2009), but they should also carry a higher value for receivers in environments of elevated information asymmetries (Janney & Folta, 2003).

Indeed, there is empirical support for that expectation. Stuart, Hoang, and Hybels (1999) find that signals, in the form of prominent alliance partners, are effective in transactions that involve young firms with limited track records. Janney and Folta (2006) conclude that signals, in the form of private placements of equity, are more relevant for those young firms that are subject to higher uncertainty. Park and Mezias (2005) show that the stock market relies more heavily on alliances as signals when the level of industry uncertainty is high. Arthurs, Busenitz, Hoskisson, and Johnson (2009), in the context of initial public offerings, report that the higher the uncertainty surrounding a given firm, the more effective the signals it transmits. Finally, Hsu and Ziedonis (2013) and Hoenen, Kolympiris, Schoenmakers, and Kalaitzandonakes (2014) find that the signalling function of patent activity is more effective in inducing venture capital investments for early rounds of financing, when information asymmetries between venture capitalists and target firms are elevated.

Prior studies, then, have contextualized the level of information asymmetries and have approximated the value receivers ascribe to signals by studying the age of the sender, the uncertainty of its environment and the degree of familiarity between senders and receivers. However, little attention has been paid to an additional transactional characteristic that can

[71] Extended literature demonstrates the effectiveness of signals in communicating value to customers, investors, potential employees and possible alliance partners (e.g. Chung & Kalnins, 2001; Cohen & Dean, 2005; Davila et al., 2003; Higgins & Gulati, 2006; Mishra et al., 1998; Ozmel, Reuer, & Gulati, 2012).

significantly determine the degree of information asymmetries between transacting parties and can ultimately shape the value receivers place on signals: the geographic distance between the sender and the receiver of the signal.

Information asymmetries increase with distance (Coval & Moskowitz, 1999; Ivkovic & Weisbenner, 2005; Portes, Rey, & Oh, 2001). It is therefore important to know whether the value receivers ascribe to signals also increases with the distance between two transacting parties, and we examine this question in this study. Because knowledge is sticky and hence difficult to move across space (von Hippel, 1994), the marginal cost of knowledge transmission is an increasing function of distance. This explains why larger distances may discourage the transmission of (tacit) knowledge (Audretsch, 1998) and could lead to increases in information asymmetries. Given that the costs of signalling do not typically vary with geographic distance, signals may be even more relevant and valuable for transactions between geographically distant parties.

To study this proposition, we analyze two signals often employed by emerging knowledge-intensive firms that can lack a track record: patent activity, including patent applications and granted patents, and the entrepreneurial experience and academic status of firm founders. Using data from first round venture capital investments in 586 U.S-based emerging biotechnology firms from 2001 to 2011, we associate the amount of capital raised by each firm through first round of financing with its patent activity and indicators of serial entrepreneurship and academic excellence among firm founders prior to the investment. Methodologically, to test whether the geographic distance between venture capitalists and the biotechnology firms they invest in conditions the impact of those signals on the firm funding level, we interact the measures of signals with the measures of the distance between the two parties and examine the statistical significance of the combined measure. We also control for many factors that can influence the size of venture capital investment in a given firm, including the market value of patents which arises from the monopoly rights they afford. We therefore first approximate the signalling value of patents and then investigate how such value is affected by the distance between the investor and the recipient. Along the same lines, by separating out the effects of academic and entrepreneurial experience of firm founders we also examine what venture capitalists value most when they invest in firms founded by academics.

Our focus on emerging firms is consistent with the notion that signalling is more important during the early stages of firm growth, when the typical lack of a track record and increased level of information asymmetries make the evaluation of investment targets a thorny task. As such, it is at this stage we expect venture capitalists to place more value to quality signals. We break new ground by examining whether the value that venture capitalists place on signals depends on their distance with target firms. We also complement previous studies that have examined the effect of signals in attracting distant investors in later stages of firm growth where the venture capitalist is already in the firm and the next stepping stone for the company is the attraction of additional investors, often via an initial public offering (Mäkelä & Maula, 2008; Powell, Koput, Bowie, & Smith-Doerr, 2002; Ragozzino & Reuer, 2011).

Relatedly, we contribute to the literature on the function of patents and other forms of intellectual property for attracting firm financing (Block, De Vries, Schumann, & Sandner, 2014; Conti, Thursby, & Thursby, 2013; Greenberg, 2013; Hoenen et al., 2014; Hsu & Ziedonis, 2013). These studies analyze a number of issues, including whether patents act as a signal and whether the signalling function of patents is more pronounced during early stages of firm growth, but do not examine the impact of the geographic distance between agents on the strength and value of the signal. Accordingly, our work improves the understanding of the conditions where patents lead to greater external funding for a given firm. Furthermore, our study offers a novel test on whether patents act primarily as a signal or whether they are valued by their investors mostly for the monopoly rents they can bring about. If patents act mainly as a signal, then we would not expect them to have as significant an impact on venture capital investments in short distance transactions. Locally circulated knowledge about a given firm can reduce the degree of information asymmetries between investors and potential investees (Asheim & Gertler, 2005; Bathelt, Malmberg, & Maskell, 2004; Florida & Kenney, 1988) and hence mitigate the need for signals as well as the value that investors may place on them. In contrast, if patents are valued mostly for the exclusion rights they carry, we would expect them to increase venture capital funding even for investors who allocate funds to nearby firms.

Finally, our work informs the literature on the geography of venture capital investments (Gupta & Sapienza, 1992; Kolympiris et al., 2011; Lutz, Bender, Achleitner, & Kaserer, 2013; Powell et al., 2002; Sorenson & Stuart, 2001). While venture capital firms have a general preference to invest locally (Cumming & Dai, 2010; Powell et al., 2002; Sorenson & Stuart, 2001), here we investigate whether signals can induce larger investments in distant targets at their early stages of firm growth.

We focus on venture capital investments in biotechnology for several reasons. First, biotechnology firms are frequent investment targets of venture capitalists reflecting not only the potential for high returns but also their need for external capital, which is difficult to meet through bank lending and other forms of traditional finance due to inherent risks in the industry (Baum & Silverman, 2004; Gompers & Lerner, 2001). Second, long distance venture capital investments occur in the industry with some frequency. East/West Cost investors fund West/East Coast firms (Powell et al., 2002). Third, the lengthy R&D cycles of biotechnology coupled with strict regulatory regimes prohibit emerging firms from developing an early track record which can approximate future performance. The very same structural characteristics of biotechnology startups lead venture capitalists investing in this industry to often rely on signals (Higgins et al., 2011; Janney & Folta, 2003). All in all, these circumstances suggest that if the value venture capitalists place on signals is influenced by the geographic distance of their potential targets we should be able to detect such an influence in that industry.

We proceed as follows: In section 2, we explore the existing literature and discuss our theoretical expectations. In sections 3 and 4 we discuss the methodology and the dataset of the empirical study. In section 5, we present our empirical results and we conclude in section 6.

How geographic distance can influence the effectiveness of signals

In their most common form, venture capital firms (VCFs) raise funds from institutional investors such as pension funds and university endowments, invest these funds in new ventures that have the potential to yield high returns and, in large part, tie their compensation to the performance of the investment targets (Zider, 1998). Because VCFs seek high returns they tend to invest in relatively young promising companies in knowledge-based industries, such as biotechnology, in which the risks are pronounced but the returns, if realized, can also be considerable (Gompers & Lerner, 2001, 2004).

Mainly because of the long research cycles in biotechnology, firms in this industry rarely have a track record in their early stages of development. Even when these firms are fully aware of their potential, they typically possess private information regarding their quality, which is not easily discerned by the VCFs (Amit, Glosten, & Muller, 1990; Gompers, 1995; Gompers & Lerner, 2004; Sahlman, 1990). In turn, such information asymmetries complicate the investment decisions of VCFs because the problem of adverse selection is ever-present (Akerlof, 1970; Amit et al., 1990a; Mishra et al., 1998).[72] In order to mitigate adverse selection VCFs typically invest in rounds of financing. Under this scheme, funds are provided in separate sequential points in time and financing continues only if firms meet certain, mainly technical, milestones (Gompers, 1995). Information asymmetries between VCFs and target firms are therefore more acute before the first round of financing as VCFs have not previously worked with the firm and the level of familiarity between investors and investees is low. It follows that because first round investments present an environment of exacerbated uncertainty, it is in this round we expect VCFs to place more value to signals. This is why we focus our discussion and subsequent empirical analysis on this round.

To prevent investments in 'lemons' VCFs are highly selective and put substantial time and effort in scouting firms and evaluating the promise of their investments targets (Amit et al., 1990a; Baum & Silverman, 2004). This time and effort is primarily devoted towards assessing the quality of the firm before the first investment takes place. However, in the case of knowledge-based young firms, overall quality and promise are tightly linked to the quality of knowledge supporting their research efforts. Precisely because knowledge quality can be tacit (Johnson, Lorenz, & Lundvall, 2002), the selection process of VCFs can become increasingly difficult when the target firm is at a distance as tacit knowledge is more easily gained when investors and investees are closely located (Coval & Moskowitz, 1999; Foray, 2004; von Hippel, 1994). For this reason, VCFs circulate knowledge about investment targets via networks which are often built on social capital, interpersonal contacts and other spatially bounded means of knowledge transfer (Bygrave, 1988; Florida & Kenney, 1988). It follows that the *ex ante* evaluation of untested target firms that are under consideration for first time investments is generally easier when these firms are located nearby.[73] Spatial proximity assists VCFs in gathering (tacit) knowledge about the target firms and decreases the level of information asymmetries. Indeed, empirical evidence

[72] Uncertain market conditions, complex regulatory regimes and a general scarcity of tangible assets exacerbate the issue (Carpenter & Petersen, 2002c; Gompers & Lerner, 2001). Also note that under certain conditions a firm might have incentives to purposely withhold information, either because private information implicates the entrepreneurial opportunity that it is trying to protect, or because the entrepreneur might want to conceal negative information regarding the quality of the firm (Shane & Cable, 2002; Shane & Venkataraman, 2000).
[73] Note that contrary to other forms of capital infusion, the involvement of VCFs in target firms extends to providing advice, management support and other value-added activities (Sahlman, 1990). Spatial proximity is also relevant for those activities (Lerner, 1995) because it can ease the oversight of the target firms.

indicates that VCFs have a general preference for local investments (Chen, Chu, & Billota, 2011; Cumming & Dai, 2010; Powell et al., 2002; Sorenson & Stuart, 2001; Tian, 2011).[74]

Notwithstanding the general tendency for local investments, VCFs do engage in long distance financing (Powell et al., 2002), especially when the promise of the target firm is significant. In such cases, VCFs use alternative strategies to cope with the associated information asymmetries. Most frequently, for first round investments, but sometimes in later rounds too, VCFs use syndication schemes in which they co-invest with one or more local VCF(s) (Fritsch & Schilder, 2008; Sorenson & Stuart, 2001). Beyond syndication, VCFs may also rely on signals as a way to mitigate the effects of information asymmetries for long distance first round transactions (Busenitz et al., 2005; Toole & Turvey, 2009). Indeed, there is evidence that VCFs are more likely to invest in distant firms in which other VCFs have previously invested (Mäkelä & Maula, 2008; Powell et al., 2002; Ragozzino & Reuer, 2011). This behavior is consistent with the idea that VCFs use signals in distant transactions and indicates the trust VCFs show to the investment choices of their peers. However, little is known about the value placed by VCFs on the *ex ante* signals sent by start-ups prior to first round financing.

All in all, given that receivers of signals place more value to them in environments characterized by increased information asymmetries (Arthurs et al., 2009; Hoenen et al., 2014; Hsu & Ziedonis, 2013; Ozmel et al., 2012; Stuart et al., 1999) we expect signals to be more effective in raising the amount of first round financing for distant transactions when compared to transactions between closely located VCFs and target firms. We build this expectation on the observation that short distance transactions are typically less susceptible to the sort of information asymmetries that underpin most first round investments.

Signals Used by Biotechnology Firms before the First Round of Financing

A relevant question then is which signals are available to biotechnology firms during their early stages of growth and more specifically before the first round of financing? These signals need to satisfy three main conditions. First, they need to be observable and costly to imitate (Spence,

[74] In related evidence outside the venture capital industry, the number of local investments in the portfolio of fund managers is disproportionally large (Coval & Moskowitz, 1999) and fund managers perform better when investing in these local funds (Coval & Moskowitz, 2001).

1973). Second, they need to adequately convey the knowledge available to emerging biotechnology firms since their tangible assets are limited (Hicks, 1995). Third, they need to be valued by VCFs so that they lead to increases in the level of first round of financing.

One way by which biotechnology firms can convey their knowledge is through certain characteristics of their founder(s). Founder characteristics are observable through firm presentations, websites and other information featuring the biographies of the founding team. They are also costly. For instance, the opportunity costs of eminent university professors and other high profile professionals who are often among the founders of biotechnology firms are high (Audretsch & Stephan, 1996; Zucker, Darby, & Brewer, 1998). As such, founder characteristics meet condition 1 described above. Founder characteristics can also convey knowledge because high technology firms at the early development stages often resemble the qualities of their founders (Cooper & Bruno, 1977). Hence, high profile professionals can leverage their reputation to convey the underlying quality of their firms (Bonardo, Paleari, & Vismara, 2011; Certo, 2003) and as such founder characteristics meet condition 2 above. But what kinds of founder characteristics are valued by venture capitalists so that condition 3 is also met? Within the broad literature documenting the effects of founders on firm growth (Ding, 2011; Hannan, Baron, Hsu, & Koçak, 2006; Klepper, 2002; Roberts, Klepper, & Hayward, 2011), a number of studies has shown that VCFs prefer to invest in entrepreneurs with earlier business experience (Gompers et al., 2010; Hsu, 2007; Mueller, Westhead, & Wright, 2012; Wright, Robbie, & Ennew, 1997). This is likely so because experience can help entrepreneurs cope with recurring problems, enhance their ability to spot profitable opportunities and the like (Baron & Ensley, 2006). For academic founders, previous business/entrepreneurial experience may therefore be important (Lockett & Wright, 2005).

VCFs may also value the academic prominence of founders of early stage biotechnology firms as an additional signal of their knowledge. Because of the knowledge-intensive character of biotechnology, the core technological innovations upon which the firms are built often rely on academics (Wright, Vohora, & Lockett, 2004) who are regularly founders of biotechnology firms (Zucker et al., 1998). Importantly, preeminent academic scientists tend to start successful biotechnology firms (Zucker et al., 1998). When considering these observations together with the favorable attitude of VCFs towards firms founded/managed by individuals with high academic achievements (Engel & Keilbach, 2007; Hsu, 2007; Mueller et al., 2012) we conclude that the presence of academics in the founding team, especially eminent ones, may serve as a signal of quality for biotechnology firms with limited track record.

Patent activity is yet another signal that biotechnology firms can use. Patent information is freely available from public sources but patents themselves are costly to acquire and maintain (Graham et al., 2009). Hence, patents conform to the basic characteristics of a signal. But do patents convey knowledge and are they valued by VCFs? A number of studies have demonstrated that VCFs are attracted to firms with patent activity (Audretsch et al., 2012; Conti et al., 2013a; Engel & Keilbach, 2007; Hoenen et al., 2014; Hsu & Ziedonis, 2013). Patents also convey knowledge for two main reasons: First, they represent inventions and innovations (Igami, 2013) which are the outcomes of knowledge development efforts. Second, the patent acquisition process entails interactions with patent examiners so that the prior art of the submitted application is adjusted, and the claims of the patents are clarified and placed within the context of existing technologies and innovations. As such, the patent application process compels firms to keep up to date with the latest scientific developments in rapidly evolving fields such as biotechnology, enhance their knowledge and refine their technology development strategies.

In sum, we expect patent activity, as well as the entrepreneurial experience and academic prominence in the founding team to act as signals that can help firms to increase their first round of investment as they are costly, observable, they transmit knowledge and they are valued by venture capitalists. We expect these signals to be more effective and valuable in long distance transactions because it is in these types of transactions that information asymmetries are elevated and hence venture capitalists place more value to signals.

Methods

To test whether signals are more effective and valuable for long distance transactions between VCFs and biotechnology firms we build econometric models in which the level of funding raised during the first round of financing is regressed on variables that measure patent activity and founding team characteristics prior to the investment. To explicitly test the impact of geographic distance on the effectiveness of these signals in stimulating larger investments, we include a variable that measures the distance between the VCF and the target firm and we interact this variable with the signals we study. We expect the interaction terms to be positive, indicating that signals are more valuable for long distance transactions.

Formally, the model takes the following form:

$$\ln(Y_i) = X_i\beta + \varepsilon \tag{1}$$

where the dependent variable Y_i is the natural logarithm of the amount of funds received by the focal firm i in the first round of venture capital funding, X_i is the design matrix including the variables we discuss below and the βs are the associated coefficients.

The first signal we study is patent activity which we measure with the patent applications submitted by the firms in our sample prior to the first round financing they received and with the patents granted to the firms during the same period. More specifically, following previous works that constructed patent variables in the same way (e.g. Czarnitzki, Ebersberger, & Fier, 2007; Toole & Czarnitzki, 2007) each of the two measures takes the value of 1 if the firm had applied for a patent or was granted a patent before the investment occurred and 0 otherwise. [75] [76]

The reason we employ two measures of patent activity is that the signal transmitted by granted patents can be meaningfully different than the signal transmitted by patent applications. For instance, throughout the examination process patent applications may signal a firm that is not sitting idle but it updates its knowledge and extends its experience by revising the claims of the patent, populating the list of prior art with new references, and refining its innovation strategy. These are important considerations since knowledge in biotechnology is continuously updated and breakthroughs may come from newer discoveries at any time (see Humphries, 2010; McNamee & Ledley, 2012 for specific examples). As such, new knowledge development is crucial and patent

[75] To avoid double-counting if an application is granted patent rights before the first round of financing, we measure only the granted patent as a measure of patent activity and not the application.

[76] Originally we used the count of patents and applications as our measures of patent activity. However, constructing the interaction terms using the counts and including them in the empirical specifications increased the multicollinearity index well above the safe threshold of 30 and hence raised inference concerns. When we measured patent activity with dummy variables (and constructed the interaction terms) the index dropped significantly to below 30. Importantly, the dummy variables are roughly equivalent to continuous measures of patent activity as the latter are heavily left skewed with the vast majority of the firms having no patent activity. As such, we opt to use the dummy variables because they lead to lower multicollinearity indices, and, hence higher confidence in inference. Still, in section 5.2 we present estimates from models omitting from the analysis firms with inflated records of patent activity. The results are qualitatively similar to the baseline estimates we present in Table 3. Alternatively, we could omit certain control variables in order to reduce the multicollinearity index. That option raises significant concerns on the interpretation of our findings due to omitted variable bias. Such bias is particularly relevant in our application as teasing out the signaling function of patents is challenging mainly because a host of factors can explain the growth of venture capital funds for a given firm.

applications may capture such a process more effectively than granted patents. Instead, granted patents can signal a firm that has developed original knowledge and has gone through the patent application process successfully in the past. Conceptually, then, we expect granted patents to approximate the knowledge a company has already developed and owns while patent applications to approximate the knowledge a company is developing. It is interesting to note that there is empirical evidence which reinforces the potential for differential signalling function of granted patents and patent applications. Specifically, a few studies have shown that patent applications are more effective than granted patents in shortening the time that venture capitalists invest in a firm and in increasing the amount of funds invested (Baum & Silverman, 2004; Haeussler, Harhoff, & Muller, 2014; Hoenen et al., 2014).

Because we are interested in the signalling value of patent activity, we need to account for the market value of monopoly rights that patents offer, which can also attract investors and raise the amount of invested capital. Estimating with precision the market value that patent monopoly rights can bring about is a difficult task partly because the true market value of an invention is often unobservable and, if observed, it is difficult to attribute solely to the patent that protects the invention. A setting in which patent market value can be closely approximated is at patent auctions where patents are traded between interested parties. This setting is appropriate not only because the auction price is observed but also, and perhaps more importantly, because what is traded is only the patent and not its owner. Accordingly, it is unlikely that the signalling function of granted patents drive their auction prices. Crucially, the price paid for a patent in such auctions correlates strongly with an observed feature of the patent: the number of times the patent is cited by later patents (forward citations) (Fischer & Leidinger, 2014; Odasso, Scellato, & Ughetto, 2014; Sneed & Johnson, 2009). Based on this evidence, and with an eye on previous works demonstrating the relevance of forward citations as a measure of patent value (e.g. Gambardella et al., 2008; Harhoff et al., 2003), we employ forward citations as a measure of the economic value of a patent. Because older patents have a longer time frame to gather forward citations we measure forward citations per year.

The second signal we examine is the entrepreneurial experience and academic standing of the founding team. We employ two different empirical specifications to more extensively test their potential impacts. Specification 1 employs the signal used in Hoenen et al. (2014). In particular, we approximate the academic standing and business experience of the founding team with a dummy variable that takes the value of 1 if a member of the founding team has high academic standing and/or earlier experience in founding a firm (*Foundersignal*). In Specification 2 we use two separate measures to characterize the standing of the founding team. The first measure, *Entrepreneurialsignal,* indicates whether one of the members of the founding team has previously started a firm.[77] The second measure, *Academicsignal,* assumes increasing values with the highest academic rank held by members of the founding team and ranges from 0 to 5 with 0 indicating that there is no academic in the founding team, 1 through 4 indicate increasing professorial standing (a lecturer, an assistant, an associate and a full professor) while 5 indicates that a member of the founding team holds a distinguished and/or named professorship and/or is a member of the Academy of Sciences and/or has won a Nobel Prize.

To test our expectation that signals are more valuable for long distance transactions we include an additional variable which measures (in logarithmic form) the distance between the funding VCF and the target firm (for syndicate investments we measure the distance to the closest VCF).[78] We then interact the distance variable with the signal measures described above and expect a positive sign for these interaction terms.

Control Variables

The design matrix X in equation 1 above includes a number of control variables which can influence the level of first round financing each firm receives.[79] Each VCF investment that a firm receives is proportional to the valuation of the firm *ex ante* and the equity level the VCFs collects. It follows that we need to account for both of those factors but finding direct measures for such factors is empirically challenging. As such, we use two separate indicators that can approximate

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[77] Alternatively, it could be argued that serial entrepreneurs have more access to venture capital because a VCF might be more willing to engage in repeated interactions with an entrepreneur, because private information regarding the entrepreneur is gained in earlier investment. However, in general the frequency of such repeated interactions is relatively low (Bengtsson, 2013; Wright et al., 1997).

[78] We do not expect distance to have a linear effect on the effectiveness of signals. For instance, a move from the 5th to the 6th mile should not have the same meaning as a move from, say, the 1005th to the 1006th mile even though in both cases the change (1 mile) is the same. This is why we use the natural log of distance. To calculate the distances we use the straight distance formula (arcos(sin(lat1).sin(lat2)+cos(lat1).cos(lat2).cos(long2−long1)) ×3963). For the (short) distances that we look at, the straight line distance closely resembles the driving distance but unlike the driving distance, it does not change over time due to newly constructed roads and other residential developments. This is relevant for our application because we study transactions that spread over a decade and, hence, need comparable distances across time. In cases where more than one VCF invested in the focal firm we measure the distance to the closest VCF because in syndication schemes the closest VCF typically assumes most of the oversight and consulting roles (Ferrary, 2010; Fritsch & Schilder, 2012) .

[79] Additional discussion on the impact of certain control variables included in our model on venture capital funding is presented in some of previous work (Hoenen et al., 2014).

the conceptual variables. Specifically, we first include dummy variables (*seed, early,* and *expansion*) that correspond to the growth stage of the firm when the VCF investment took place.[80] Because the valuation of firms, *ex ante,* increases with the stage of firm growth (Cumming & Dai, 2011) these indicators should approximate firm valuation. Importantly, early and later stage investments by VCFs are also associated with different equity levels acquired (Beaton, 2010; Kaplan & Strömberg, 2003). As such, the dummy indicators should be correlated with the amount of equity secured by VCFs. Given the increased valuation of firms at later stages of firm growth, we expect a positive sign for the indicators representing later stages of firm growth. We also construct a second indicator to approximate the level of equity VCFs receive for their investments. Because VCFs with stronger reputation typically receive larger equity than investors with weaker reputation for similar investments (Hsu, 2004) we also include a variable that reflects the Lee et al. (2011) reputation score of the highest ranked funding VCF of the first round of financing (*VCFreputation*).

The availability of funds from the VCFs may also influence the amount invested in the first round of financing, overall. Because such availability is often largely determined by the number of investors that spread the risks of their investments (i.e. by the syndication size) (Lockett & Wright, 2001) as well as by the capital available to the investors (Gupta & Sapienza, 1992; Tian, 2011) we include two variables that measure the number of investors as well as their average size (*SyndicateInvestors, SyndicateSize*), and expect positive signs for both coefficients.

We also include the age of the focal firm at the round of financing (*Age*) as a control variable in the model. We do not form strong priors with regard to the direction the age of firms can move the amount of funds received because VCFs may evaluate positively older firms due to higher experience and survival but they may also view negatively older firms that have not received previous financing.

To incorporate in the analysis year-to-year variations, such as “hot IPO market” periods (Lowry & Schwert, 2002), that can encourage or discourage venture capital investments at an aggregate level we include in our empirical models a set of year dummies that match with the year in which the investment took place. We do not form expectations for the signs of their coefficients.

[80] Seed stage funds are typically small amounts directed primarily towards proving a concept. Early stage funds are directed mainly towards product development. Funds directed towards the expansion stage are used, in large part, to boost market entry or strengthen R&D (Jeng & Wells, 2000). There are also funds directed towards later stage financing, such as buy-outs or acquisitions.

Agglomeration externalities (e.g. knowledge spillovers and network effects) can also help biotechnology firms improve their performance and thus increase their funding levels (Coenen et al., 2004; Döring & Schnellenbach, 2006; Gittelman, 2007; Kolympiris et al., 2011). To account for such effects we include the following variables in the model: a) *UniversitiesInMSA* which measures the number of universities that perform biotechnology related research and are located in the same Metropolitan Statistical Area as the focal firm and b) several indicators that measure the density of VCFs (*VCFarea 0010*, *VCFarea 1020)* and the number of patents granted to biotechnology firms (*PATENTarea 0010*, *PATENTarea 1020*) within 0–10 and 10–20 miles from the origin firm, respectively. We expect positive signs for the corresponding coefficients.

Data Sources and Presentation

To conduct the analysis we started by sourcing all venture capital first round investments by independent VCFs in dedicated biotechnology firms from 2001 up to 2011[81] using Thomson Reuter's SDC Platinum Database (SDC). In the remaining part of this section, we focus on the variables we employ in our empirical models as shown in Table 1.

[81] We start our analysis in 2001 because before then the United States Patent and Trademark Office (USPTO) did not publish patent applications. Also note that the dataset does not include investments from corporate venture capital. As well, while SDC reports the total amount invested in each round, it does not report the round investment per venture capital firm. As such, we cannot weight the distance to the closest VCF by the amount it invested. While this issue does not hold for the majority of the sample firms because they received first round investment only from one VCF (see Table 1), the finding that in syndicated investments the closest VCF is typically the one conducting the main scouting for investment targets (Fritsch & Schilder, 2012) alleviates concerns about the effect of this non-weighting on the estimated parameters.

Table 1. Descriptive Statistics of Selected Variables Used in the Empirical Models.

Variable Description	N	MEAN	STD. DEV	MIN.	MEDIAN	MAX.	MODE
Investment size	586	7.21	11.04	0.001	3.56	100.00	1.00
Patent applications	66						
Granted patents	32						
Forward citations	586	0.06	0.44	0.00	0.00	6.83	0.00
Founder signal	119						
Entrepreneurial signal	61						
Academic signal[1]	**d=0**	**d=1**	**d=2**	**d=3**	**d=4**	**d=5**	
	445	5	4	9	49	74	
Distance between firm and closest VCF	586	398.49	747.92	0.00	20.63	3146.00	0.01
Seed	248						
Early	246						
Expansion	78						
Firm age	586	2.54	3.12	0.00	1.37	27.73	0.00
VCF reputation	586	0.36	0.45	0.00	0.00	1.00	0.00
Syndicate investors	586	2.61	1.84	1.00	2.00	13.00	1.00
Syndicate size	586	366.99	616.60	0.00	75.47	4155.00	0.00
Number of universities located in the MSA	586	9.30	8.09	0.00	9.00	37.00	17.00
Density of VCFs in 0 to 10 miles from the firm	586	23.46	29.36	0.00	10.00	103.00	1.00
Density of VCFs in 10 to 20 miles from the firm	586	15.21	25.37	0.00	5.00	127.00	0.00
Number of patents granted to biotechnology firms located 0 to 10 miles from the firm	586	126.55	155.87	0.00	61.00	531.00	0.00
Number of patents granted to biotechnology firms located 10 to 20 miles from the firm	586	69.73	115.16	0.00	18.00	608.00	1.00

[1]The variable takes the value of 0 if none of the founding team members had an academic title, 1 if a member of the founding team is an instructor or lecturer, 2 if a member of the founding team is an assistant professor, 3 if a member of the founding team is an associate professor, 4 if a member of the founding team is a full professor, 5 if a member of the founding team holds a distinguished and/or named professorship and/or is a member of the Academy of Sciences and/or has won a Nobel Prize.
Note: 64 observations in 2001, 60 observations in 2002, 52 observations in 2003, 49 observations in 2004, 66 observations in 2005, 74 observations in 2006, 78 observations in 2007, 63 observations in 2008, 33 observations in 2009, 39 observations in 2010 and 8 observations in 2011

The sample we employ draws upon Hoenen et al. (2014).[82] As noted above, a noteworthy change from Hoenen et al. (2014) is that in Specification 2 we use a sharper way to account for the signalling function of the founding team as we decompose the *Foundersignal* variable into two separate indicators: *EntrepreneurialSignal* and *AcademicSignal.* We collected the data for both of these variables by visiting the websites of the sample firms.

[82] The main finding from that study was that having applied for a patent increased the level of first round of financing for biotechnology firms by 7.7 percent while patent activity had no impact on the level of funds raised during the second round of financing.

In total, the dataset includes 586 first round venture capital investments in 586 biotechnology firms. As shown in *Table* 1 the average distance between the recipient firms and the closest VCFs investing in such firms is 400 miles. Given that almost half of the observations are within a 20 miles threshold level (median: 20.63) the sample average is influenced by a small number of firms that received investments from VCFs located across the country. On average, the sample firms received $7.2 million in the first round of financing which was realized for half of the firms when they were less than 1.3 years old. The average $7.2 million investment is, however, inflated by few firms that attracted significantly more funds than the rest (e.g. the modal value is $1million).

With regards to the signals we study, the vast majority of the firms did not have any patent activity before the first round of financing. 66 firms had applied for at least one patent and 32 were granted at least one patent before the investment.[83]

The *Foundersignal* indicates that 1 out of 5 firms had at least one member in the founding team with entrepreneurial experience and/or with academic standing. In particular, approximately 1 out of 10 founders had earlier entrepreneurial experience while a sizeable portion of sample firms were (co)founded by academicians, a small share of which of preeminent status. Most founding teams, however, did not include an academic or a serial entrepreneur.

As it pertains to the regional environment, on average, a firm in the sample was surrounded by high patent activity and 39 VCFs located within a 20 miles radius. Figure 1 explains, in large part, these statistics as it shows that the majority of the sample firms were located in traditional biotechnology clusters of the East and West Coast of the United States. Nevertheless, a meaningful share of the firms was located outside the traditional biotechnology hubs in locations such as Austin, TX and Boulder, CO. This latter observation implies that our results are not specific to the traditional biotech clusters.

[83] The heavy representation of firms without patent activity in the sample supports our empirical choice to employ corresponding dummy variables. More specifically, 531 firms did not have any applications, 29 firms had 1 application, 9 firms had 2 applications, 14 firms had between 2 and 7 applications and 2 firms had 10 and 13 applications respectively. Granted patents had a similar left skewed distribution as well. The fact that the sample includes firms with varying degrees of patent activity is relevant in that it mitigates potential concerns of overstressing the significance of patents that could result from the tendency of better firms to patent more and generally better protect their intellectual property assets (Helmers & Rogers, 2011).

Figure 1. Location of biotechnology firms in the sample

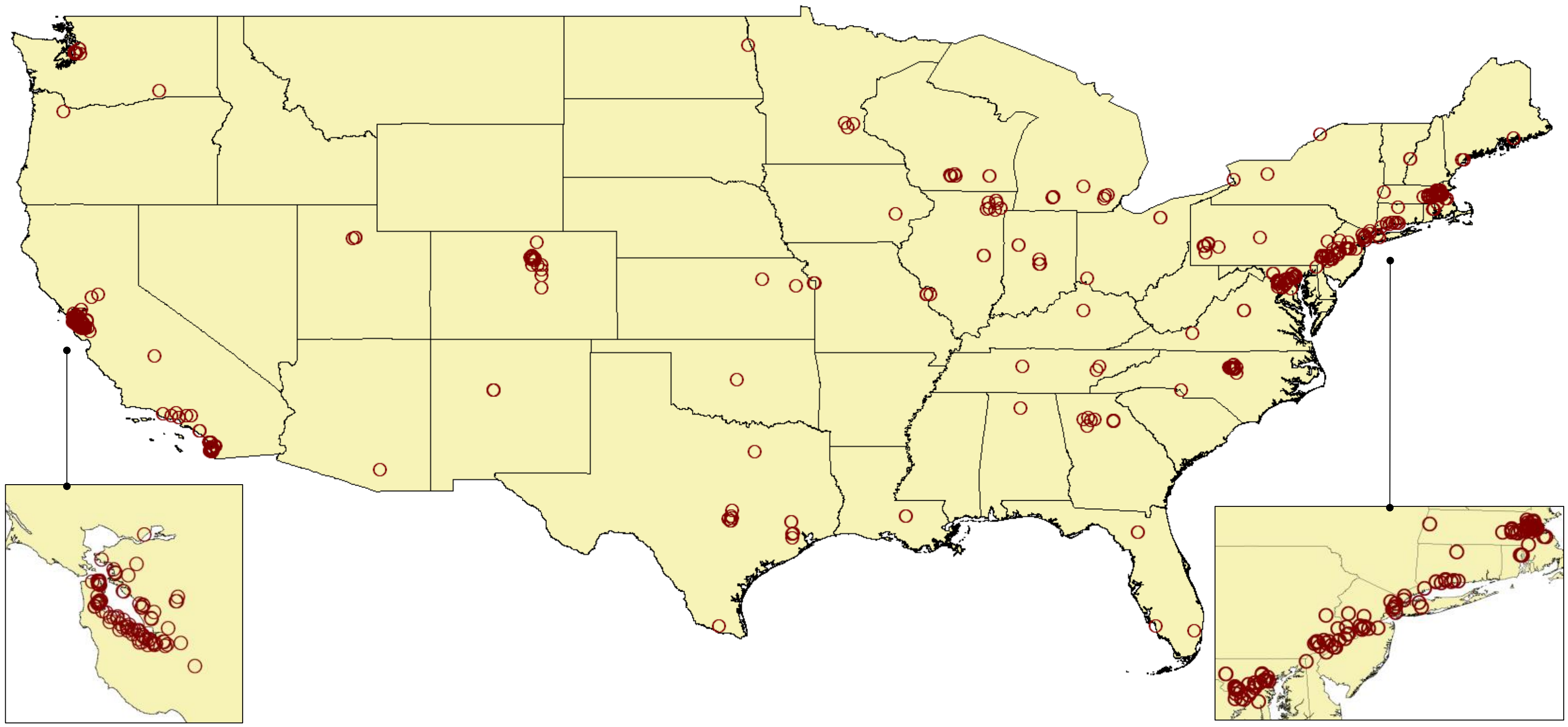

Table 2. Correlation matrix for variables used in the analysis

		1	2	3	4	5	6	7	8	9	10	11	12
Patent applications	1	1.00											
Granted patents	2	0.22	1.00										
Founder signal	3	-0.03	0.03	1.00									
Academic signal	4	-0.02	0.00	0.62	1.00								
Entrepreneurial signal	5	-0.02	0.02	0.68	0.14	1.00							
Distance between firm and closest VCF	6	0.10	0.07	0.00	-0.06	0.04	1.00						
Distance between firm and closest VCF * Patent applications	7	*0.81*	0.24	-0.04	-0.02	0.01	0.28	1.00					
Distance between firm and closest VCF * Granted patents	8	0.12	*0.50*	0.09	0.08	-0.01	0.13	0.17	1.00				
Distance between firm and closest VCF * Founder signal	9	-0.02	0.06	*0.79*	0.44	0.60	0.24	0.01	0.15	1.00			
Distance between firm and closest VCF * Academic signal	10	0.02	0.04	0.47	*0.75*	0.13	0.25	0.07	0.16	0.61	1.00		
Distance between firm and closest VCF * Entrepreneurial signa	11	0.02	0.05	0.56	0.10	*0.83*	0.19	0.05	0.01	0.74	0.20	1.00	
Forward citations	12	0.08	0.59	0.01	-0.02	0.02	0.02	0.11	0.27	0.04	0.01	0.04	1.00
Seed	13	-0.17	-0.13	0.01	0.03	-0.01	-0.13	-0.15	-0.04	0.00	0.02	-0.05	-0.10
Early	14	0.04	-0.05	0.02	0.01	0.03	0.01	-0.01	-0.07	-0.02	-0.04	0.02	0.00
Expansion	15	0.19	0.26	-0.05	-0.05	-0.03	0.15	0.22	0.17	0.03	0.03	0.03	0.16
Firm age	16	0.34	0.31	-0.02	-0.01	-0.03	0.19	0.35	0.24	0.05	0.06	0.02	0.11
VCF reputation	17	-0.12	-0.08	0.17	0.13	0.12	-0.15	-0.11	-0.03	0.08	0.03	0.05	-0.03
Syndicate investors	18	0.03	-0.01	0.04	0.01	0.10	-0.09	0.03	-0.04	-0.02	-0.07	0.05	-0.06
Syndicate size	19	-0.06	-0.12	0.09	0.10	0.04	0.10	-0.03	-0.06	0.11	0.11	0.05	-0.07
Number of universities located in the MSA	20	-0.02	-0.04	0.03	0.01	-0.01	-0.14	-0.09	-0.08	-0.06	-0.08	-0.06	-0.10
Density of VCFs in 0 to 10 miles from the firm	21	-0.04	-0.07	0.11	0.15	0.01	-0.24	-0.10	-0.07	-0.04	-0.01	-0.07	-0.08
Density of VCFs in 10 to 20 miles from the firm	22	-0.04	-0.02	-0.04	-0.06	-0.02	-0.02	-0.06	-0.04	-0.05	-0.07	-0.03	-0.04
Number of patents granted to biotechnology firms located 0 to 10 miles from the firm	23	0.01	-0.04	0.01	0.09	0.01	0.00	0.00	-0.07	-0.03	0.04	-0.02	-0.01
Number of patents granted to biotechnology firms located 10 to 20 miles from the firm	24	-0.02	-0.04	-0.03	0.00	-0.02	-0.02	-0.04	-0.04	-0.06	-0.03	-0.05	-0.06

Table 2 Continued. Correlation matrix for variables used in the analysis

		13	14	15	16	17	18	19	20	21	22	23	24
Seed	13	1.00											
Early	14	-0.73	1.00										
Expansion	15	-0.34	-0.33	1.00									
Firm age	16	-0.25	-0.08	0.43	1.00								
VCF reputation	17	-0.03	0.12	-0.14	-0.13	1.00							
Syndicate investors	18	-0.16	0.16	0.01	-0.09	0.36	1.00						
Syndicate size	19	0.13	-0.06	-0.13	-0.12	0.28	0.09	1.00					
Number of universities located in the MSA	20	-0.05	0.09	-0.07	0.00	0.06	0.03	0.05	1.00				
Density of VCFs in 0 to 10 miles from the firm	21	0.06	0.01	-0.09	-0.10	0.19	0.11	0.15	0.45	1.00			
Density of VCFs in 10 to 20 miles from the firm	22	-0.07	0.08	-0.02	-0.08	0.09	0.02	0.04	0.20	0.06	1.00		
Number of patents granted to biotechnology firms located 0 to 10 miles from the firm	23	0.03	0.03	-0.08	-0.16	0.12	0.10	0.18	0.03	0.28	0.13	1.00	
Number of patents granted to biotechnology firms located 10 to 20 miles from the firm	24	-0.03	0.04	-0.04	-0.10	0.05	0.02	0.07	0.09	0.25	0.64	0.16	1.00

In Table 2 we present the correlation coefficients for the variables described above. While in general the correlation coefficients assume low values, those between the level terms of the signal variables and the interaction terms between the signals and the distance are high (0.5, 0.75, 0.79, 0.81, 0.83). This suggests that there may be some overlap in the information provided by the level and interaction terms on the dependent variable. As we explain below, this point becomes relevant when we opt to not include the level terms in our baseline specifications.

Results

Baseline Model

Table 3 includes the estimates from the baseline specifications in which we omit the level terms. Model 1 does not include the interaction terms we use to test our theoretical expectations. We include it for comparison purposes to Models 2 and 3, which present the coefficients from Specifications 1 and 2, respectively. We cluster the standard errors at the state level.[84] We do so to account for the possibility that firms located in the same state underperform or overperform jointly due to unobserved state-specific features promoting innovation, such as the quality of entrepreneurial coaching provided by local agencies, and because we expect the distance measures to be more similar among firms in the same state. The F-tests across all empirical models as well as the adjusted R^2 suggest that our empirical models have explanatory power. The multicollinearity condition index is below the generally regarded as safe threshold of 30 (Belsley, Kuh, & Welsch, 1980).

[84] Inference remains unchanged even when we employ White's heteroskedasticity robust standard errors.

Table 3. Baseline Estimates. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing.

			Specification 1	
Model	**Model 1 (No signals)**		**Model 2 (Including founder signal only)**	
Variable	Coefficient	Standard errors	Coefficient	Standard errors
Intercept	13.3103	0.3477 ***	13.2968	0.3714 ***
Distance between firm and closest VCF	0.1016	0.0280 ***	0.0806	0.0299 **
Distance between firm and closest VCF * Granted patents			-0.0129	0.0062 **
Distance between firm and closest VCF * Patent applications			0.0733	0.0188 ***
Distance between firm and closest VCF * Founder signal			0.0981	0.0196 ***
Distance between firm and closest VCF * Academic signal				
Distance between firm and closest VCF * Entrepreneurial signal				
Forward citations	-0.0554	0.0958	-0.0287	0.0835
Seed	-0.9806	0.2483 ***	-0.9299	0.2506 ***
Early	-0.2413	0.1820	-0.2094	0.2052
Expansion	-0.1253	0.3156	-0.0968	0.3078
Firm age	0.0640	0.0231 ***	0.0608	0.0233 **
VCF reputation	0.2904	0.1707	0.2697	0.1623
Syndicate investors	0.3732	0.0547 ***	0.3687	0.0526 ***
Syndicate size	0.0003	0.0001	0.0003	0.0001
Number of universities located in the MSA	-0.0010	0.0102	-0.0004	0.0100
Density of VCFs in 0 to 10 miles from the firm	0.0112	0.0031 ***	0.0110	0.0031 ***
Density of VCFs in 10 to 20 miles from the firm	0.0027	0.0023	0.0030	0.0025
Number of patents granted to biotechnology firms located 0 to 10 miles from the firm	0.0008	0.0004	0.0007	0.0004
Number of patents granted to biotechnology firms located 10 to 20 miles from the firm	0.0008	0.0004	0.0007	0.0004
Year Dummies included	YES		YES	
Obervations	586		586	
Adjusted R^2	0.3997		0.4116	
F test for overall model significance	157.9900 ***		152.1700 ***	
Multicollinearity Condition Index	27.4842		28.0051	

Standard errors are clustered at the state level

* Significant at 5%. ** Significant at 1%.

[1]For model 3, the founder signal in the joint tests of significance refers to the academic and entrepreneurial signal

Table 3 Continued. Baseline Estimates. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing.

	Specification 2					
Model	**Model 3a (Including academic signal only)**		**Model 3b (Including entrepreneurial signal only)**		**Model 3c (Including both entrepreneurial and academic signals)**	
Variable	Coefficient	Standard errors	Coefficient	Standard errors	Coefficient	Standard errors
Intercept	13.2875	0.3616 ***	13.2841	0.3505 ***	13.2781	0.3625 ***
Distance between firm and closest VCF	0.0875	0.0307 ***	0.0881	0.0288 ***	0.0812	0.0315 **
Distance between firm and closest VCF * Granted patents	-0.0120	0.0062	-0.0100	0.0060	-0.0114	0.0061
Distance between firm and closest VCF * Patent applications	0.0656	0.0179 ***	0.0655	0.0186 ***	0.0658	0.0178 ***
Distance between firm and closest VCF * Founder signal						
Distance between firm and closest VCF * Academic signal	0.0129	0.0061 **			0.0106	0.0068
Distance between firm and closest VCF * Entrepreneurial signal			0.0886	0.0280 ***	0.0789	0.0308 **
Forward citations	-0.0165	0.0793	-0.0365	0.0853	-0.0282	0.0792
Seed	-0.9600	0.2412 ***	-0.9169	0.2651 ***	-0.9325	0.2629 ***
Early	-0.2360	0.1943	-0.2045	0.2108	-0.2135	0.2155
Expansion	-0.1228	0.3018	-0.0923	0.3093	-0.1011	0.3111
Firm age	0.0607	0.0227 **	0.0615	0.0230 **	0.0613	0.0230 **
VCF reputation	0.2961	0.1648	0.2961	0.1669	0.2824	0.1649
Syndicate investors	0.3709	0.0537 ***	0.3627	0.0532 ***	0.3668	0.0526 ***
Syndicate size	0.0003	0.0001	0.0003	0.0002	0.0003	0.0001
Number of universities located in the MSA	-0.0003	0.0101	-0.0008	0.0103	-0.0002	0.0101
Density of VCFs in 0 to 10 miles from the firm	0.0110	0.0031 ***	0.0113	0.0032 ***	0.0111	0.0031 ***
Density of VCFs in 10 to 20 miles from the firm	0.0031	0.0024	0.0029	0.0024	0.0031	0.0024
Number of patents granted to biotechnology firms located 0 to 10 miles from the firm	0.0007	0.0004	0.0007	0.0004	0.0007	0.0004
Number of patents granted to biotechnology firms located 10 to 20 miles from the firm	-0.0005	0.0005	-0.0005	0.0005	-0.0005	0.0005
Year Dummies included	YES		YES		YES	
Obervations	586		586		586	
Adjusted R^2	0.4056		0.4073		0.4085	
F test for overall model significance	228.6300 ***		196.6400 ***		225.35 ***	
Multicollinearity Condition Index	28.0077		27.8823		28.1721	

Standard errors are clustered at the state level

* Significant at 5%. ** Significant at 1%.

[1]For model 3, the founder signal in the joint tests of significance refers to the academic and entrepreneurial signal

We first evaluate whether geographic distance influences the value of the *Foundersignal* to VCFs in Model 2 (Table 3). In this model, the slope coefficient associated with distance between the firm and the nearest VCF is allowed to change when founders are eminent and/or have business experience. Based on the fitted model, we find that the coefficient of the interaction term is significantly positive (0.0981), and the marginal effect of distance on VC funding levels more than doubles when the firm's founder is eminent/experienced. Hence, we find empirical support for the hypothesis that geographic distance influences the signalling value of the founding team characteristics, as measured by the *Foundersignal* indicator. This result is also consistent with simple averages as firms that were founded by serial entrepreneurs and/or eminent academics received, on average, $4.2 million more funding than the rest of the firms in our sample.

Next, we evaluate whether the academic standing and previous experience with starting a firm among firm founders have different value as signals and whether they are more effective in raising the amount of first round financing for distant transactions. In Models 3a-3c we use two separate measures to characterize the standing of the founding team: *AcademicSignal* and *EntrepreneurialSignal*. We evaluate the relevance of first for each of these signals separately (in Models 3a and 3b) and then jointly (in Model 3c).

While *AcademicSignal*Distance* is statistically significant and positive (0.0129) in Model 3a, the marginal effect of distance on VC funding levels when the firm's founder has high academic standing does not increase appreciably due to the weak quantitative impact of this signal. In contrast, when we estimate the joint impact of distance and the firm founders' business experience on the VC funding levels, through *EntrepreneurialSignal*Distance* in Model 3b, the result is quite different. Based on the fitted version of this model, we find that the estimated coefficient on this variable is significantly positive (0.088) and the marginal effect of distance on VC funding levels increases by 75% when the firm's founder is a serial entrepreneur. These results are confirmed when both indicators are included in Model 3c as their coefficients remain roughly the same. In addition, the *AcademicSignal* interaction is now statistically not different from zero. Taken together these results suggest that business experience as a signal matters more when the distance between investors and recipients increases while academic prominence does not seem to have such an effect.

In all of the Models 2 and 3, the estimated coefficient on the interaction term between patent applications and distance is significantly positive and varies between 0.0655 and 0.0733 in value. As such, the marginal effect of distance on VC funding levels increases (depending on the model) by 50-70% when the firm has patent applications. The positive and statistically significant coefficient of the interaction term between patent applications and distance is therefore also supportive of the theoretical expectation that the larger the distance, the larger the positive effect of patent applications on the level of venture capital funds received by the firms in the sample.

The interaction term between granted patents and distance in all empirical models (Models 2 and 3) is very small in size and, for the most part, statistically not different from zero. The insignificance of granted patents as a signal is an interesting result, especially since patent applications are found to have signalling value. By definition, applications do not have an exclusion value because patent claims are not finalized until the patent issues. As such, patent applications may be a stronger signal than granted patents because they convey both a learning-by-doing process and a fine-tuning process (Hoenen et al., 2014). The learning-by-doing process refers to the fact that every patent needs to conform to the same criteria of novelty, usefulness and non-obviousness. Accordingly, the more often a firm submits patent applications the more likely it will learn how to satisfy these three criteria. The fine-tuning process refers to the interactions between applicants and patent officers after an application is submitted. Following the initial application, firms learn more about the prior art in their technology development area from communication with the patent examiner, redefine their claims, and overall get exposed to a process that can deepen and update their knowledge. This deepening and updating of knowledge is particularly important in fast evolving industries such as biotechnology where breakthroughs are often the result of the very latest techniques and cutting edge discoveries (see Humphries, 2010; McNamee and Ledley, 2012 for specific examples). Hence, while a granted patent may represent what a firm has learned, an application may better signify what a firm is learning. Given that learning processes are important for fast-evolving industries, patent applications in biotechnology may be a stronger signal because investors value firms that can evolve over time by keeping up with the latest developments in the industry and do not sit idle.

It is worth noting, that the estimated coefficients in Model 3c where all the interaction terms of the signals with distance are included suggest that the marginal effect of distance on VC funding levels increases by 125% when the firm's founder is a serial entrepreneur *and* the firm has patent applications. The individual effects of the two signals are distinct and remain stable across all specifications. Hence, our findings suggest that signals increase the level of venture capital funding primarily in environments where information asymmetries are more pronounced, and hence investors place more value on them, such as when the geographic distance between the VCF and the target firm is extended. For distant target firms, VCFs appear less able to assess the quality of the firm in question (Rosiello & Parris, 2009; Sorenson & Stuart, 2001; Zook, 2002) and as a means to mitigate the effects of the associated increase in information asymmetries they tend to rely on signals transmitted by firms seeking for investments.

Importantly, our findings also shed new light on the ongoing discussion whether patent activity is valued by investors primarily as a signal or as a means to gain monopoly rights (Hoenig & Henkel, 2014). The granted patents signal and the forward citations control proxy for the economic value of patents are statistically insignificant across specifications. Therefore, similar to previous works (Hoenen et al., 2014; Hsu & Ziedonis, 2013) our findings are supportive of the explanation that patents serve, in large part, a signalling function. More to it, if patents were valued more for the exclusion value they carry, then we would expect them to attract investors even in environments of reduced information asymmetries. Short distance investments are an example of such an environment. Yet, what we consistently find is that patent activity does not increase VC investments for short distance transactions, which then provides evidence in favor of a signalling function. Perhaps, what can explain this finding is that specifically for patents covering drug-related inventions (hence the sorts of patents we study), infringements are common (Lanjouw & Schankerman, 2001). Accordingly, while in principle the exclusion value afforded by the monopoly rights of a patent is present, VCFs might be discounting such value in light of potential infringements.

With regards to the control variables we include in the analysis, the results indicate that older firms receive more funds and firms receiving seed stage investments receive less (*firmage and seed*). The number of VCFs in the syndication also increases the amount of investment received by firms in the sample while the reputation of VCFs has no effect. The density of VCFs within a 10 miles radius from the recipient firm increases the level of first round financing for the firms in the sample as well. Finally, several other control variables, including the number of universities in the metropolitan statistical area (MSA) and the density of granted patents, do not affect the level of investments.

Sensitivity Analysis of Baseline Results

The estimated empirical models presented in Table 3 are very stable. The coefficients of all the signal and control variables have been largely unchanged across the various specifications. Still, to further test the robustness of our baseline empirical results we conducted a number of additional sensitivity tests. In Table 4 we present the estimates for these robustness checks only for Specification 2 (model 3c) and we note that the results are qualitatively similar for Specification 1 as well.[85]

Because we rely on a sample of firms that received venture capital investments, our estimates could suffer from selection bias if the sample firms were more likely to receive funds than other firms in the first place. To check whether this potential bias influences our results in sensitivity test 1 we construct a Heckman selection model where in the first stage we model the probability that a firm receives venture capital and in the second stage we conduct the baseline analysis. In the set of regressors in the first stage we include variables such as patents, founder's status and receipt of government grants that have been previously shown to affect the chances of receiving venture capital (Kaplan & Strömberg, 2004; Lerner, 1999; MacMillan et al., 1986). To source the sample of firms that had not received venture capital funds we relied on proprietary data from InKnowVation reflecting all biotechnology firms that had won grants from the Small Business Innovation Research (SBIR) program from 1983 to 2006.

[85] In Hoenen et al. (2014) we demonstrate the robustness of the model without the interaction terms to a number of observations that include a) different time frames of analysis and, b) different measures of patent quality. We obtain similar results when we conduct the same tests here. Along the same lines, on top of the tests we present in section 5.2, we also conducted a) a test where we employ the density of VCFs in a region as an alternative proxy for the existence of environments characterized by strong information asymmetries and b) a test where we replace the minimum distance to the VCF with the average distance (in case of syndicate investments). By and large, our estimates are qualitatively similar to the estimates reported in Table 3.

Table 4. Sensitivity Analysis. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing.

Model	**1 Heckman Selection Model**		**2 Hausman test**	
Variable	Coefficient	Standard errors	Coefficient	Standard errors
Intercept	13.2210	0.3806 ***	12.6878	0.8759 ***
Distance between firm and closest VCF	0.0787	0.0302 ***	0.2069	0.1717
Distance between firm and closest VCF * Granted patents	-0.0107	0.0057	-0.0114	0.0061
Distance between firm and closest VCF * Patent applications	0.0741	0.0175 ***	0.0658	0.0178 ***
Distance between firm and closest VCF * Academic signal	0.0122	0.0068	0.0106	0.0068
Distance between firm and closest VCF * Entrepreneurial signal	0.0724	0.0318 **	0.0789	0.0308 **
Forward citations	-0.0152	0.0708	-0.0282	0.0792
Seed	-0.8591	0.2527 ***	-0.8133	0.2675 ***
Early	-0.1280	0.2222	-0.1811	0.2169
Expansion	0.0108	0.3080	-0.1224	0.3207
Firm age	0.0706	0.0226 ***	0.0473	0.0237
VCF reputation	0.2757	0.1558	0.3796	0.2299
Syndicate investors	0.3678	0.0523 ***	0.3757	0.0591 ***
Syndicate size	0.0003	0.0001	0.0002	0.0001
Number of universities located in the MSA	-0.0005	0.0097	0.0018	0.0096
Density of VCFs in 0 to 10 miles from the firm	0.0110	0.0030 ***	0.0138	0.0053 **
Density of VCFs in 10 to 20 miles from the firm	0.0031	0.0022	0.0033	0.0025
Number of patents granted to biotechnology firms located 0 to 10 miles from the firm	0.0007	0.0003 **	0.0006	0.0005
Number of patents granted to biotechnology firms located 10 to 20 miles from the firm	-0.0005	0.0005	-0.0006	0.0006
First stage residuals of Distance between firm and closest VCF			-0.1257	0.1574
Year Dummies included	YES		YES	
Obervations	586		586	
Adjusted R^2			0.4085	
F test for overall model significance			225.3500 ***	
Multicollinearity Condition Index	28.1721		75.5719	
Wald test for Rho	3.7300			

Standard errors are clustered at the state level

** Significant at 5%. *** Significant at 1%.

Table 4 Continued. Sensitivity Analysis. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing.

Model	3 Regional environment with dummy variables for traditional biotechnology clusters			4 Omit firms with more than four patent applications		
Variable	Coefficient	Standard errors		Coefficient	Standard errors	
Intercept	13.7132	0.4232	***	13.2886	0.3676	***
Distance between firm and closest VCF	0.0534	0.0320		0.0830	0.0316	**
Distance between firm and closest VCF * Granted patents	-0.0119	0.0065	*	-0.0144	0.0059	**
Distance between firm and closest VCF * Patent applications	0.0635	0.0170	***	0.0599	0.0178	***
Distance between firm and closest VCF * Academic signal	0.0123	0.0072	*	0.0108	0.0066	
Distance between firm and closest VCF * Entrepreneurial signal	0.0705	0.0308	**	0.0803	0.0328	**
Forward citations	-0.0488	0.0706		-0.0146	0.0820	
Seed	-0.9327	0.2603	***	-0.9401	0.2621	***
Early	-0.1828	0.2137		-0.2225	0.2157	
Expansion	-0.0654	0.3469		-0.1137	0.3140	
Firm age	0.0557	0.0266	**	0.0597	0.0224	**
VCF reputation	0.3763	0.1806	**	0.2733	0.1654	
Syndicate investors	0.3731	0.0536	***	0.3680	0.0537	***
Syndicate size	0.0003	0.0002	**	0.0003	0.0001	
Number of universities located in the MSA				0.0001	0.0100	
Density of VCFs in 0 to 10 miles from the firm				0.0112	0.0031	***
Density of VCFs in 10 to 20 miles from the firm				0.0031	0.0024	
Number of patents granted to biotechnology firms located 0 to 10 miles from the firm				0.0007	0.0004	
Number of patents granted to biotechnology firms located 10 to 20 miles from the firm				-0.0005	0.0005	
Firm located in Boston	1.1250	0.2584	***			
Firm located in San Francisco	0.3837	0.1303	***			
Firm located in San Diego	0.1341	0.1102				
Year Dummies included	YES			YES		
Obervations	586			578		
Adjusted R^2	0.3779			0.4055		
F test for overall model significance	14.6700 ***			195.5600 ***		
Multicollinearity Condition Index	24.3924			27.9837		

Standard errors are clustered at the state level

** Significant at 5%. *** Significant at 1%.

Table 4 Continued. Sensitivity Analysis. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing.

Model	**4 Omit firms with more than four patent applications**			**5 Omit firms with more that five patent applications**		
Variable	Coefficient	Standard errors		Coefficient	Standard errors	
Intercept	13.2886	0.3676	***	13.2751	0.3633	***
Distance between firm and closest VCF	0.0830	0.0316	**	0.0824	0.0317	**
Distance between firm and closest VCF * Granted patents	-0.0144	0.0059	**	-0.0116	0.0060	
Distance between firm and closest VCF * Patent applications	0.0599	0.0178	***	0.0692	0.0187	***
Distance between firm and closest VCF * Academic signal	0.0108	0.0066		0.0105	0.0070	
Distance between firm and closest VCF * Entrepreneurial signal	0.0803	0.0328	**	0.0799	0.0322	**
Forward citations	-0.0146	0.0820		-0.0144	0.0834	
Seed	-0.9401	0.2621	***	-0.9282	0.2633	***
Early	-0.2225	0.2157		-0.2131	0.2174	
Expansion	-0.1137	0.3140		-0.1013	0.3098	
Firm age	0.0597	0.0224	**	0.0610	0.0230	**
VCF reputation	0.2733	0.1654		0.2759	0.1640	
Syndicate investors	0.3680	0.0537	***	0.3672	0.0525	***
Syndicate size	0.0003	0.0001		0.0003	0.0001	
Number of universities located in the MSA	0.0001	0.0100		-0.0001	0.0101	
Density of VCFs in 0 to 10 miles from the firm	0.0112	0.0031	***	0.0112	0.0031	***
Density of VCFs in 10 to 20 miles from the firm	0.0031	0.0024		0.0031	0.0024	
Number of patents granted to biotechnology firms located 0 to 10 miles from the firm	0.0007	0.0004		0.0007	0.0004	
Number of patents granted to biotechnology firms located 10 to 20 miles from the firm	-0.0005	0.0005		-0.0005	0.0005	
Year Dummies included	YES			YES		
Obervations	578			581		
Adjusted R^2	0.4055			0.4063		
F test for overall model significance	195.5600 ***			231.8600 ***		
Multicollinearity Condition Index	27.9837			28.0500		

Standard errors are clustered at the state level

** Significant at 5%. *** Significant at 1%.

Table 4 Continued. Sensitivity Analysis. The dependent variable is the natural logarithm of the amount of venture capital funding in the first round of financing.

Model	6			7		
	Omit patent activity signal interactions			**Omit academic and entrepreneurial signal interactions**		
Variable	Coefficient	Standard errors		Coefficient	Standard errors	
Intercept	13.2958	0.3639	***	13.3395	0.3389	***
Distance between firm and closest VCF	0.0865	0.0315	***	0.0941	0.0280	***
Distance between firm and closest VCF * Granted patents						
Distance between firm and closest VCF * Patent applications				0.0612	0.0187	***
Distance between firm and closest VCF * Academic signal	0.0089	0.0073				
Distance between firm and closest VCF * Entrepreneurial signal	0.0819	0.0308	**			
Forward citations	-0.0637	0.0925		-0.0722	0.0903	
Seed	-0.9674	0.2688	***	-0.9720	0.2441	***
Early	-0.2256	0.2136		-0.2415	0.1813	
Expansion	-0.1113	0.3263		-0.1396	0.3031	
Firm age	0.0642	0.0238	**	0.0551	0.0229	**
VCF reputation	0.2587	0.1690		0.3066	0.1723	
Syndicate investors	0.3729	0.0529	***	0.3672	0.0538	***
Syndicate size	0.0003	0.0001		0.0003	0.0001	
Number of universities located in the MSA	-0.0003	0.0100		-0.0004	0.0103	
Density of VCFs in 0 to 10 miles from the firm	0.0111	0.0031	***	0.0112	0.0032	***
Density of VCFs in 10 to 20 miles from the firm	0.0030	0.0023		0.0028	0.0024	
Number of patents granted to biotechnology firms located 0 to 10 miles from the firm	0.0008	0.0004		0.0007	0.0004	
Number of patents granted to biotechnology firms located 10 to 20 miles from the firm	-0.0005	0.0005		-0.0005	0.0005	
Year Dummies included	YES			YES		
Obervations	586			586		
Adjusted R^2	0.4045			0.4015		
F test for overall model significance	140.7900	***		142.4600	***	
Multicollinearity Condition Index	27.9250			27.6536		

Standard errors are clustered at the state level

** Significant at 5%. *** Significant at 1%.

The dataset included firm-specific information such as patents and year of foundation as well as an indicator of whether or not the SBIR winner firms received venture capital investments, with the majority of those firms not having received funds from VCFs.[86] The estimates of Heckman selection model remain similar in magnitude, sign and statistical significance to our baseline estimates and indicate that any potential selection bias does not materially change our findings.

If the amount invested in a biotechnology firm is endogenously determined with the distance between the VCF and the firm, our estimates would suffer from endogeneity bias.[87] For instance, if local investors could not provide sufficient amounts of capital to local firms, the only option for such firms would be to raise funds from distant investors. In such a case, distance and the amount raised (our dependent variable) would be determined simultaneously. To test whether distance is an endogenous variable we performed the Hausman endogeneity test described in Wooldridge (2010, p. 119) and present the second stage estimates in test 2.[88] The coefficient of the residuals of the first stage is not statistically significant, thus, rejecting endogeneity. This implies that our estimates are not plagued by endogeneity bias. Further, the magnitude, sign and statistical significance of the signal interactions remain qualitatively similar to the baseline estimates.

To measure the effects of the regional environment and clustering in general, we include variables measuring the density of VCFs and patent activity within a 20 miles radius from the focal firm. However, clusters are not defined solely by geography but also through professional and social ties (Casper, 2007). It is, thus, possible that nearby firms might not belong in a cluster or

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[86] Instead of using the age variable in the first stage of the Heckman model we use the year of foundation. We do so because for the age variable to be meaningful in our application we would need to model the probability that a firm receives venture capital investment within a specific period of time. However, by definition, such period of time does not exist for firms that did not receive venture capital investments. For the selection equation, we also use only granted patents as measures of patent activity in the first stage because a number of recipient firms received the award before 2001 and as such the full list of submitted applications is not available as it was not recorded by the USPTO. The selection of the remaining variables in the first stage of the Heckman model is guided, primarily, by findings of previous literature. To illustrate, for the selection equation we include the SBIR and the location dummies based on the findings that SBIR winners are more likely to attract venture capital funds (Lerner, 1999) and that firms located in Massachusetts or California are more likely to attract funds (Lerner, 1999). The relationship of those factors with the amount of venture capital raised in the first round was not replicated in the existing literature. As such, we consider these factors as relevant for the first but not for the second stage of the Heckman model. Factors for which empirical evidence is scarce, we theorize, are relevant for both stages (e.g. *FounderSignal*) and are included in both stages (we opt for *FounderSignal* and not *AcademicSignal* and *EntrepreneurialSignal* because of better model fit). Finally, when we include different groups of variables in the selection equation we find that the results remain largely unchanged.

[87] We thank an anonymous reviewer for bringing up this point.

[88] More specifically, we first run the reduced form regression with distance as the dependent variable against the exogenous variables and use the residuals of this regression as an explanatory variable in our baseline model.

that firms located further away are still part of the cluster. To address this possibility, in sensitivity test 3 we replace the variables describing the regional environment with variables that take the value of 1 for firms located in the MSAs of the three traditional biotech clusters in the US: Boston, San Diego and San Francisco. As shown in Table 3, the estimates of this sensitivity test are nearly identical to the estimates of the baseline specification.

As we explained above, we opted to represent patent activity in our baseline model with dummy variables that take the value of 1 if the firm was granted a patent or had applied for a patent before the investment and 0 otherwise. We did so chiefly because of multicollinearity concerns and because the left skewed distribution of patent activity made the dummy variables we used roughly equivalent to continuous measures. In sensitivity tests 4 and 5 we put this modelling choice to test. In those tests we omit firms with well above average patent applications, thus, checking whether these outliers drive our estimates. In both tests the results are qualitatively similar to the baseline estimates and hence provide additional support to our representation of patent activity with dummy variables.

Finally, in tests 6 and 7 we test for the separate significance of the interaction terms – patent activity measures and distance as well as founder characteristics and distance—as those are tested jointly in the baseline model. The coefficients are similar to the baseline coefficients we present in Table 3. Patent applications and the entrepreneurial experience interaction variables remains significant and granted patents and academic eminence interaction variables remain insignificant.

Conclusion and Discussion

A long stream of literature based on signalling theory has analyzed the factors that make signals more valuable to receivers. The general consensus in this literature is that signals are more valuable to receivers when transmitted in environments of elevated information asymmetries between senders and receivers, such as when firms are untested and when industries are risky. However, despite extensive evidence of increasing information asymmetries between transacting parties over geographic distance, the value of signals relative to geographic distance remains largely unknown. Against this background, and keeping in mind that signals are often more relevant for early stages of firm growth, in this paper we pose the following question: are signals of start-up firm quality more valuable to distant than nearby investors and, if so, do they lead to higher investments?

To address the question we examine venture capital investments in 586 US-based biotechnology firms over a 10 year period. In line with the notion that information asymmetries are more pronounced in long distance transactions we find that firm patent activity and the business experience of the founder team carry a stronger signalling value for long distance transactions.

Overall, our empirical results corroborate the idea that because tacit knowledge circulates mostly within local circles, it diminishes the value that receivers place on signals for local transactions. Notably, our analysis sheds new light on why patents and patent applications of start-up firms attract investors. If patents were valued mostly for their monopoly rights, we would expect them to attract investors, equally, in environments of low and high information asymmetries. If, however, they were valued primarily as a signal of unobserved firm quality, we would expect them to attract investors, chiefly, when information asymmetries are pronounced. We find strong support for the latter argument: patent activity, especially patent applications, seems to attract venture capitalists mostly because of its signalling function.

Our study also has managerial and policy implications. For instance, for start-up firms located outside the traditional venture capital hubs seeking early stage venture capital investments, our study suggests that signals can help them overcome any potential disadvantages of their location. This finding is particularly relevant because, early stage firms are often tempted to relocate to increase their access to financial resources (Tian, 2011). In contrast, potential senders of signals located close to intended receivers, may benefit more from conveying quality information through local networks. Our study shows that in close proximity the value of signals tends to diminish and, hence, the costs of signalling may outweigh the potential benefits. For policy makers our findings imply that signalling is a way to attract venture capital from outside the region. If local governments are able to assist local firms with signalling, through certification or award programs or technical assistance for patent and grant acquisition, this could attract distant venture capital and therefore contribute to the innovativeness and economic growth of the region (Samila & Sorenson, 2011).

We close with a note on the limits of our study and on potential extensions. Our focus on biotechnology is largely motivated by the spatial configuration and the types of investments that occur in the industry, which present a suitable setting for studying the strength of signals across different distances between senders and receivers. The spatial configuration of the biotechnology industry and of investments in it may not be representative of other industries thereby limiting the generality of our conclusions. Extending the analysis to different industries could leverage the presence of shorter research cycles, differential locations, industry structures, and overall information asymmetries and risks thereby providing opportunities for new signals and additional insights.

A potential limitation of our work is that common factors could affect the location of biotechnology firms and venture capital firms. For instance, biotech firms with low patent activity aware of its signalling value to distant investors could purposefully locate close to VCFs. If that holds, the analysis would be subject to an identification concern.[89] Existing empirical evidence from a broad set of industries indicates that the effect of regional venture capital activity *per se* on firm births is not strong (Samila & Sorenson, 2010, 2011). Specifically for biotechnology the impact of venture capital activity on firm births is either non-existent (Kolympiris, Kalaitzandonakes, & Miller, 2015) or weakly positive and lessens even more when other factors (e.g. university presence) are explicitly considered (Stuart & Sorenson, 2003). While such evidence suggests that the concern at hand is not particularly acute, the possibility cannot be fully ruled out.

The focus of the study coupled with data limitations does not allow us to use sharper measures of the regional environment in which the focal firms are located. Relevant measures could account for the ties between nearby organizations and the overall network structure surrounding the firms receiving funding. Along the same lines, investigating whether social and industrial distance between investors and recipient firms impacts the effects of geographic distance on the valuation of signals *a la* Sorenson and Stuart (2001) is a fruitful avenue for further work.

Finally, the correlation of the signals and their interactions with the distance between VCFs and target firms in our data set constraints, somewhat, our model specification. Our empirical tests provide some comfort on the robustness of our results but future work could explore further their separate effects.

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[89] Along the same lines, an additional identification concern could arise if venture capitalists encourage firms to apply for patents. Given that we measure patent activity before the first round of investment, this would hold only for cases under which the venture capitalist plays a role in the decision process of the firm before the investment. However, because of the well-established *ex ante* scanning function and *ex post* coaching function of venture capitalists, this sort of identification is not a particularly strong concern in our work.

Chapter 6. Conclusions and Discussion

The knowledge economy demands constant feeding of new knowledge. As conducting science is an expensive activity with uncertain results, resource scarcity constrains industry and academia from producing knowledge at socially optimal levels (Acs et al., 2002; Cohen et al., 2002; Nelson, 1959). Emerging firms and academia, two major contributors to the advancement of science (OECD, 2005), face the largest of these resource constraints. One important reason for this is that both high-technology start-ups and academics have to participate in resource acquisition from public or private parties. However, knowing how to successfully attract resources is a tacit knowledge that is not easily learned and is typically beyond their core skillset. This is an important topic because individual academics and high-technology start-ups who raise funds from private or public sources are more likely to capitalize on research trajectories that allow them to become 1) a major form of human capital for the advancement and direction of science, and 2) connect science to society in the knowledge economy (Lerner, 1996; Oyer, 2006; Petersen et al., 2011; Waldinger, 2016). Given the important contribution academics and start-ups make to the knowledge economy, we formulated the following research objective for this dissertation:

Investigate how start-up firms and researchers in the knowledge economy can acquire resources that allow them to innovate and advance science.

To complete the main research objective, we guide ourselves with the knowledge that the two groups (start-ups and academics) approach the issues around resource acquisition in their own way as they have different tools available and their problems with resource acquisition stem from different foundations. For instance, academic researchers rely heavily on the experience and knowledge of academic peers in their department (Stigler, 2003) and start-ups look for ways to reduce information asymmetries. (Zhang & Wiersema, 2009).

In this chapter, we start with answering our main research question for researchers and start-ups separately in 6.1. Then in 6.2, we follow with the theoretical contributions that the four research chapters make. After, 6.3 discusses the main limitations and accordingly recommendations for future research. Finally, 6.4 closes the thesis by providing implications for policy makers and managers.

Conclusions per group

Resource Acquisition by Academic Researchers

In the first two essays in this dissertation, we study how academics with little to no experience in attracting research funding can learn from colleagues with specific knowledge on this subject. In order to tease out the subtleties of how learning between peers occurs and to rule out competing explanations as the causal factor behind performance gains including increases in research funding in this paper we are the first to exploit the rotation program at the National Science Foundation (NSF).

The rotation program presents a rare research opportunity in that it equips academics with unique knowledge that is difficult to acquire when following an academic career trajectory that does not include experience outside academia. Further, the rotation setting provides an opportunity for this knowledge to spill over to the colleagues of rotators. Exploiting such richness and with an eye on the fact that the rotation program has never been analyzed empirically the question we ask in chapter 2 whether, upon return, rotators cause scientists who are early in their career to increase their NSF funding? Such learning could occur with the returning rotator providing hints on topics NSF is keen on funding, guidance on available but difficult to detect funding opportunities and other forms on knowledge transfer (Argote, Beckman, & Epple, 1990; Argote et al., 2000; Gruenfeld et al., 2000). Then, in Chapter 3, we ask what are the conditions that magnify the effects that result from knowledge transfer.

To study these questions, we split academics who are inexperienced with acquiring funding in two groups: 1) early career academics who have only recently taken on their first faculty positon at the target department and 2) seasoned academics who are further in their career but have been unable to acquiring funding for a significant amount of time. These two groups are heterogeneous in their characteristics as they are in different stages of their careers and have different knowledge bases and standings within the department.

In chapter 2, we reveal evidence consistent with a causal link between increases in the NSF funding record of newly hired assistant professors and exposure to academics in their department who return from their tenure at the National Science Foundation as Program Directors (rotators). We construct novel data that follows PhD graduates from the moment they land their first faculty position in departments with and without a rotator. However, different sources of endogeneity may allocate individuals to treatment and control groups non-randomly, labor market conditions differ across years, the best candidates will land the best positions, and university-wide policies around grant-writing support and tenure track incentives may boost funding rates. We tackle these issues by creating three datasets: In the first dataset we exploit time variation by including new hires joining the same department at different points in time when labor market conditions vary, the focal colleague had or not left for the NSF and had or not the rotation experience. Indeed, these factors are the prime determinants of initial job placement (Miller et al., 2005). In the second dataset we include PhD holders (some landing a job in a department with a rotator and some without a rotator) who had the same PhD advisor, worked in the same science field and graduated about the same year (Kahn & MacGarvie, 2016). In the third dataset we hold university-wide factors constant. This allows us to compare the funding records of new hires who joined the same university at approximately the same time but in different, yet comparable, departments having one main difference: some have a rotator as a faculty member and some do not. Finally, the three datasets reveal reveal that rotators have a causal impact on the funding acquisition records of new hires as they raise close to $200,000 more from the NSF when compared to similar others who do not have a rotator as a colleague.

These gains are realized in the first two years after the rotator returns. Given that the average assistant professor in our sample start their tenure-track position two years prior to the rotator returning, the two years after the rotator returns are at a critical moment in their career: successfully raising research funding often means the difference between getting tenure or leaving the department (Feinberg & Price, 2004; Stephan et al., 2017). Through a number of empirical tests we reveal that the effect originates from knowledge transfer from the rotator to the early stage academic.

In chapter 3, we find causal evidence that rotator's colleagues with no NSF funding in the ex-ante period raise close to $140,000 more than scientists who do not have a rotator as a colleague in the ex-post period. Additionally, we go one step further and study how the personal characteristics of the rotator and his colleagues affect the transfer of knowledge. We find strong evidence that rotators with longer tenure and a similar knowledge base as the focal colleague affect the NSF funds the focal colleague acquires. Additionally, as the focal academics in this chapter are not early stage academics but rather academics with a longer career history, we compare the effect similar productivity between rotator and focal academic has on raising research funding. To this we find evidence that suggests that the more similar the rotator and focal colleague are in terms of productivity, the more knowledge transfer happens.

We conclude that researchers in the knowledge economy can acquire resources through positive knowledge spillovers that stem from interactions with peers who have specific knowledge and experience in how funding works.

Resource Acquisition by Start-Ups

In the last two essays of this dissertation, we study how start-up firms can signal their quality to funding providers in order to overcome information asymmetries. Strong and valuable signals need to be observable and costly to imitate (Cohen & Dean, 2005; Spence, 1978). Additionally, signals that are governed by strong institutions and hence conform to a certain institutional standard tend to increase in value (Janney & Folta, 2003). Patents meet these requirements because they are easily observable, have high, up-front costs (Graham, Merges, Samuelson, & Sichelman, 2009) and are governed strictly. Indeed, a number of studies have shown the value patents have in signalling quality to investors such as venture capital firms (Baum & Silverman, 2004; Häussler et al., 2012; Mann & Sager, 2007).

However, what is difficult to conclude from these empirical studies is what the dynamics are of the signalling strength that patents carry. Is the value of patents as signal equal to all high-technology firms looking for funding? To answer this question we look at two factors that influence the level of information asymmetry between start-up and venture capital investor, namely, time and distance.

In chapter 4, we investigate how the value of patents or patent applications as signal develops as the venture capitalist firm (VCF) and target firm become more familiar over time. To do so, we exploit the fact that a popular mechanism VCFs use towards that end is to provide funds in rounds (Wang & Zhou, 2004). Between these rounds, VCFs spend considerable time at the firm and involve themselves with day-to-day activities through mentoring and consulting (Gorman & Sahlman, 1989). As they spend time at the firm, they have a chance to evaluate the potential of the firm and the skills of its founder. It follows then that these VCFs become more acquainted with the firm and information asymmetries reduce.

Our empirical estimates strongly support our theoretical expectations that patent activity before the first round of financing increases the growth of funds for that round. However, once investors and target firms decrease the information asymmetries between them, patent activity ceases to serve as a signal that increase the level of funds raised at the second round of financing.

In chapter 5, we investigate whether the geographic distance between VCFs and high-technology start-ups influences the value of signals transmitted by emerging biotechnology firms. We do so because prior work has found that information asymmetries increase with distance (Coval & Moskowitz, 1999; Ivkovic & Weisbenner, 2005; Portes et al., 2001), yet they are nearly silent about the impact of the geographic distance between agents on the strength of the signal. In line with our expectations, we find that the larger the distance between VCF and target firm, the more important signalling becomes.

Combined, these studies shed new light on the reasons why patents attract investors such as venture capital firms and how high-technology start-ups can leverage their intellectual property to attract funding.

We conclude that start-ups in the knowledge economy can acquire resources by signalling their competence to venture capital firms when information asymmetries are inflated due to the two parties being unfamiliar with one another and geographic distance is high.

Theoretical Contributions

By studying how start-ups and academic researchers in the knowledge economy acquire resources, this thesis contributed to a number of research streams.

First, chapter 2 contributes to previous research on the academic labor market. More specifically, we submit novel evidence to prior work on the effects of access to high human capital in academia (Azoulay et al., 2010; Borjas & Doran, 2012; Borjas & Doran, 2015; Waldinger, 2010, 2012; Waldinger, 2016), success in science (Kahn & MacGarvie, 2016; Kelchtermans & Veugelers, 2013) and academic mentoring (Blau et al., 2010). The study also shows *–for the first time-* how scholars can use the rotation program of the NSF to study a range of economic and social science topics (eg. advancement of science, peer effects, knowledge transfer and diffusion, and networking).

Second, the findings in chapter 3 speak directly to the research on knowledge transfer, academic mobility and organizational learning by showing how academics with brief spells of work outside the normal environment can generate positive spillovers for their colleagues (Argote & Ingram, 2000; Herrera, Muñoz-Doyague, & Nieto, 2010; Song et al., 2003). This research has an original contribution to these research streams by presenting how organizations can learn not only by *learning by doing* and *learning by hiring*, but also by *learning by seconding*. Additionally, we contribute to the literature on social identity and organizational by studying how employees use the positive effects of a common social identity to improve their position. For instance, scientists with a common knowledgebase transfer knowledge between them more, even when this knowledge is outside their core field.

Third, chapter 4 contributes to prior work on start-up and SME financing (Baum & Silverman, 2004; Carpenter & Petersen, 2002) and patent valuation (Harhoff et al., 2003; Häussler et al., 2012). Above all, we extend the research on signalling theory and information asymmetries (Fama, 1980; Jensen & Meckling, 1976). Prior research established that the value of signals differs between the type of signal and the agents that receive them (Janney & Folta, 2003; Zhang & Wiersema, 2009). We show that the value of the same signals between the same actors changes in line with changes in information asymmetries.

Last, in chapter 5 we extend the contribution chapter 4 makes on the existing literature. Starting with the premise that the value signals carry is dynamic, we investigate other factors and additional signals. We find that not only does the value of signals change over time (as information asymmetries reduce), but they also change with distance between transferor and receiver. Additionally, and conflicting with earlier work, we find no evidence that the founding team of start-ups act as a signal.

Limitations of the Dissertation and Recommendations for Further Research

This dissertation adds to existing theories in transferring knowledge and information to overcome resource constrains in the knowledge economy and does so through novel methodological approaches. However, the research findings should be treated with caution and its limitations should be considered before the conclusions in this chapter can be generalized. This sections presents the identified limitations and provides recommendations for future research.

First, the main limitation of this research is that there are more ways for academics and start-ups in the knowledge economy to overcome resource constraints. In this dissertation, we look solely at how resource acquisition improves for academics and start-ups when they use knowledgeable peers to overcome gaps in their knowledge repository or signalling to overcome information asymmetries. These parties can improve their funding records by many more ways. For instance, academics may also overcome barriers to funding by interacting with current NSF staff (Custer et al., 2000) and improve their scientific writing skills (Porter, 2007). Likewise, start-ups can improve their funding levels by improving internal capabilities and improving their network linkages (Lee, Lee, & Pennings, 2001), hiring staff with experience and ability in attracting funding (Gartner et al., 1999) and applying for a mentorship (Waters, McCabe, Kiellerup, & Kiellerup, 2002).

Second, the essays in this study looked only at a single form of funding for both academics and start-ups, namely public research funding from the NSF and venture capital funding. Although these two are major funding sources for the two parties in the US, they are not the only options available. Academics can look at other public funding agencies such as the NIH, Department of Energy, NASA and Department of Defense (AAAS, 2016). In addition, the private sector can be a source of funding as industry has an increasing role in funding academic research (Gulbrandsen & Smeby, 2005). Therefore, reaching out to industry parties and partaking in contract research is a viable solution to many academics who are unable to get public funding (Hoenen, Kolympiris, Wubben, & Omta, 2018). Generally for start-ups, self-funding and funding from friends and families are the major sources of funding. However, start-ups in the knowledge economy typically require more funding and a longer time to market (Vohora, Wright, & Lockett, 2004). As a result, self-funding or friends and families become less viable funding sources. Other sources of funding for high-technology start-ups are business angles, banks and the public sector and the way these start-ups should deal with them might differ from how they deal with venture capital firms. For instance, because business angels do not have agency problems from their fund providers, they are not under pressure to behave professionally, leading to a more informal, incomplete contracts approach (Van Osnabrugge, 2000). Also, because venture capital firms conduct more and better pre-investment due diligence to reduce information asymmetries, it might be the case that business angles are more attracted to signals from start-ups. Public funding also allows start-up firms to overcome funding constraints. The highly successful United States SBIR program allocates funding to innovative start-ups and SMEs. Because agency problems are less relevant here as the SBIR does note acquire a share in the firm, and there is generally less uncertainty on the technical merit of a proposed innovation, the value of signals might be lower or less relevant.

The last main limitation to our research is that we focus solely on academics and high-technology start-ups in the United States. As such, the results may not be generalizable directly to other (developed or developing) countries. Although resource constraints affect academics and start-ups everywhere, the level of experienced funding limitations and how these academics and firms get funding differs from country to country. For instance, the uniqueness of the rotation program at the NSF together with our estimates makes one wonder whether other funding agencies elsewhere would benefit from a similar setting.

Given the above limitations to our research, we arrive at a number of general recommendations for future research.

First, we recommend further research to conduct studies on other sources of finance for academics and high-technology start-ups. The NSF is unique in its use of rotators. Other public funding agencies use different methods to award grants. For instance, many funding agencies use academics not as rotators but as panelists. Do these panelists at other agencies also gain new knowledge in how to acquire research grants, and do they transmit this knowledge at their home institution? In a similar vein, do start-ups also benefit from patent signals when they try to acquire funding from business angels and government programs? The SBIR is similar to venture capital funding in that it provides funding in stages. Future research can investigate whether the dynamic mechanism explained in chapter 4 and 5 also affects SBIR grants. Additionally, the ones who make the funding decisions at the SBIR have academic backgrounds. Do they look for different signals than venture capitalists?

Finally, we close with the recommendation that going more deeply into the qualitative approach can yield answers to a number of questions that the essays in this dissertation were unable to answer. Exactly what type of knowledge do rotators transmit, how do they transmit this knowledge and why do they do it? Likewise, interviews with start-ups and venture capital firms could have extended the scope of this research: Do start-ups know that patents are a signal and do they deliberately use the signalling value? Are venture capital firms aware that they might be valuing patents more than they are economically worth? We would have liked to study these questions in depth, but because our goal was to investigate at a large scale how academics and start-ups attract funding, we leave such refinements for future work.

Managerial and Policy Implications

This dissertation investigated how two major actors in the knowledge economy can attract funding that allows them to innovate and advance science. Considering the relevancy and importance of this research, this section presents the policy and decision making implications at public and private organizations.

Our results in chapter 2 and 3 show that it is not peers *per se* that induce gains but peers with valuable experience that are willing to share their knowledge and insights with others. Still, the challenge for universities is that scientists with unique experiences are not in ample supply. Competition for talent is already pronounced in academia and the evidence we present in this dissertation may intensify it. Importantly, though, universities typically compete for one's individual record of academic achievements. The rotation setting implies that competition for one's unique experience may also pay off: winning the race may bring about significant multiplier effects because the benefits from such cohort of hires appear to spill over to other faculty members and especially to those who might be in the most need for help. Alternatively, and keeping in mind that most rotators have had a limited number of career moves, if any, an alternative means for universities to create spill-over effects via scientists with unique experience is to promote NSF rotation within existing faculty members. Still, as became clear during our interviews, rotation, for the largest part, comes at the expense of one's own, at least short term, research productivity. Therefore, universities must balance the sorts of benefits we document with the decline in academic productivity that rotation tends to entail. The way forward may be to promote rotation primarily towards targeted faculty members. The actual forms such promotion may take depend on the field of science, the university rules and norms and other factors.

From a policy perspective, the paper speaks directly to the design of the rotation program. Under the premise that home universities gain from the rotation program a recent policy mandates that they cover part of the rotation program bill (Mervis, 2016a). Here, while we do not fully measure the benefits and the costs of the program, we do nevertheless find that home institutions realize gains from returning rotators. Also, given the importance of getting funded and the difficulty many academics have to achieve this, policy makers have started to react by implementing measures that improves the chances of early stage and inexperienced academics to get granted. Yet, focus has been on large scale institutional changes on the supply side. We show to policy makers that exploiting existing knowledge held by colleagues' (the demand side) might also be a complementary, less resource-intensive strategy.

Regarding our findings in chapter 4 and 5, the empirical estimates can inform managers of biotechnology firms on the benefits that arise from patent activity. We estimated that, on average, an additional pending patent application can increase the amount of venture capital funds raised in the first round of financing. The size of the coefficient clearly surpasses the existing estimates for the direct costs of being granted a patent (which ranges from \$10,000 to \$38,000). Moreover, in line with previous research, our estimates strongly point managers of biotechnology firms towards patents of higher quality since investors appear to be able to detect patents of higher value and invest in the firms that possess them instead of investing in firms that are granted a large number of patents (Häussler et al. 2009). Additionally, our findings that patent activity matters only for the first round of financing imply that after the attraction of venture capital alternative protection mechanisms such as licensing may not be suboptimal in terms of venture capital attraction. Assessing the strength of alternative protection mechanisms in attracting venture capital investments is a potential avenue for further research that can complement the present work. Finally, our results on the effect of distance on funding and patent signals indicate that firms that are not able to produce sufficient patent signals may need to locate closer to innovative clusters where there is a higher supply of venture capital firms. On the other hand, senders of signals located in the proximity of the intended receiver, should carefully consider whether signalling indeed delivers the expected returns. Our study shows that in such cases the value of signals is not particularly high. Accordingly, the costs of signalling may eventually outweigh the potential benefits.

From a policy perspective, a number of concerns have been raised about the current status of the patenting system and the degree that it hinders innovation. The \$630,000 figure we presented in chapter 4 can be informative towards that end if the federal costs per patent are discernible and if, as expected, higher investments eventually translate to higher innovation measures via the strengthening of firms with potential to innovate. Additionally, our findings show that signals are a way to attract investments into regions outside the main technology clusters. Governments in these ‘barren’ regions may improve the attractiveness of their region by providing technical assistance for patent acquisition.

Summary

Academia and industry are major actors in the knowledge economy. The contributions these actors make to the knowledge economy is largely constrained by resource scarcities. Such resource scarcity is more pronounced for the two actors I focus on in this dissertation, start-ups and academic scientists.

First, mainly due to a lack of revenue streams, high-technology start-ups seek funding to fuel their research activities from outside sources, such as governmental subsidies, venture capital and business angels (Audretsch, 2003; Hellmann & Puri, 2002; Shane, 2012). However, the uncertainty surrounding embryonic inventions as well as complex regulatory environments create information asymmetries between these firms and the potential financers that make investment decisions a difficult task (Sahlman, 1990). Second, academics source their research funding generally from the public. They do so generally primarily by submitting research proposals to funding agencies. However, fund raising is challenging as knowing where possible funding opportunities exist and being able to submit competitive research proposals requires tacit knowledge that is difficult to get access to (Feinberg & Price, 2004; Stephan et al., 2017).

Because resource acquisition is one of the main drivers for knowledge production for academics and start-ups alike, and the difficulty of resource acquisition is inversely correlated with the available knowledge, competence and experience the parties have in securing resources, the aim of this dissertation is to

Investigate how resource constrained start-up firms and researchers in the knowledge economy can gain access to resources in order to innovate and advance science.

We start with the premise that the two groups, start-ups and academics, approach the issues around resource acquisition in their own way as they have different tools available:

How academics overcome resource constraints.

Academic researchers rely heavily on experience and knowledge of academic peers in their department (Stigler, 2003). Collegial behavior manifested in help towards the generation of valuable ideas, feedback and criticism via formal or informal interactions is recognized as a key input for the advancement of one's (academic) career (Laband & Tollison, 2000; Laband & Tollison, 2003). Therefore, in the first two essays in this dissertation, we study how academics with little to no experience in attracting research funding can learn from colleagues with tacit knowledge how to do so. In order to tease out the subtleties of how learning between peers occurs and to rule out competing explanations as the causal factor behind performance gains including increases in research funding in this paper we are the first to exploit the rotation program at the National Science Foundation (NSF).

Under the rotation program, since 1970, NSF employs academic scientists, called rotators, who step out of their academic institution for a period of usually 1 to 2 years to manage its review process as Program Directors (PDs), make recommendations on the allocation of the 5 billion dollars per year across the 45,000 competing proposals it receives, and essentially shape the direction of science (Li & Marrongelle, 2013). Once these scientists return to their academic homes they are armed with experience and unique knowledge of the NSF, they carry insights on how funding decisions are made, they have inside knowledge on the potential funding directions and priorities of the agency, and ultimately they know what makes a proposal competitive and what does not. Simply put, they gain knowledge that is difficult to acquire unless they jump out of academia, even only temporarily.

In chapters 2 and 3, we split academics in departments with a returning rotator and who are inexperienced with acquiring funding in two groups: 1) early career academics who have only recently taken on their first faculty positon at the target department and 2) seasoned academics who are further in their career but have been unable to acquiring funding for a significant amount of time. These two groups are heterogeneous in their characteristics as they are in different stages of their careers and have different standings within the department.

In chapter 2, we construct novel longitudinal data that follows PhD graduates from the moment they land their first faculty position in departments with and without a rotator. However, different sources of endogeneity may allocate individuals to treatment and control groups non-randomly, labor market conditions differ across years, the best candidates will land the best positions, and university-wide policies around grant-writing support and tenure track incentives may boost funding rates. We tackle these issues by creating three datasets: In the first dataset we exploit time variation by including new hires joining the same department at different points in time when labor market conditions vary, the focal colleague had or not left for the NSF and had or not the rotation experience. Indeed, these factors are the prime determinants of initial job placement (Miller et al., 2005). In the second dataset we include PhD holders (some landing a job in a department with a rotator and some without a rotator) who had the same PhD advisor, worked in the same science field and graduated about the same year (Kahn & MacGarvie, 2016). In the third dataset we hold university-wide factors constant. This allows us to compare the funding records of new hires who joined the same university at approximately the same time but in different, yet comparable, departments having one main difference: some have a rotator as a faculty member and some do not. Finally, the three datasets reveal reveal that rotators have a causal impact on the funding acquisition records of new hires as they raise close to $200,000 more from the NSF when compared to similar others who do not have a rotator as a colleague.

In chapter 3, we exploit the academic experience of over 1,500 seasoned academics and the familiarity they have with their department colleagues and use this to study whether intensity of knowledge transfer hinges, in large part, on the *relationships* between the transferor (the rotator) and the recipient of knowledge (Argote & Ingram, 2000; Singh & Agrawal, 2011). We use *coarsened exact matching* to create a dataset that contains similar academics in similar departments with and without a rotator. In line with our hypotheses, we find that rotators have a stronger effect on funding acquisition of seasoned academics who have not raised NSF funding in the prior 5 years when they 1) are more familiar with the department, 2) do similar research, and 3) are closer to each other in terms of research productivity.

Combined, both studies reveal evidence consistent with a causal link between increases in the NSF funding record of academics who are inexperienced with raising funds and exposure to academics in their department who return from their tenure at the National Science Foundation as Program Directors (rotators). Additionally, the studies speak directly to the research on knowledge transfer, academic mobility and organizational learning by showing how academics with brief spells of work outside the normal environment can generate positive spillovers for their colleagues (Argote & Ingram, 2000; Herrera et al., 2010; Song et al., 2003). This research has an original contribution to these research streams by presenting how organizations can learn not only by *learning by doing* and *learning by hiring,* but also by *learning by seconding*.

Regarding our research objective, we conclude that researchers in the knowledge economy can acquire resources by having access to superior human capital gained via experience outside academia.

How start-ups overcome resource constraints

In chapters 4 and 5, we study how high-technology start-ups overcome resource constraints. In order to overcome resource constraints, start-ups look for ways to reduce information asymmetries. One way firms can reduce information asymmetries is to use *signals* that that can shine a light on the potential of the firm (Zhang & Wiersema, 2009). Indeed, a number of studies demonstrate that signals reduce information asymmetries and improve funding of start-ups (Baum & Silverman, 2004; Cohen & Dean, 2005; Häussler et al., 2012; Hsu, 2007; Janney & Folta, 2003; Mann & Sager, 2007; Mishra et al., 1998a; Spence, 1978). However, what is difficult to conclude from these empirical studies is what the dynamics are of the value that different signals carry. To answer this question, in the last two essays of this dissertation, we study two factors that influence the level of information asymmetry between start-up and venture capital investor, namely, time and distance.

In chapter 4, we investigate how the value of patents or patent applications as signal develops as the venture capitalist firm (VCF) and target firm become more familiar over time. To do so, we exploit the fact that a popular mechanism VCFs use towards that end is to provide funds in rounds (Wang & Zhou, 2004). Between these rounds, VCFs spend considerable time at the firm and involve themselves with day-to-day activities through mentoring and consulting (Gorman & Sahlman, 1989). As they spend time at the firm, they have a chance to evaluate the potential of the firm and the skills of its founder. It follows then that these VCFs become more acquainted with the firm and information asymmetries reduce. To test our hypothesis we use a rich dataset that measures patent and investment activities of over 1500 biotechnology start-ups between 1974 and 2001. In line with our theoretical expectations, we find that patent activity only influences the size of the first round of financing and not the second.

In chapter 5, we investigate whether the geographic distance between VCFs and high-technology start-ups influences the value of signals transmitted by emerging biotechnology firms.

We do so because prior work has found that information asymmetries increase with distance (Coval & Moskowitz, 1999; Ivkovic & Weisbenner, 2005; Portes et al., 2001), yet they are nearly silent about the impact of the geographic distance between agents on the strength of the signal. In line with our expectations, we find that the larger the distance between VCF and target firm, the more important signalling becomes.

Combined, these two studies shed light on the reasons why patents attract investors such as venture capital firms and how high-technology start-ups can leverage their intellectual property to attract funding. The two chapters contribute to prior work on start-up and SME financing (Baum & Silverman, 2004; Carpenter & Petersen, 2002) and patent valuation (Harhoff et al., 2003; Häussler et al., 2012). Additionally, we extend the research on signalling theory and information asymmetries (Fama, 1980a; Jensen & Meckling, 1976). We find that not only does the value of signals change over time (as information asymmetries reduce), but they also change with distance between transferor and receiver.

Regarding our research objective, we conclude that start-ups in the knowledge economy can acquire resources by signalling their competence to venture capital firms when information asymmetries are inflated due to the two parties being unfamiliar with one another and geographic distance is high.

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Sebastian Joseph Hoenen
Wageningen School of Social Sciences (WASS)
Completed Training and Supervision Plan

Wageningen School of Social Sciences

Name of the learning activity	Department/Institute	Year	ECTS*
A) Project related competences			
Introduction course	WASS	2014	1
Econometrics of Linear Models	Bocconi University	2014	1.5
Business Economics Firm Behaviour I	Bocconi University	2014	1
Advanced Econometrics	Wageningen University	2017	6
Peer review: "Is The Economics Knowledge Production Function Constrained By Race In The United States?"	Journal of the Knowledge Economy	2017	1
Peer review: "How venture capitalists evaluate young innovative company patent portfolios: empirical evidence from Europe"	Research Policy	2017	1
B) General research related competences			
Research Proposal (accepted)	WASS	2014	6
Junior Research Grant	WASS	2016	6
Systematic Literature Reviews	WGS	2015	4
Efficient Writing Strategies	WGS	2015	1.3
C) Career related competences/personal development			
'Factors affecting the time lag before academic knowledge is used by industry'	University of Bath	2015	1
'Lifting them up: How NSF rotators induce performance improvements for their colleagues'	ETH Zurich	2016	1
'Factors affecting how peers learn from each other: the case of NSF rotators'	TECHNIS Athens	2016	1
'How NSF rotators induce performance improvements for their colleagues'	Business Economics Group	2016	1
'Learning by Seconding: Evidence from NSF Rotators'	Rotterdam School of Management	2017	1
'How peers learn from each other: The case of NSF rotators'	University of Amsterdam	2017	1
'Research funding for early stage academics'	University of Pennsylvania	2017	1
'How National Science Foundation rotators build up the ability of their colleagues to attract research resources'	University of Torino	2017	1
Total			**36.8**

*One credit according to ECTS is on average equivalent to 28 hours of study load

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