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Collaborating for Knowledge Creation and Application: The Case of Nanotechnology Research Programs

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We study how collaboration and internal resources drive knowledge creation and application in university research programs. Academic collaboration with fellow university scientists drives knowledge creation, whereas collaboration with industry partners drives knowledge application. Nevertheless, contrary to prior research that has underscored the merits of collaboration, we identify an optimal level of collaboration beyond which collaboration undermines both processes. Furthermore, the availability of internal resources can either complement or substitute for collaboration depending on the level of collaboration. In particular, we find that availability of internal resources mitigates the effect of academic collaboration on knowledge creation when collaboration is moderate and complements it as collaboration becomes excessive. Thus, our study reveals the contingent value of collaboration and the interplay between internal and network resources. It enhances understanding of collaboration in nascent science-driven industries and advances the resource-based view and knowledge management research.

Key words: knowledge; collaboration; partnering; alliance; application; network; resource; innovation; university research; nanotechnology
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Introduction

How does collaboration contribute to knowledge creation and application? Do internal resources complement or substitute for its effects? Scholars have often underscored the value of collaborative ties that furnish access to network resources that reside beyond organizational boundaries (Gulati 1999, 2007; Lavie 2006). They have also alluded to the complementary value of internal resources that generate synergies when leveraged in collaboration with partners (Dyer and Singh 1998, Lee et al. 2001, Teece 1987). Less attention has been paid to the trade-offs and contingencies that drive these effects and may undermine knowledge creation and application. We seek to shed more light on the boundary conditions for the positive performance effects of collaboration. We also draw more attention to the interplay between collaboration and internal resources by suggesting that internal resources can not only complement but also substitute for collaboration, depending on the extent of collaboration. Specifically, we argue that the availability of internal resources devalues the contribution of collaboration to knowledge creation at moderate levels of collaboration yet enhances it once the extent of collaboration exceeds a certain threshold.

We concentrate on nascent science-driven industries, where collaborative knowledge creation is essential. Studies of established industries that adopt the firm as the unit of analysis often consider interfirm alliances as a primary form of collaboration. However, in nascent science-driven industries, new knowledge often emanates from universities and entails collaboration among teams of scientists (McFadyen and Cannella 2004). Moreover, prior research has rarely distinguished between knowledge creation and application. Most studies consider either the former outcome or the latter, while implicitly or explicitly assuming a positive association between the two (DeCarolis and Deeds 1999, Gambardella 1992, Zucker et al. 2002). Nevertheless, this positive association may not hold because of the potential tension between exploration and exploitation (Levinthal and March 1993). Certain trade-offs may emerge as university research programs weigh the pursuit of new scientific knowledge against the leveraging of existing knowledge. Collaboration that facilitates knowledge application may not promote knowledge creation, and vice versa. Hence, the question of how collaboration distinctively drives knowledge creation and application remains open, with further ambiguity concerning the role of internal resources in shaping its effects.

We anchor our study in the resource-based view and knowledge management literature, adopting the university research program as our unit of analysis.

We claim that the extents to which a research program engages academic and industry collaborators correspondingly affect knowledge creation and application, and that the availability of internal resources moderates these effects. Specifically, academic collaboration contributes to knowledge creation, whereas industry collaboration independently drives knowledge application. Nevertheless, excessive academic collaboration and industry collaboration correspondingly undermine knowledge creation and application. Furthermore, internal resources limit the value of collaboration as long as the number of collaborators is not excessive. Once this number exceeds a certain threshold, internal resources can enhance its diminished contribution to knowledge creation and application.

A sample of 268 nanotechnology research programs at Israeli universities serves as a setting for testing these ideas. The nanotechnology industry is at its embryonic stage (Avenel et al. 2007), with most of the scientific progress being made at university research centers. This industry exhibits interdisciplinary collaboration, technological agglomeration, and diversity of cumulative knowledge (Robinson et al. 2007) that is embedded in cross-institutional linkages (Zucker et al. 2007). Reliance on interdisciplinary knowledge prompts collaboration among scientists who contribute de novo inventions as well as specialized knowledge that stems from their respective disciplinary domains (Mehta 2002, Meyer and Persson 1998). Nanotechnology is therefore an appropriate context for studying the underlying forces that drive knowledge creation and application. Our findings reveal that academic collaboration and industry collaboration correspondingly generate inverted U-shaped effects on knowledge creation and application. In addition, internal program resources attenuate the effect of academic collaboration.

Our study offers a nuanced account of the implications of collaboration and sheds light on the complex interplay of collaboration and internal resources. It calls attention to the contingent value of collaboration and its contribution to scientific research and innovation in nascent industries. We uncover how excessive collaboration can undermine both knowledge creation and application, thus advancing research on knowledge creation that has previously considered only the extent and strength of collaborative relationships (McFadyen and Cannella 2004). By distinguishing academic collaboration from industry collaboration, we complement mainstream literature that has focused on the structure of interfirm alliances and knowledge networks without alluding to the distinctive nature of these relationships (Ahuja 2000, Bae and Gargiulo 2004, Dyer and Nobeoka 2000, Reagans and McEvily 2003, Schilling and Phelps 2007, Shan et al. 1994, Shipilov 2006). Thus, we advance emerging research on multimode networks that simultaneously considers multiple types of interorganizational ties (Lee et al. 2001, Rosenkopf and Almeida 2003). Moreover, we question the assumption that knowledge creation drives knowledge application by identifying contingencies and potential trade-offs while demonstrating that different types of collaboration independently shape these two processes. In addition, whereas prior research has traditionally underscored the synergies arising from complementarities between internal resources and network resources (Dyer and Singh 1998), we study the conditions under which internal resources substitute for collaborative relationships. Finally, by studying knowledge creation and application from the perspective of university research programs, we complement prior research on collaboration between university scientists and industry partners that has focused on knowledge transfer from the perspective of firms that leverage their ties to universities (Agrawal 2001, Cohen et al. 2002, Gittelman and Kogut 2003, Rothaermel and Thursby 2005). We demonstrate that ties that serve industry partners do not necessarily benefit university research programs, and we reveal the contingent value of collaboration from the latter's standpoint.

Theory and Hypotheses

The creation and application of knowledge are fundamental organizational processes (DeCarolis and Deeds 1999, Grant 1996). Knowledge creation corresponds to exploration, whereas knowledge application is associated with exploitation (Levinthal and March 1993). Specifically, knowledge creation involves searching for, discovering, and integrating knowledge (Kogut and Zander 1992, Nonaka and von Krogh 2009); developing innovative ideas and new practices (Nonaka 1994); and learning from newcomers and parties that furnish external knowledge (Argote and Ophir 2002). Newly created knowledge can be then codified and disseminated for subsequent application (Garud and Nayyar 1994, Zahra and George 2002). Knowledge application concerns the exploitation and transformation of knowledge into commercial technologies and products (DeCarolis and Deeds 1999, Yli-Renko et al. 2001).

In nascent science-driven industries, the distinction between knowledge creation and application is essential because the locus of knowledge creation is often found in research universities, yet its application is led by firms that commercialize innovations. Besides the inherent tension between exploration and exploitation that correspondingly guides knowledge creation and application (March 1991), conflicting value systems serve for assessing their outcomes. Specifically, university scientists are evaluated based on their publication records rather than on contributions to technology development and transfer. Patenting and committing to industry partners consume research time, may delay publication, and restrict knowledge dissemination, thus challenging the traditional mission of universities (Cohen et al. 1998, Florida and

Cohen 1999). Emerging industries benefit from scientific discovery, yet new knowledge judged as important by the scientific community may not produce immediate valuable applications (Gittelman and Kogut 2003). Given this distinction between knowledge creation and application, we expect their outcomes to be associated with different forms of collaboration. Academic collaboration is likely to influence knowledge creation, whereas industry collaboration can affect its application. Nevertheless, although university scientists are mostly concerned with knowledge creation, their contribution to knowledge application is essential. Furthermore, industry requirements may instigate new knowledge creation, with prospective knowledge application ultimately serving the mission of universities by granting support and relevance to newly created knowledge.

The Ambivalent Role of Collaboration in Driving Knowledge Creation and Application

Scholars often recognize the merits of collaboration, noting that embeddedness in social networks can influence economic outcomes depending on the nature of dyadic ties and the overall network structure (Granovetter 1985, Podolny 1994, Powell 1990, Uzzi 1996). In particular, the strategic alliance literature has examined the benefits of collaboration, relating them to trust, compatibility between the partners, knowledge sharing, and effective governance (e.g., Dyer and Singh 1998, Gulati 1995, Kale et al. 2000, Madhok and Tallman 1998, Saxton 1997, Zaheer et al. 1998). Nevertheless, the contribution of collaboration to knowledge creation in nascent science-driven industries requires careful attention. In particular, it is often collaboration between teams of university scientists rather than interfirm alliances that promotes knowledge creation in this context. Academic collaboration takes place when teams of scientists work together to produce scientific knowledge. Academic collaborators promote research at several stages, including research design, provision of equipment, experiments, analysis, and the write-up of scientific reports (Katz and Martin 1997). This collaboration advances knowledge creation by building social capital, enhancing creativity, integrating specialized skills, pooling resources, and improving efficiency.

First, as the number of academic collaborators increases, scientists build their social capital in the form of weak and strong ties, which can facilitate idea generation, furnish information on research opportunities, and enhance reputation (Nahapiet and Ghoshal 1998). Second, interactions with fellow scientists stimulate creativity and learning of tacit knowledge, and they provide access to recent scientific advances that cannot be inferred from published work. Third, intellectual exchange and cross-fertilization with an increasing number of academic collaborators enable research programs to tap into external knowledge bases and combine complementary skills. In this sense, each team can contribute its strongest skills while relying on the strengths of collaborators for other skills (Lee and Bozeman 2005). Fourth, an increase in the number of academic collaborators enables university research programs to share costs by pooling resources, including research funding, facilities, equipment, and materials. Fifth, academic collaboration enables division of labor and expertise, which enhances the efficiency of performed research tasks (Katz and Martin 1997). Thus, collaboration between teams of scientists can enhance scientific productivity (Defazio et al. 2009, Landry et al. 1996, Lee and Bozeman 2005) so that knowledge creation initially increases with the number of academic collaborators.

Nevertheless, some boundary conditions limit the contribution of collaboration to knowledge creation. As the number of academic collaborators increases beyond a certain threshold, collaboration can undermine knowledge creation as a result of mounting coordination and monitoring costs, diluted relationships, constraints on internal learning, and operational challenges. First, excessive collaboration consumes managerial attention and investments of time and effort needed to maintain relationships and coordinate joint activities (Ocasio 1997). Additional costs can be ascribed to searching for suitable partners, negotiating and crafting contracts, and monitoring the progress of uncertain research tasks (Williamson 1983). These costs become exorbitant when a research team engages numerous academic collaborators (McFadyen and Cannella 2004). Second, excessive collaboration limits the intensity of each tie to a fellow scientist, thus undermining the exchange of tacit knowledge, the ability to jointly resolve complex problems, and the interaction needed for generating new insights (Uzzi 1996). Third, the excess time invested in collaboration may come at the expense of independently pursuing promising research avenues, nurturing internal research skills, and carrying out internal activities that are also essential for knowledge creation (Arora and Gambardella 1994, Kogut and Zander 1992). Finally, given bounded rationality and limits to absorptive capacity (Cohen and Levinthal 1990, Cyert and March 1963), excessive collaboration strains the ability to coordinate multiple relationships, handle emerging conflicts among collaborators, and integrate knowledge flows from collaborators, resulting in less fruitful knowledge creation. Accordingly, the marginal cost of academic collaboration is likely to exceed its contribution to knowledge creation (McFadyen and Cannella 2004). Overall, we expect knowledge creation to initially increase with the extent of academic collaboration and then decline as the research program features an excessive number of academic collaborators, resulting in an inverted U-shaped effect of academic collaboration on knowledge creation.

HYPOTHESIS 1. *Knowledge creation will initially increase and then decrease with the extent of academic collaboration.*

Whereas knowledge creation is associated with academic collaboration, we expect collaboration with industry partners to influence knowledge application. University–industry collaboration takes various forms, including corporate visits, consultation, licensing of technology, commercialization, agreements with prospective customers and suppliers, and involvement in research consortia (Perkmann and Walsh 2007, Schartinger et al. 2002). Commercialization efforts and collaboration between university research programs and industry partners have increased with the advancement of legislation such as the Bayh-Dole Act, which granted intellectual property rights to universities (Mowery et al. 2001). Yet the distribution of industry collaborations is skewed, with a few research programs involved in the majority of collaborations (Agrawal and Henderson 2002). Collaboration with industry partners is a common channel for knowledge transfer, especially in nascent science-driven industries (Meyer-Krahmer and Schmoch 1998, Schartinger et al. 2002).

Collaboration with industry partners can promote knowledge application by providing complementary resources for commercialization. In the early stages of knowledge application, industry partners can share information on technological developments, market requirements, and practical problems that necessitate scientific solutions. At later stages, they can grant access to essential research and development (R&D) experience and skills that support knowledge application. For example, they can offer access to qualified engineers, production facilities, and marketing support for product development. Hence, industry collaboration institutes a division of labor between university research programs that focus on exploration and industry partners that facilitate exploitation (Lavie and Rosenkopf 2006, Rothaermel and Deeds 2004). Unlike passive knowledge transfer, whereby firms license patents and study scientific publications, industry collaboration furnishes complementary assets such as equipment and skilled personnel (Dyer and Singh 1998, Perkmann and Walsh 2007). It also enhances the absorptive capacity of university research programs (Cohen and Levinthal 1990) that is needed to assess opportunities for knowledge application.

Moreover, industry partners offer R&D funding that can be used for hiring personnel or purchasing laboratory equipment and materials. These resources encourage university research programs to become involved in technology development and commercialization by motivating change in behavior and modifying organizational routines, norms, and systems (Benner and Sandstorm 2000, Markman et al. 2008). Industry resources are often accompanied by expectations or formal contracts that commit university research programs to the objectives and deliverables of industry partners (Bozeman and Gaughan 2007). Commitments to an increasing number of industry partners facilitate technology development and commercialization. Indeed, entrepreneurial outputs such as patents and commercial products can be related to the availability of industry resources (Gulbrandsen and Smeby 2005). Accordingly, we expect knowledge application to initially increase with the number of industry partners involved in the research program.

Counterintuitively, as the number of industry partners exceeds a certain threshold, we expect a decline in knowledge application. First, industry collaboration often involves integrating unique knowledge assets of the university research program with generic resources of industry partners. Hence, the complementary resources and skills of industry partners are likely to become redundant as the number of partners becomes excessive (Baum et al. 2000). Second, given limits to their capacity and managerial attention, scientists at university research programs are less likely to achieve progress when spreading their efforts across a large number of industry engagements. This strain is exacerbated because industry partners often divert priorities from knowledge creation to its application, which forces scientists to learn new skills and expertise needed for knowledge application. Third, involvement with multiple industry partners may result in coordination problems and conflicts of interest because different partners expect their projects to receive priority. Unlike knowledge creation, which often produces a public good, knowledge application assigns intellectual property rights to industry partners, which can impose conflicting requirements when involving a large number of partners with commercial interests (Cohen et al. 2002). Thus, juggling numerous industry partners can undermine knowledge application.

Moreover, an initial increase in the number of industry partners advances knowledge application. However, given the inherent uncertainty of innovation (Van De Ven 1986, von Krogh et al. 2000), few projects are likely to reach a stage of commercialization, at which point university research programs are less motivated to invest in various other industry collaborations. Thus, an intermediate degree of industry collaboration is optimal for knowledge application. Indeed, universities can facilitate innovation with partial embeddedness whereby they are not isolated from the industry nor held captive by self-interested industry partners (Owen-Smith and Powell 2003). Consequently, knowledge application is likely to initially increase with the number of industry partners but then decrease as an excessive number of industry partners become involved, resulting in an inverted U-shaped effect of industry collaboration on knowledge application.

HYPOTHESIS 2. *Knowledge application will initially increase and then decrease with the extent of industry collaboration.*

The Interplay Between Internal Resources and Collaboration

The implications of collaboration for knowledge creation and application are not independent of the internal resources available to the research program. The resource-based view underscores the synergies emanating from combinations of internal resources and network resources furnished by partners (Dyer and Singh 1998; Lavie 2006, 2007; Teece 1987). Sharing knowledge and integrating complementary assets of university research programs and their partners can thus contribute to both knowledge creation and application. In addition, the availability of social capital in the form of collaborations with academic or industry partners increases the range of opportunities for leveraging internal resources (Lee et al. 2001). Moreover, the internal knowledge base needs to be sufficiently developed to assess, internalize, and apply external knowledge in related domains (Cohen and Levinthal 1990). To the extent that the research program possesses diverse expertise and technologies it can absorb external knowledge more effectively (Mowery et al. 1996). Hence, the prevalent supposition in the literature underscores the complementarity of internal resources and network resources made available via collaboration.

Nevertheless, few scholars have alluded to the possible substitution between internal resources and collaboration, indicating that resource-poor firms are most likely to benefit from collaboration with resource-rich partners. In particular, the technological and marketing resources furnished by partners are most valuable to young and small ventures that have limited access to such resources and strive for legitimacy in light of their liabilities of newness (Stinchcombe 1965, Stuart 2000). In addition, affluent partners can endorse an entrepreneurial venture and contribute to its reputation and legitimacy in the eyes of external stakeholders (Pfeffer and Salancik 1978). More generally, the smaller the scale and scope of internal resources relative to network resources shared by partners, the greater the expected benefits of collaboration (Lavie 2006). The availability of internal resources can thus limit the value of network resources furnished by partners. The larger the pool of internal resources, the weaker the contribution of collaboration to the research program. This alternative perspective implies substitution between internal resources and collaboration when studying the implications for knowledge creation and application.

Seeking to reconcile these conflicting perspectives on complementarity versus substitution, we claim that the interplay between collaboration and internal resources depends on the extent of collaboration. When a university research program engages a relatively small number of collaborators, its internal resources become critical for carrying out R&D activities. As the number of collaborators increases, available internal resources support internal operations while restricting the dependence of the research program on partners. This leads to reduced investment in collaboration, which eventually limits the benefits of collaboration (Khanna et al. 1998). The larger the stock of internal resources, the smaller the contribution of each added collaborator to knowledge creation and application. Yet as the number of collaborators becomes excessive, the availability of internal resources mitigates some of the negative implications of excessive collaboration. Specifically, university research programs can use internal resources such as administrative assistance and laboratory personnel to effectively manage a very large number of collaborations. These resources help overcome cognitive constraints, relax trade-offs that emanate from diverse priorities and objectives, facilitate coordination, and resolve emerging conflicts (Kale et al. 2002).

Considering knowledge creation, when the number of academic collaborators is small yet increasing, internal resources available to the research program attenuate the knowledge-creating benefits of collaboration. In particular, internal resources can be used for hosting visiting scholars and employing postdocs and junior scientists as part of the research team. Such resources can be used for procuring equipment and conducting activities typically performed by collaborators. To an extent, internal resources obtained by winning prestigious grants can also substitute for the reputation of respected collaborators. Hence, availability of internal resources is likely to devalue the contribution of academic collaboration to knowledge creation at a moderate level of collaboration. At that level, internal resources restrict the dependence of the research program on academic collaborators. Consequently, the intensity of collaborative relationships is likely to decline (Gulati and Sytch 2007), and the resource endowments of academic collaborators may be inefficiently deployed given their redundancy with internal resources. Therefore, as long as academic collaboration advances knowledge creation, availability of internal program resources is likely to undermine its contribution.

However, once a threshold is reached beyond which an excessive number of academic collaborators constrains knowledge creation, the availability of internal resources mitigates some of the impediments associated with extensive academic collaboration. For instance, internal resources can be used for appointing dedicated administrative personnel to coordinate multiple collaborative relationships (Kale et al. 2002), thus facilitating efficient exchange of knowledge, swift resolution of emerging conflicts, and the meeting of joint milestones

(Dyer and Singh 1998). Overall, we expect available internal resources to attenuate the effect of academic collaboration on knowledge creation—that is, limit the benefits of collaboration at the lower bound and mitigate its negative effects at the higher bound.

Hypothesis 3. *The curvilinear* (*inverted U-shaped*) *association between knowledge creation and academic collaboration will become weaker with the availability of internal resources.*

In the same vein, university research programs often collaborate with industry partners to promote knowledge application. The availability of internal program resources can substitute for the beneficial endowments of industry partners as long as such endowments facilitate knowledge application. In particular, internal resources can be used for acquiring materials, conducting experiments, developing prototypes, applying for patents, conducting market research, and subcontracting production. Allocating internal resources to such uses diminishes the contribution of industry partners that often furnish equivalent services. Hence, as long as industry collaborators promote knowledge application, internal program resources are expected to mitigate their contribution.

However, to the extent that industry collaboration becomes excessive and undermines knowledge application, internal resources can be used for overcoming some of the impediments associated with a complex portfolio of industry partners. For instance, liaisons and support staff can be hired to manage the relationships of the research program with industry partners, thus relaxing constraints on managerial attention and improving coordination across industry partners that furnish various network resources. The research team can be expanded to enhance the capacity for involving a large number of industry partners in joint R&D projects. Internal resources can be also used for retaining intellectual property rights, thus avoiding potential conflicts among multiple partners with overlapping appropriation claims. Therefore, the availability of internal program resources can mitigate some overembeddedness costs (Uzzi 1997) associated with an excessive number of industry partners. In sum, internal resources are expected to attenuate the effect of industry collaboration on knowledge application, thus limiting the benefits of collaboration at the lower bound and mitigating its negative effects at the higher bound.

Hypothesis 4. *The curvilinear* (*inverted U-shaped*) *association between knowledge application and industry collaboration will become weaker with the availability of internal resources.*

Research Methods

Research Setting and Sample

We study research programs affiliated with nanotechnology centers in Israeli universities. Nanotechnology is an emerging field of research and development, nurtured primarily in university research centers. According to the U.S. National Nanotechnology Initiative (NNI), nanotechnology refers to understanding, controlling, and organizing matter at dimensions of roughly −1 to 100 billionths of a meter. It calls for integration of physics, chemistry, biology, materials science, and engineering disciplines. Applications include new cancer therapies, pollution-eating compounds, durable consumer products, and detectors for biohazards such as anthrax. Nanotechnology is considered a revolutionary method of inventing and has the potential for transforming traditional industries (Bozeman et al. 2007, Zucker et al. 2007). Several governments promote national nanotechnology research. In particular, the NNI, which coordinates the U.S. government's efforts in nanoscale science, engineering, and technology, operates with an annual budget of $1.3 billion. In Israel, the Israel National Nanotechnology Initiative (INNI) supports $230 million in funding of nanotechnology research in universities through 2011. Still, it is unclear what direction this nascent industry may take or whether it will live up to its promise (Bozeman et al. 2007).

The Israeli nanotechnology industry has witnessed major progress in recent years. According to the INNI (http://www.nanoisrael.org/nanoisrael.asp, accessed May 6, 2011), the standardized number of Israeli nanotechnology publications and patents were ranked second and third in the world in 2002. As of 2009, 301 lead scientists were affiliated with six nanotechnology centers at Bar-Ilan University, Ben-Gurion University, the Hebrew University, Technion, Tel Aviv University, and the Weizmann Institute. Although each of the lead scientists is employed by a disciplinary faculty at one of these universities, the nanotechnology center in that university is responsible for supporting individual nanotechnology research programs. This responsibility typically includes recruiting faculty, administering research grants, raising funds for procuring and maintaining infrastructure, initiating educational programs, and introducing and supporting new research directions, as well as facilitating collaboration with other academic institutions and industry partners. By 2009, 75 Israeli firms had initiated development of nanotechnology products, most of which were start-up firms with core missions in the nanotechnology field. The rest were established corporations that engaged in nanotechnology R&D, either independently or in collaboration with academic or industry partners. The increasing focus on nanotechnology commercialization has been supported by government agencies such as the Israeli Academy of Science and Humanities, the Office of the Chief Scientist at the Ministry of Industry and Trade, and the Technological Incubator Program. Structured investment programs have furnished matching funds from universities and the government, thus tripling the potential value of a benefactor's donation to Israeli nanotechnology centers.

Given that knowledge creation in nanotechnology has been concentrated primarily in university research centers, for our purposes, we focus on research programs conducted at these centers. Each research program is led by a senior scientist whose team may involve also junior scientists, graduate students, engineers, and technicians that together engage in multiple research projects in the field of nanotechnology. Although each project assumes a distinctive research question or objective, all projects associated with a research program are related to the lead scientist's research interests and often share facilities, equipment, funding, and personnel. For this reason, the research program served as our unit of analysis, with lead scientists acting as respondents who provided information on their respective programs. We managed to gather data on all research centers and the most active research programs in Israel's nanotechnology sector.

We obtained the endorsement of the INNI's board and contacted the directors of the six Israeli research centers as well as individual scientists to compile a list of active nanotechnology scientists and their respective research programs. After accounting for newly appointed scientists and delisting retired scientists, dependent junior scientists, and scientists not directly involved in nanotechnology research, our initial sample included 298 research programs affiliated with Bar-Ilan University (30 programs), Ben-Gurion University (37 programs), the Hebrew University (34 programs), Technion (107 programs), Tel Aviv University (55 programs), and the Weizmann Institute (35 programs). Our final sample included 268 usable responses. Respondents were affiliated with the following disciplinary faculties: chemistry (25.37%), physics (21.64%), electrical engineering (10.07%), chemical engineering (8.21%), materials engineering (7.09%), biology (5.60%), biomedical engineering (5.60%), medicine (5.22%), mechanical engineering (4.85%), biotechnology (4.85%), mathematics (1.11%), and aerospace engineering (0.37%). The research programs focused on several areas: materials (49.47%), electronics and photonics (38.06%), biotechnology (30.60%), test and measurement tools (19.03%), filtration and membranes (6.72%), and other research fields (23.51%). On average, a research program employed 2.21 senior and junior scientists with Ph.D.'s, 2.88 researchers with M.S.'s, 2.02 M.S. students and engineers, and 0.74 technicians and other staff. On average, a research program involved 3.79 nanotechnology projects and operated for 9.95 years.

Data Collection

We incorporated multiple data sources including personal interviews, questionnaire responses, and archival data. We first conducted in-depth personal interviews with key informants in the Israeli nanotechnology sector, including the deputy chief scientist at the Ministry of Industry, Trade and Labor; the operating manager of the Forum for National R&D Infrastructures; the president of the Israel National Academy of Sciences and Humanities; INNI board members; directors of nanotechnology research centers; senior scientists; entrepreneurs; and executives of start-up firms. These interviews generated profound insights into the nanotechnology industry and the roles of various actors in driving knowledge creation and application. We leveraged these insights in our questionnaire, whose items referred to the field of nanotechnology research, the type and nature of research, the number of research projects, the availability and quality of laboratory equipment, the composition of the research team, the duration and progress of the research program, institutional affiliation, the number and types of academic collaborators and industry partners, and funding sources. We sought objective information that can be used to develop nonreactive measures that are unsusceptible to perceptual biases. Before issuing the questionnaire, we conducted a pretest study involving several scientists who provided additional feedback that helped refine the questionnaire design.

We issued the questionnaire to the population of 298 lead scientists who were invited to complete it on a secured website between May 2007 and January 2008. On average, it took respondents less than 15 minutes to complete a questionnaire. To maximize the response rate, we took several precautionary steps: (1) prior to our issuing the questionnaire, the INNI board of directors contacted directors of research centers to explain the objectives and importance of our research and ask for their cooperation; (2) the INNI board endorsed our questionnaire by including a cover letter that encouraged scientists to complete the questionnaire; (3) we assured respondents that their responses would be kept anonymous and confidential; (4) we offered to send them a report with findings and conclusions of the study; and finally (5) we issued three waves of the questionnaire, including e-mail and phone reminders. Moreover, between January 2008 and May 2008, we initiated personal meetings with reluctant scientists and encouraged them to complete the questionnaire. During that time frame, we also conducted follow-up phone interviews with scientists to update their records and complete missing information. In addition, we validated responses based on information documented in their resumes.

After discarding three responses with incomplete data, our final sample included 268 research programs (a 90% response rate). Our t-tests comparing the response and nonresponse groups revealed no significant differences in the mean number of issued patents ($t = 1.06$, $p = 0.30$) and patent applications ($t = 0.82$, $p = 0.42$) in fields related to nanotechnology. A multinomial logistic regression analysis showed only a marginally significant difference between the disciplinary faculty affiliations of scientists in the two groups ($\chi^2_{\mathrm{df}=12} = 19.90$, $p = 0.07$). These statistics establish the representativeness of our sample and attenuate concerns of nonresponse bias. To further assess nonresponse bias, we split our sample to early versus late respondents (Armstrong and Overton 1977), finding no significant differences between these groups. To mitigate concerns of common method bias, we incorporated archival data on the publication records of lead scientists instead of relying on self-reported measures. Unless noted otherwise, all the reported questionnaire-based measures correspond to the time frame since the initiation of the research program until May 2008.

Measures

Knowledge Creation (Dependent Variable). Our interviewees identified publication counts as the most relevant indicator of knowledge creation for university research programs. Scientific publications are considered highly relevant channels for knowledge dissemination in industries that leverage basic science and university research (Cohen et al. 2002). Regardless of whether scientific knowledge is produced via theoretical modeling, simulation, or laboratory experiments, the resulting knowledge is documented in scholarly publications. We have limited our focus to scientific journal articles that subject contributions to peer review prior to dissemination. We excluded books, which are considered a less relevant outlet for publishing new knowledge and which leverage a weaker and less transparent peer review system.

Our interviews suggested that the lead scientists are designated as authors in all the publications resulting from their respective research programs. We used Thomson's ISI Web of Knowledge database to extract their journal articles published since the initiation of the current research program until January 2009. We considered name variations of authors and verified their university affiliations by matching their publication records to their employment history. Following prior research that advocates keyword search for tracking scientific output in evolving technology fields (Mogoutov and Kahane 2007, Porter et al. 2008), we adopted an established and commonly used algorithm that isolates publications in the field of nanotechnology by searching the titles, keywords, and abstracts of publications for relevant keywords associated with nanotechnology (Huang et al. 2003, Rothaermel and Thursby 2007).[1] We verified that the publication years correspond to years in which the research programs were active. Overall, the 268 lead scientists published 25,124 articles, of which 3,919 (15.60%) were counted in the field of nanotechnology during the lifespan of corresponding research programs prior to January 2009. We measured knowledge creation by counting the nanotechnology publications associated with each research program.[2]

Knowledge Application (Dependent Variable). Applying scientific knowledge in new product development involves sequential progress from early research to development, manufacturing, and marketing (Cohen et al. 1996, Knudsen 2007). Our interviewees identified four stages of knowledge application in nanotechnology research programs: preliminary studies, prototype, testing, and commercialization. Preliminary studies involve initial exploration of ideas to determine the viability of technological concepts and to identify probable solutions to a scientific problem. Prototypes are then constructed for selected solutions to facilitate subsequent design and testing. At the testing stage, prototypes are subject to a range of conditions to verify robustness and finalize the product design. Subsequently, commercialization entails engineering, large-scale manufacturing, and marketing to introduce the new product to designated market segments. Respondents were asked to indicate the current progress of their research programs as of May 2008 using one of the following values: 1 for preliminary studies, 2 for prototype, 3 for testing, and 4 for commercialization. When the research program involved multiple projects at different stages, we coded the most advanced stage of knowledge application.[3] We preferred this measure to patent counts that only partially capture the innovative output of early-stage research and fail to reveal the extent to which knowledge has been practically applied.[4]

Academic Collaboration (Independent Variable). Any nonmember university scientist who had been working with members of the nanotechnology research program to produce new knowledge was considered a collaborator (Katz and Martin 1997). We measured the extent of academic collaboration with the cumulative number of all collaborators ever associated with each research program, as reported by the lead scientist. Based on these reports, 94.78% of the research programs involved academic collaboration. To enhance the accuracy of this measure, we prompted respondents to list the names and affiliations of their collaborators. Following prior research that underscores the differences between scientific collaboration and coauthorship (Bozeman and Corley 2004, Katz and Martin 1997), we preferred this measure to an alternative measure based on counts of coauthors listed on joint publications.[5]

Industry Collaboration (Independent Variable). Industry collaboration was measured with the cumulative number of industry partners ever involved in the nanotechnology research program as reported by the lead scientist. Industry partners included start-up firms and established corporations, and domestic as well as international firms. Industry partners were involved in the research program in various roles and to different extents. Nevertheless, only 46.27% of the research programs engaged industry partners. To enhance the accuracy of this measure, we asked respondents to identify their industry partners.

Internal Resources (Moderator). We focused on the research program's funding as a primary resource that serves for garnering all types of internal resources employed by the research program, including personnel, laboratory equipment, and materials. Program funding is critical in science-driven industries given the capital intensity of laboratory equipment and scientific operations as well as the need for highly qualified personnel. It can serve as a source of both tangible and intangible resources because prestigious research grants regenerate resources and bestow recognition (Benner and Sandstorm 2000). We asked respondents to indicate the cumulative funding available for their nanotechnology research programs. Given the sensitivity of this information, we used a categorical variable indicating the range of available funding: 0 for no funding, 1 for less than \$100,000, 2 for \$100,000–\$500,000, 3 for \$500,000–\$1 million, 4 for \$1 million–\$5 million, and 5 for funds larger than \$5 million. To enhance the accuracy of this measure, we also asked respondents to identify their funding sources, which included the host institution, Israeli/international scientific funds, Israeli/international government programs, independent funds/donors, Israeli/foreign corporations, and venture capital investors. *Internal resources* was incorporated as a moderator of the associations between knowledge creation and academic collaboration and between knowledge application and industry collaboration.

Control Variables. We included several control variables that may affect knowledge creation and application. First, we considered research program resources, including internal resources in the form of program funding, the research team's size and seniority, and the quality of laboratory equipment. *Internal resources* serves for obtaining dedicated personnel, equipment, and materials needed for carrying out scientific research. We measured *research team size* as the number of full-time equivalent personnel involved in the nanotechnology program, including the lead scientist, junior scientists, graduate students, engineers, and technicians. We also accounted for the qualifications of team members by coding *research team seniority* as the mean value of members' most recent degrees: 4 for a Ph.D., 3 for an M.S., 2 for a B.S., and 1 for other professional degrees. The team's composition may affect knowledge creation and application given the distinctive roles of team members. Also, equipment quality may affect the ability to run experiments that contribute to knowledge creation and application. *Lab equipment quality* was measured as the mean value of available equipment: 3 for state-of-the-art equipment, 2 for standard equipment, and 1 for below-standard equipment.

Additional controls refer to the nature of the research program. We included dummy variables describing the field of research: *materials* (e.g., particles, lubricants, bio materials, metals, polymers), *test and measurement tools* (e.g., positioning, metrology, surface analysis, optical test and measurement), *biotechnology* (e.g., disease treatment, genomics, antimicrobial agents, drug delivery), *electronics and photonics* (e.g., quantum computing, quantum dots, lithography and inspection), *filtration and membranes* (e.g., desalination, water purification), and *other research field*. A research program may involve multiple research fields. We also controlled for *applied research* (1 for applied research, 0 for basic research, and 0.5 for a combination), which is geared toward knowledge application. When studying the effects on knowledge application, we also accounted for *theoretical modeling* with a self-reported dummy variable, because research programs of theoreticians typically involve limited knowledge application.

Finally, we incorporated several control variables that may directly affect knowledge creation and application, such as the *number of projects* and *program duration*, which are likely to be positively related to the productivity and progress of the research program. We also included a count of *non-nano projects* because lead scientists who split their efforts between nanotechnology research and other research projects in their disciplinary fields are likely to contribute less to knowledge creation in nanotechnology, although such projects may or may not complement their efforts of knowledge application. Another categorical variable served for indicating the *nanotechnology center* with which the research program was affiliated (Bar-Ilan University, Ben-Gurion University, the Hebrew University, Technion, Tel Aviv University, or the Weizmann Institute). Such affiliation fixed effects may be relevant to the extent that particular institutions offer incentives and facilities that are not captured by other control variables.

Analysis

We measured knowledge creation with publication counts that are bounded at zero and assume integer values. We address the discrete nature of this dependent variable by using negative binomial regression with maximum likelihood estimation. The negative binomial model is a generalization of the Poisson model that adjusts for overdispersion that occurs when the variance of the estimated number of events exceeds its mean. This model corrects for overdispersion by including a varying error term that captures the overdispersion effects (Barron 1992). A comparison of our negative binomial models and the corresponding Poisson models using the Bayesian information criterion, the Akaike information criterion, and likelihood ratio tests revealed that the negative binomial models provide better fit to the data.

Our knowledge application variable is based on ordinal data describing the progress of the research program. Preliminary studies must be completed before the research program progresses to the prototype stage, which in turn leads to testing and finally to commercialization. Thus, we implemented continuation ratio logit models for knowledge application, using maximum likelihood estimation. Such models are appropriate when the ordered categories represent progression through stages, whereby one must pass through each preceding stage before moving to the subsequent one (Allison 1999). The continuation ratio model relies on conditional incremental cut points in which outcomes are omitted at a given stage following comparison to subsequent stages. To mitigate potential multicollinearity, we standardized all variables to have zero sample mean and unit variance. The variance inflation factor indexes ranged between 1.61 and 2.46 for the knowledge creation models and between 1.73 and 6.86 for the knowledge application models, both below critical values (Kleinbaum et al. 1998).

Results

Descriptive statistics including means, standard deviations, and correlations are reported in Table 1. On average, a research program produced 14.62 publications in the field of nanotechnology, with 55.97% of the programs operating at the preliminary studies stage, 22.39% at the prototype stage, 15.67% at the testing stage, and 5.97% reaching commercialization. No significant correlation was observed between knowledge creation and knowledge application. This result is consistent with prior research that reports no association between entrepreneurial activities and the traditional scientific work of university scientists (Gulbrandsen and Smeby 2005, Van Looy et al. 2004). Whereas knowledge creation precedes commercialization efforts, such efforts also consume resources otherwise invested in knowledge creation, so that the overall association is ambivalent.

Table 1 Descriptive Statistics and Correlations ($N = 268$)

Variable	Mean	Std. dev.	1	2	3	4	5	6	7	8	9	10	11
1. *Knowledge creation*	14.62	25.56											
2. *Knowledge application*	1.72	0.94	0.06										
3. *Academic collaboration*	6.51	5.76	0.45***	0.08									
4. *Industry collaboration*	1.32	2.14	0.36***	0.28***	0.46***								
5. *Nano Center 1*	0.14	0.35	−0.02	−0.11†	0.14*	−0.04							
6. *Nano Center 2*	0.12	0.32	0.05	0.14*	0.03	−0.02	−0.15*						
7. *Nano Center 3*	0.35	0.48	−0.09	0.05	−0.08	0.04	−0.29***	−0.27***					
8. *Nano Center 4*	0.17	0.38	−0.07	0.09	−0.07	−0.06	−0.18**	−0.17**	−0.33***				
9. *Nano Center 5*	0.11	0.32	0.09	−0.16**	−0.03	−0.06	−0.14*	−0.13*	−0.26***	−0.16**			
10. *Nano Center 6*	0.11	0.32	0.10†	−0.03	0.06	0.13*	−0.14*	−0.13*	−0.26	−0.16**	−0.13*		
11. *Field: Materials*	0.58	0.49	0.17**	0.11†	0.17**	0.20***	0.08	−0.04	0.04	−0.01	−0.06	−0.03	
12. *Field: Test and measurement tools*	0.19	0.39	0.10†	0.09	0.17**	0.18**	−0.08	−0.03	0.05	0.08	−0.02	−0.02	0.28***
13. *Field: Biotechnology*	0.31	0.46	−0.12*	0.15*	0.01	0.05	0.04	0.01	−0.11†	0.13*	−0.16**	0.12*	−0.07
14. *Field: Electronics and photonics*	0.38	0.49	0.07	−0.12*	0.05	−0.04	0.02	−0.05	−0.00	0.07	0.06	−0.11†	−0.06
15. *Field: Filtration and membranes*	0.07	0.25	−0.04	0.05	0.02	0.08	0.15*	−0.01	0.02	−0.08	−0.00	−0.10	−0.14*
16. *Other research field*	0.24	0.42	−0.03	−0.00	−0.07	0.01	−0.12*	0.09	0.02	0.05	−0.00	−0.06	−0.24***
17. *Applied research*	0.39	0.33	0.00	0.34***	−0.06	0.23***	−0.14*	0.02	0.15*	−0.02	−0.16**	0.09	0.04
18. *Number of projects*	3.79	3.06	0.50***	0.22***	0.45***	0.53***	0.10	0.01	−0.09	0.02	−0.08	0.07	0.18**
19. *Program duration*	9.95	7.49	0.23***	0.15*	0.25***	0.16*	0.00	0.08	−0.07	−0.13*	0.08	0.09	0.01
20. *Lab equipment quality*	2.33	0.81	−0.02	0.16**	0.03	0.16**	−0.18**	−0.11†	0.07	0.13*	0.11†	−0.06	0.22***
21. *Research team seniority*	2.93	0.44	0.03	−0.09	−0.10	−0.16**	−0.02	−0.05	−0.04	0.01	0.18**	−0.05	−0.17**
22. *Research team size*	7.35	5.00	0.33***	0.32***	0.34***	0.48***	−0.06	0.13*	0.16**	0.05	0.01	0.11†	0.11†
23. *Internal resources*	2.38	1.15	0.25***	0.32***	0.40***	0.40***	0.06	0.12*	−0.10†	0.06	−0.06	−0.03	0.10
24. *Non-nano projects*	2.09	2.43	−0.20***	0.06	−0.22***	−0.12*	−0.19**	0.01	0.04	0.08	−0.01	0.04	−0.15*
25. *Theoretical modeling*	0.07	0.26	0.02	−0.14	−0.00	−0.11†	0.17**	0.03	−0.03	−0.09	−0.06	−0.01	−0.13*

Variable	12	13	14	15	16	17	18	19	20	21	22	23	24
13. *Field: Biotechnology*	0.01												
14. *Field: Electronics and photonics*	0.07	−0.17**											
15. *Field: Filtration and membranes*	0.06	0.05	−0.06										
16. *Other research field*	−0.07	−0.12*	−0.22***	−0.04									
17. *Applied research*	−0.03	0.13*	0.01	0.18**	−0.01								
18. *Number of projects*	−0.20**	0.06	−0.00	0.03	0.07	0.04							
19. *Program duration*	0.07	−0.04	−0.12*	0.04	−0.08	−0.08	0.21***						
20. *Lab equipment quality*	0.11†	0.01	−0.02	−0.02	−0.08	0.16**	0.11†	−0.03					
21. *Research team seniority*	−0.17**	−0.16**	0.06	0.01	0.13*	−0.05	−0.19**	−0.09	−0.24***				
22. *Research team size*	0.14*	0.16**	−0.05	0.08	0.02	0.19**	0.62***	0.25***	0.19**	−0.30***			
23. *Internal resources*	0.16*	0.10	−0.00	0.02	−0.11†	0.01	0.44***	0.27***	0.15*	−0.24***	0.49***		
24. *Non-nano projects*	−0.05	0.02	−0.19**	0.02	0.14*	0.12*	−0.15*	−0.13*	−0.00	0.05	−0.03	−0.23***	
25. *Theoretical modeling*	−0.14*	−0.16**	0.07	−0.08	0.08	−0.18**	−0.03	0.02	−0.73***	0.27***	−0.12*	−0.09	−0.03

† $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (two-tailed).

On average, a nanotechnology research program featured 6.51 academic collaborators, of which 2.37 were from the same university, 1.34 were from other universities in Israel, and 2.80 were from foreign universities. A research program engaged 1.32 industry partners, with high correlation between industry collaboration and academic collaboration ($r = 0.46$, $p < 0.001$). Internal resources are positively related to the research team size ($r = 0.49$, $p < 0.001$), which is correlated with industry collaboration ($r = 0.48$, $p < 0.001$).

Table 2 reports the results of negative binomial models for knowledge creation. The baseline model (Model 1) shows the effects of our control variables, revealing no significant heterogeneity across nanotechnology research centers. Nevertheless, we found significant differences in knowledge creation across nanotechnology fields, with a greater number of publications in the fields of materials ($\beta = 0.32$, $p < 0.001$) and electronics and photonics ($\beta = 0.24$, $p < 0.001$), and fewer publications in biotechnology ($\beta = -0.23$, $p < 0.01$). As expected, knowledge creation is positively related to available internal resources ($\beta = 0.20$, $p < 0.05$), the number of nanotechnology projects ($\beta = 0.18$, $p < 0.05$), and program duration ($\beta = 0.30$, $p < 0.001$), but negatively related to the number of non-nano projects ($\beta = -0.20$, $p < 0.01$).

Model 3 served for testing Hypothesis 1. Consistent with our prediction, knowledge creation is positively related to academic collaboration ($\beta = 0.07$, $p < 0.001$) yet negatively associated with its quadratic term ($\beta = -0.002$, $p < 0.05$), suggesting an overall inverted U-shaped effect of academic collaboration on knowledge creation. The curvilinear model (Model 3) achieved better fit to the data than the linear model (Model 2) (2Δ log likelihood (LL) $= 5.58$, $p < 0.05$). Maximum productivity is within range, so that knowledge creation reaches a peak of 20.096 nanotechnology publications for 24 academic collaborators when other variables are held at their mean values. Next, we tested Hypothesis 3 by introducing internal resources as a moderator of the association between knowledge creation and academic collaboration (Model 4). Consistent with our prediction, internal resources negatively moderated the positive association between knowledge creation and academic collaboration ($\beta = -0.05$, $p < 0.01$) while positively moderating its quadratic term ($\beta = 0.003$, $p < 0.05$). Hence, internal resources attenuated the inverted U-shaped association between knowledge creation and academic collaboration (see Figure 1).[6]

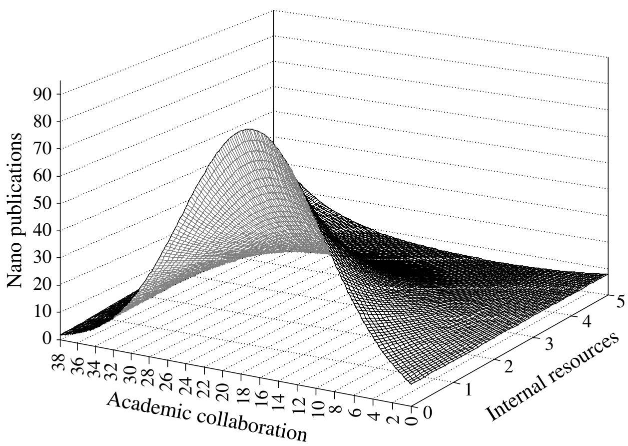
Table 3 reports the results of continuation ratio models for knowledge application. According to the baseline model (Model 5), certain nanotechnology research

Table 2 Negative Binomial Models for Knowledge Creation ($N = 268$)

Dependent variable: *Knowledge creation*	Model 1		Model 2		Model 3		Model 4	
Nano Center 1	−0.08	(0.09)	−0.06	(0.09)	−0.09	(0.09)	−0.08	(0.09)
Nano Center 2	0.03	(0.08)	0.06	(0.08)	0.06	(0.08)	0.07	(0.08)
Nano Center 3	−0.12	(0.11)	−0.08	(0.10)	−0.10	(0.10)	−0.09	(0.10)
Nano Center 4	−0.10	(0.09)	−0.04	(0.09)	−0.05	(0.09)	−0.05	(0.09)
Nano Center 5	0.09	(0.09)	0.11	(0.08)	0.09	(0.08)	0.07	(0.08)
Field: Materials	0.32***	(0.07)	0.32***	(0.06)	0.30***	(0.07)	0.29***	(0.07)
Field: Test and measurement tools	0.02	(0.07)	0.01	(0.07)	0.01	(0.06)	0.04	(0.07)
Field: Biotechnology	−0.23**	(0.07)	−0.23**	(0.07)	−0.25***	(0.07)	−0.26***	(0.07)
Field: Electronics and photonics	0.24***	(0.07)	0.23***	(0.07)	0.21**	(0.06)	0.19**	(0.06)
Field: Filtration and membranes	−0.07	(0.07)	−0.06	(0.06)	−0.05	(0.06)	−0.06	(0.06)
Applied research	−0.00	(0.07)	−0.01	(0.07)	−0.02	(0.07)	−0.03	(0.07)
Number of projects	0.18*	(0.08)	0.10	(0.08)	0.16†	(0.08)	0.11	(0.08)
Program duration	0.30***	(0.07)	0.29***	(0.07)	0.28***	(0.07)	0.27***	(0.07)
Lab equipment quality	−0.12†	(0.07)	−0.10	(0.07)	−0.08	(0.07)	−0.08	(0.07)
Research team seniority	0.03	(0.07)	0.01	(0.06)	0.01	(0.06)	0.003	(0.06)
Research team size	0.11	(0.09)	0.11	(0.09)	0.09	(0.09)	0.11	(0.09)
Internal resources	0.20*	(0.08)	0.14†	(0.08)	0.12	(0.08)	0.03	(0.08)
Non-nano projects	−0.20**	(0.07)	−0.16*	(0.07)	−0.16*	(0.07)	−0.16*	(0.07)
Academic collaboration			0.05**	(0.01)	0.07***	(0.02)	0.08***	(0.02)
Academic collaboration^2					−0.002*	(0.001)	−0.003†	(0.002)
Academic collaboration × *Internal resources*							−0.05**	(0.02)
Academic collaboration^2 × *Internal resources*							0.003*	(0.001)
Dispersion	0.85		0.80		0.78		0.76	
LL	−908.51		−902.26		−899.47		−895.45	
Pseudo-R^2	0.076		0.082		0.085		0.089	
2Δ LL			12.51***		18.09***		26.14***	

Note. Standard errors are in parentheses.
†$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0$ (two-tailed).

Figure 1 Knowledge Creation by Academic Collaboration and Internal Resources



centers host research programs at more advanced stages, yet such differences are only marginally significant. We found no significant differences in knowledge application across nanotechnology fields with the exception of electronics and photonics, which show marginally slower progress. As we expected, knowledge application is positively associated with applied research projects ($\beta = 0.61$, $p < 0.001$) and internal resources ($\beta = 0.50$, $p < 0.001$). Model 7 served for testing Hypothesis 2. Consistent with this hypothesis, the linear term of industry collaboration is positive ($\beta = 0.54$, $p < 0.05$), whereas its quadratic term is negative ($\beta = -0.48$, $p < 0.05$), suggesting an inverted U-shaped association between knowledge application and industry collaboration. This curvilinear model offered better fit to the data than the linear model (Model 6) ($2\Delta\,\mathrm{LL} = 3.82$, $p < 0.05$). The maximum level of productivity fell within range, so that knowledge application reached a peak at seven industry partners. At this level, the probabilities of commercialization (probability = 0.36) and testing (probability = 0.34) were highest, and those of preliminary studies (probability = 0.14) and prototype (probability = 0.16) were lowest (see Figure 2). We tested Hypothesis 4 by introducing internal resources as a moderator of the association between knowledge application and industry collaboration (Model 8). Because the interaction terms with internal resources are insignificant, we find no evidence that internal resources moderate the curvilinear association between knowledge application and industry collaboration. We suspect that this interaction effect is insignificant because industry partners may sponsor the research program in exchange for contract research and consulting (Perkmann and Walsh 2007). Indeed, some research programs received funding from Israeli firms (19.78%), foreign firms (12.69%), or venture capital investors (2.99%), which may obscure the moderating effect of internal resources.

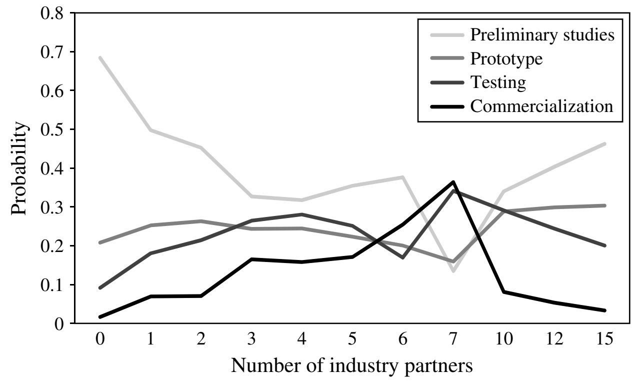
We conducted several auxiliary analyses to assess the robustness of our findings. First, we introduced separate measures for local collaboration (academic collaborators affiliated with the same university), domestic

Table 3 Continuation Ratio Models for Knowledge Application ($N = 268$)

Dependent variable: *Knowledge application*	Model 5	Model 6	Model 7	Model 8
Nano Center 1	0.02 (0.18)	0.05 (0.18)	−0.004 (0.18)	−0.01 (0.18)
Nano Center 2	0.27† (0.15)	0.30† (0.15)	0.26† (0.16)	0.29† (0.16)
Nano Center 3	0.32† (0.19)	0.35† (0.20)	0.27 (0.20)	0.26 (0.20)
Nano Center 4	0.31† (0.17)	0.35* (0.18)	0.31† (0.18)	0.33† (0.18)
Nano Center 5	−0.09 (0.18)	−0.06 (0.18)	−0.11 (0.18)	−0.08 (0.18)
Field: Materials	0.16 (0.13)	0.14 (0.13)	0.13 (0.13)	0.13 (0.13)
Field: Test and measurement tools	0.02 (0.12)	0.02 (0.12)	0.01 (0.12)	0.02 (0.12)
Field: Biotechnology	0.08 (0.12)	0.08 (0.12)	0.09 (0.11)	0.08 (0.12)
Field: Electronics and photonics	−0.23† (0.12)	−0.23† (0.12)	−0.24† (0.12)	−0.23† (0.12)
Field: Filtration and membranes	−0.09 (0.11)	−0.09 (0.11)	−0.08 (0.11)	−0.07 (0.11)
Applied research	0.61*** (0.13)	0.59*** (0.13)	0.58*** (0.13)	0.57*** (0.13)
Number of projects	0.06 (0.15)	0.04 (0.16)	0.10 (0.16)	0.11 (0.16)
Program duration	0.21† (0.12)	0.22† (0.12)	0.20† (0.12)	0.19† (0.12)
Lab equipment quality	0.01 (0.18)	0.01 (0.18)	−0.02 (0.18)	−0.01 (0.18)
Research team seniority	0.17 (0.13)	0.16 (0.13)	0.18 (0.13)	0.16 (0.13)
Research team size	0.21 (0.16)	0.18 (0.17)	0.14 (0.17)	0.10 (0.17)
Internal resources	0.50*** (0.14)	0.47** (0.14)	0.46** (0.14)	0.43** (0.15)
Non-nano projects	0.16 (0.12)	0.17 (0.12)	0.17 (0.12)	0.19 (0.12)
Theoretical modeling	−0.22 (0.19)	−0.22 (0.13)	−0.25 (0.19)	−0.27 (0.19)
Industry collaboration		0.14 (0.14)	0.54* (0.25)	0.30 (0.37)
Industry collaboration^2			−0.48* (0.24)	−0.02 (0.69)
Industry collaboration × *Internal resources*				0.45 (0.32)
Industry collaboration^2 × *Internal resources*				−0.51 (0.50)
LL	−251.28	−250.76	−248.85	−247.80
Pseudo-R^2	0.162	0.164	0.170	0.173
2Δ LL		1.03	4.85†	6.95

Note. Standard errors are in parentheses.
†$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0$ (two-tailed).

Figure 2 Industry Collaboration and the Likelihood of Knowledge Application



collaboration (collaborators affiliated with other Israeli universities), and international collaboration (collaborators affiliated with foreign universities) when studying the association between knowledge creation and academic collaboration. This auxiliary analysis revealed that although knowledge creation increases linearly with domestic collaboration, its association with the effects of local collaboration and international collaboration assumes an inverted U-shaped pattern in accordance with Hypothesis 1. In particular, knowledge creation reached a peak of 15.46 nanotechnology publications for 8 local collaborators and a peak of 17.17 publications for 12 international collaborators when all other variables were held at their mean values. We believe that domestic collaboration exhibits no diminishing returns because the mean number of domestic collaborators is significantly lower than the number of local or international collaborators, so that the maximum values may fall outside of the observed range. Overall, these results suggest that the inverted U-shaped association between knowledge creation and academic collaboration is almost insensitive to the composition and proximity of collaborators.

Next, we examined whether the effects of collaboration can be ascribed to the diversity of collaborators rather than to their increasing number. We constructed a Blau diversity index: $D = 1 - \sum_k (c_k/C)^2$, with C being the total number of academic collaborators and c_k denoting the number of collaborators of type k, namely, collaborators from the same university ($k = 1$), from other domestic universities ($k = 2$), or from foreign universities ($k = 3$). When the number of academic collaborators was replaced with the diversity of collaborators in Model 4 (Table 2), its effects were insignificant with the exception of a marginally significant positive linear effect. Thus, although knowledge creation may benefit from the diversity of academic collaborators, such an effect does not account for our reported inverted U-shaped association between knowledge creation and academic collaboration. Similarly, we constructed a measure of the diversity of industry partners by counting the types of industry relationships formed by each research program, including corporate visits, consultation, licensing of technology, joint research programs, commercialization, agreements with customers or suppliers, collaboration with government agencies, and involvement in domestic or foreign research consortia. When the number of industry partners was replaced with the corresponding diversity measure in Model 7 (Table 3), its effects were insignificant, suggesting that the inverted U-shaped association between knowledge application and industry collaboration can be ascribed to the number of industry partners rather than to their diversity.

In addition, we considered an alternative measure of knowledge creation based on a weighted citation count for publications in nanotechnology. Consistent with Hypothesis 1, the results revealed an inverted U-shaped association between academic collaboration and citations. Hence, academic collaboration affects not only productivity but also the quality or impact of knowledge created. Yet the moderating effect of internal resources was insignificant, suggesting that although internal resources affect the amount of jointly created knowledge, they do not influence the quality of such knowledge. Additionally, we found that our results remained virtually unchanged when excluding publications documented during years in which researchers were not affiliated with their home institutions.[7] Moreover, we tested an alternative measure of knowledge application based on the average progress of projects in the research program. Consistent with Hypothesis 2, we found an inverted U-shaped effect of industry collaboration on this alternative measure, yet the effects were less significant than our reported results.

In addition, we considered alternative measures of internal resources, such as the availability of laboratory equipment and the size of the research team. These auxiliary analyses revealed that available laboratory equipment negatively moderates the positive effect of industry collaboration on knowledge application, suggesting that such equipment substitutes for the endowments of industry partners. Consistent with Hypothesis 3, research team size negatively moderates the inverted U-shaped relationship between knowledge creation and academic collaboration. To gain further insights, we also tested models in which we considered the quality of laboratory equipment and the seniority of the research team as alternative moderators. Consistent with our reported findings, the quality of these resources does not modify the inverted U-shaped association between knowledge application and industry collaboration. Yet, whereas research team seniority enhances the contribution of academic collaboration to knowledge creation, the quality of equipment undermines that contribution. These inconsistent findings can be ascribed to the fact that each alternative measure captures a narrow aspect of the research program's internal resources and cannot effectively account for unobserved heterogeneity. These results further support our decision to measure internal resources with the proxy of accumulated program funding.

In another analysis we studied the effects of alternative measures of internal resources on the association between academic collaboration and the quality of knowledge created, captured by a weighted citation count of nanotechnology publications. With the exception of the seniority of the research team, which enhances the positive contribution of academic collaboration to the quality of produced knowledge, other measures such as the availability of laboratory equipment and the quality and the size of the research team do not affect that association. We conclude that the quality of knowledge developed is not sensitive to the availability of resources other than those related to the qualifications of scientists.

Following Wiersema and Bowen (2009), we accounted for the fact that knowledge creation and knowledge application are operationalized as limited dependent variables. We examined the marginal effects of our explanatory variables, which may vary nonlinearly with the values of the model variables, by using the sample mean of all variables. Corresponding results were fully consistent with our reported findings.

Moreover, given the cross-sectional nature of our data, we tested for reversed causality whereby knowledge creation and application correspondingly facilitate academic and industry collaboration. With respect to academic collaboration, the results of a negative binomial model revealed a decrease in the explanatory power of the model when the number of academic collaborators served as the dependent variable (from pseudo-$R^2 = 0.085$ to pseudo-$R^2 = 0.074$). Similarly, the explanatory power of the model declined (from pseudo-$R^2 = 0.170$ to pseudo-$R^2 = 0.132$) when industry collaboration served as the dependent variable. These results are consistent with our interpretation that collaboration drives knowledge creation and application. Our interviews furnish further support for this causal relationship:

> You seek the best partner to promote your research program and maximize synergy. Scientists frequently meet with their peers in conferences. Everyone knows what is done at other institutions. Collaborations emerge spontaneously. There are no barriers. They are even encouraged. For example, a scientist at the Hebrew University knows how to define unique nanometric particles, and someone at the Technion knows how to grow layers of organic molecules that conduct electricity. They formed a collaboration that enables them to produce laser and light-emitting systems. Integrating their knowledge enabled this achievement.
>
> (A director of a nanotechnology research center)

Finally, we examined whether academic collaboration promotes knowledge application and how industry collaboration enhances knowledge creation. In both cases, we found no significant effects, suggesting that academic collaboration contributes to knowledge creation but not to knowledge application, whereas industry collaboration advances knowledge application rather than knowledge creation.

Discussion and Conclusions

Knowledge creation and application are critical to the evolution of science-driven industries. We study these processes in the field of nanotechnology, where technological and market uncertainty, reliance on interdisciplinary de novo knowledge base, a weak institutional environment, and exorbitant investments often call for collaboration (Mehta 2002, Meyer and Persson 1998). At its nascent stage of evolution, nanotechnology research has been carried out mostly in university research centers, raising intriguing questions concerning the implications of collaboration for university research programs. Offering new insights on collaboration in nascent industries, we find no evidence of the often taken-for-granted linkage between knowledge creation and application in established industries. We complement the thriving literature on the performance implications of collaborative relationships in alliance networks (e.g., Baum et al. 2000, Powell et al. 1996, Rothaermel and Deeds 2004, Stuart 2000) and advance knowledge management research (e.g., Argote and Ingram 2000, Dyer and Nobeoka 2000, Grant 1996, Hansen 2002, Nonaka 1994). Our main contribution, however, concerns the delicate interplay between internal resources and collaboration in driving knowledge creation and application.

Departing from traditional research that underscored the benefits of collaboration, our findings reveal boundary conditions for the merits of collaboration in driving knowledge creation and application. We demonstrate that collaboration with fellow scientists promotes knowledge creation only up to a point, beyond which knowledge creation is in fact undermined. We show that an optimal level of industry collaboration is needed for advancing knowledge application and its manifestation in commercialized products and technologies. Our field interviews corroborate this finding:

> We actively encourage our industry partners to visit us. It is not just their money or connections that we seek but the unique knowledge that they possess. They are more familiar with the markets and needs. Yet, when it comes to concrete collaboration, we weigh it very carefully.
>
> (A lead scientist)

Indeed, our findings suggest that collaboration produces diminishing returns and incurs costs. As the extents of academic collaboration and industry partnerships become excessive, managerial challenges mount, and interorganizational trade-offs and conflicts arise (McFadyen and Cannella 2004, Owen-Smith and Powell 2003), which render collaboration unproductive.

More importantly, we reveal how the contribution of collaboration to knowledge creation and application is contingent on the availability of internal resources. Prior research has emphasized the complementary value of network resources furnished by partners and the synergies arising from their combination with internal resources (Dyer and Singh 1998, Lavie 2007, Teece 1987). Yet few studies have regarded network resources as potential substitutes for internal resources that are short in supply (Lavie 2006, Stuart 2000). Our findings reconcile these conflicting views by demonstrating how the interplay between internal resources and network resources varies with the extent of collaboration. The availability of internal resources limits the benefits that research programs extract from academic collaboration but at the same time also mitigates some of the costs associated with excessive engagements with fellow scientists.[8] In this sense, the sourcing of knowledge is contingent upon trade-offs between in-house and external capabilities (Raflos 2007). At least some internal resources help facilitate coordination and manage the otherwise complex portfolio of collaborators. Nevertheless, we found no evidence of the attenuating effect of internal resources on the contribution of industry partners to knowledge application, perhaps because such partners can offer funding. Collaboration and program funding may endogenously affect research productivity (Defazio et al. 2009) so that scientists can enhance their productivity by strategizing on the extent and type of collaboration. In sum, our findings discern between distinctive types of partners and underscore the interplay between internal resources and external network resources, as illustrated by our interviews:

> Our initial reaction when it comes to academic collaboration or ties to industry partners is to get as much as we can. This is because we have this perception of chronic shortage in resources and skilled personnel. Our tendency as scientists who manage laboratories is to build empires. However, on second thought, we always make calculations. Can I incorporate all the resources that I can get? Can I use them effectively? Do they contribute to my objective of promoting path-breaking research? How much will I have to give and for what?
>
> (A lead scientist)

These trade-offs have been often overlooked by mainstream literature on collaboration that has focused on the structural properties of alliance networks (Ahuja 2000, Baum et al. 2000, Stuart et al. 1999, Zaheer and Bell 2005) and their relational mechanisms (Dyer and Singh 1998, Madhok and Tallman 1998).

In addition, our study informs the knowledge management literature that has traditionally concentrated on knowledge transfer while paying less attention to knowledge creation and application (Agrawal 2001, Argote and Ingram 2000, Dyer and Nobeoka 2000, Grant 1996, Hansen 2002, Nonaka 1994). We uncover the role of collaboration in driving these processes but, more importantly, challenge the linear model of innovation according to which basic research precedes applied research that leads to development and diffusion of knowledge-based products (Holland 1928, Mansfield 1968). We reveal that university scientists can contribute to knowledge application, even though this is not their primary objective:

> We informed our scientists that we will fund and support the development of basic knowledge to the point where the industry can take it. Many scientists engage in research that generates results but then face a dilemma: either store everything in the drawer or seek a venture capital firm and establish a start-up. The second option demands much more time and attention than many of them are willing to give.
>
> (A director of a nanotechnology research center)

Hence, whereas the linear model suggests that knowledge creation generates spillovers that drive knowledge application, we find no significant association between these processes. Instead, we demonstrate that these processes are driven by distinctive types of collaboration. In fact, there may be a trade-off between knowledge creation and application given the disparity between scientific research and commercial interests. Whereas knowledge creation and dissemination are the primary mission of university research programs, industry partners focus on application and value appropriation by restricting access to intellectual property (Cohen et al. 2002, Gittelman and Kogut 2003, Rothaermel and Thursby 2005). The interests of these strange bedfellows meet when scientists seek to validate their working assumptions and match scientific solutions with industry requirements (Meyer-Krahmer and Schmoch 1998). Industry partners can help support research programs because knowledge application indirectly promotes knowledge creation. Still, further research is needed to establish the prevalence of spillovers in this direction. We identified unique challenges that university research programs face when collaborating with industry partners as opposed to fellow scientists:

> We collaborate with colleagues both in our discipline and in other disciplines. I enter these collaborations because my partners can do certain things better than me. Having access to equipment and funding is insufficient. I also look for real scientific contribution to my research program.... I'm responsible for my team, especially my graduate students and technical personnel. This forces me to juggle many projects and seek large funds. In nanotechnology there are many opportunities for academy–industry collaboration.... With industry, it is more problematic since collaboration involves not only funding but also potential conflict over intellectual property.
>
> (A university scientist)

Interestingly, whereas the transformation of new knowledge into commercial applications is typically slow and highly uncertain, knowledge application can provide immediate and concrete input to knowledge creation efforts. Hence, the association between knowledge creation and application is not straightforward and entails a delicate management of trade-offs that transpire between these two processes. Our findings concur with research that highlights the complex nature of interdependence between knowledge creation and application. This often mandates going beyond the linear model of innovation whereby university research produces knowledge that is then transferred to firms that concentrate on its commercialization (e.g., Leydesdorff 2000, Stokes 1997). Future research may further examine the conditions that enable university research programs to transfer and commercialize new knowledge. Such research may also uncover collaborative practices that support the shift from knowledge creation to its application. In this regard, our study suggests that university research programs must reconcile discovery and innovation as they balance exploration and exploitation (Lavie and Rosenkopf 2006).

Finally, our findings qualify recent work on scientific research in nascent industries that has highlighted the merits of collaboration (Defazio et al. 2009, Gulbrandsen and Smeby 2005, Landry et al. 1996, Lee and Bozeman 2005). Government and university programs often encourage collaboration with fellow scientists and industry partners, yet we uncover some boundary conditions for the benefits of collaboration, demonstrating that knowledge creation and application are best served when university research programs limit their collaborative relationships and optimize their use of internal resources and network resources. Conditioning program funding on collaboration (Gulbrandsen and Smeby 2005) may constrain the ability to optimize the extent and type of collaboration that best suits the research program. Future research may consider the appropriate incentives for fostering collaboration because funding in and of itself cannot bridge the gap between university programs and their industry partners:

> In nanotechnology there is a significant gap between academy and industry. The academy is working primarily on generic research with a relatively sophisticated and long-term outlook. The industry, in turn, is interested in applications and is insufficiently advanced to bridge the gap between scientific research and its application.
> (A director of a nanotechnology research center)

Hence, our study complements the growing literature on university entrepreneurship (Rothaermel et al. 2007) by shedding light on how university–industry collaboration drives commercialization.

Future research may extend our inquiry by juxtaposing the perspective of university research programs and that of corporations that are primarily interested in commercialization (e.g., Gittelman and Kogut 2003, Rothaermel and Thursby 2005). Our reliance on cross-sectional questionnaire data limits our ability to demonstrate the direction of causality between collaboration and knowledge creation and application. Longitudinal research can shed more light on the causal mechanisms that relate collaboration to knowledge creation and application, although archival data may offer limited insights into the internal operations of university research programs. Scholars may also consider the specific role of relational mechanisms and cooperative governance in moderating the effects of collaboration (e.g., Dyer and Singh 1998, Kale et al. 2000, Madhok and Tallman 1998). Another possible extension would involve a more careful examination of the diversity of the portfolio of collaborators (Hoffmann 2007). Perhaps distinctive types of academic collaborators or industry partners offer greater potential for knowledge creation and application. Moreover, field studies can complement our research by uncovering the particular processes by which collaboration and internal resources enhance knowledge creation and application. It would be interesting to examine the extent to which distinctive internal resources substitute or complement collaboration. For instance, program funding can mitigate the benefits of external resources, but it cannot fully substitute for intellectual exchange and the fresh perspective of academic collaborators that stems from their training and recent discoveries. Field research can also reveal how collaboration in academia as well as among academia, industry, and government contributes to the emergence of science-driven industries. Finally, studying other nascent and established industries in various national contexts can serve to generalize our findings. In an established industry, knowledge application may be more critical than knowledge creation, and industry partners may contribute more than universities to industry evolution. Irrespective of such extensions, our study reveals the contingent value of collaboration and makes important strides toward understanding the role of collaboration in driving knowledge creation and application.

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Appendix. Nanotechnology Questionnaire (Selected Questions)

1. Field of Research (Select all that apply)
   [ ] Materials [ ] Tools, Test and Measurement [ ] Biotechnology [ ] Electronics and Photonics
   [ ] Filtration and Membranes [ ] Other
2. Number of research projects included in the program ——
3. Research program is affiliated with a dedicated nano center or institute ——
4. Availability of laboratory equipment for nanotechnology projects in your research program (Select all that apply)
   [ ] Available at my university [ ] Available at another Israeli university [ ] Only partially available
   [ ] No equipment required for my research program
5. Quality of laboratory equipment (Select all that apply)
   [ ] State-of-the-art [ ] Standard [ ] Below standard [ ] No equipment required for my research program
6. Type of research (Select all that apply)
   [ ] Basic research [ ] Application research (technology)
7. Number of researchers in my research program including myself
   Senior researchers and postdocs (with PhDs) —— PhD students and researchers (with MSs) ——
   MS students and engineers —— Other staff —— Total size of research team in full-time equivalent personnel ——
8. Your research program in nanotechnology was initiated in year ——
9. Current progress of nanotechnology projects in your research program (Select all that apply)
   [ ] Preliminary studies [ ] Prototype [ ] Testing [ ] Commercial [ ] I am a theoretician who focuses on theoretical modeling
10. Number of collaborators from my own university ——
11. Number of collaborators from other Israeli universities ——
12. Collaborators are affiliated with the following universities (Select all that apply)
    [ ] Technion [ ] Bar-Ilan University [ ] Tel Aviv University [ ] Ben-Gurion University [ ] Weizmann Institute
    [ ] Haifa University [ ] Hebrew University [ ] Other
13. Number of collaborators from foreign universities ——
14. List names and affiliations of all academic collaborators in connection with the research program
15. Industrial collaboration in connection with the research program (Select all that apply)
    [ ] Receiving inquiries and visits from industry companies or venture capital investors [ ] Consultation to industry companies [ ] Research collaboration with industry companies [ ] Licensing of technology [ ] Commercialization of technology with industry companies [ ] Collaboration with suppliers of materials, equipment, or technologies [ ] Collaboration with potential customers [ ] Collaboration with government agencies [ ] Involvement in Israeli research consortia [ ] Involvement in international research consortia
16. Types of industry partners (Select all that apply)
    [ ] Established companies [ ] Start-up companies
17. Origin of industry partners (Select all that apply)
    [ ] Israeli companies [ ] Foreign companies
18. Total number of industry partners ——
19. List names and countries of origin of primary industry partners
20. Total amount of funding raised so far (in US$)
    [ ] None [ ] Less than 100K [ ] 100K–500K [ ] 500K–1 million [ ] 1–5 million [ ] More than 5 million
21. Types of funding sources (Select all that apply)
    [ ] Host institution [ ] Israeli scientific funds [ ] International scientific funds [ ] Israeli government programs
    [ ] Foreign government programs [ ] Independent foundations and donors [ ] Foreign government programs
    [ ] Venture capital investors
22. Number of research projects unrelated to nanotechnology you are involved in ——

Endnotes

[1]We used the following keywords: atomic force microscopy; atomistic simulation; biomotor; molecular device; molecular electronics; molecular modeling; molecular motor; molecular sensor; molecular simulation; nano*; quantum computing; quantum dot*; quantum effect*; scanning tunneling microscop*; self assembl*; and selfassembl*.

[2]The number of journal articles published is a common measure of scientific productivity (Duque et al. 2005, Lee and Bozeman 2005, Zucker et al. 2007). We preferred this measure to alternative measures such as citation counts, which can be used for assessing the impact of scholarly contributions yet are less suitable for measuring the productivity of knowledge creation in the field of nanotechnology (Zucker et al. 2007). In this setting, citations do not reliably represent a direct linkage between technologies and the referenced knowledge (Meyer 2000). We also considered patent counts, but these were limited to certain types of knowledge that can be designated as intellectual property. In fact, only 37.31% of the scientists in our sample have applied for or were issued patents in the field of nanotechnology, as opposed to 89.93% who have published articles related to nanotechnology. Indeed, prior research suggests that patents represent a small fraction of the knowledge created by academic research programs (Agrawal and

Henderson 2002, Cohen et al. 2002). Furthermore, because of the gap between the time of knowledge creation and the time of recorded citations and patent counts, such alternative measures are less suitable for measuring knowledge creation in emerging scientific fields characterized by fast-growing and fluid knowledge development (Bozeman et al. 2007). By counting the accumulated number of publications in a time frame that extends beyond the questionnaire period, we captured all relevant knowledge including forthcoming publications.

[3]We measured the progress of the most advanced project associated with each research program rather than the average progress of all projects in the corresponding research program to avoid possible right censoring bias that may emerge given the long lifespan of nanotechnology projects and the fact that many projects were initiated relatively recently. Furthermore, our interviews with lead scientists suggested that although they initiate multiple research projects, when considering knowledge application they tend to focus only on one or a few projects that show the most promising prospects for commercialization.

[4]Besides the fact that not all knowledge is patentable, patents do not necessarily manifest in commercialized products, at least not in a foreseeable time frame (Griliches 1990, Klevorick et al. 1995, Levin et al. 1987).

[5]Self-reported measures of collaboration are preferable to coauthorship measures that may omit relevant contributors while including honorary coauthors such as laboratory directors or authors who merely perform routine tasks or provide funding or materials (Bozeman and Corley 2004, Cockburn and Henderson 1998, Katz and Martin 1997, Lee and Bozeman 2005). Bibliometric measures of collaboration based on coauthored publications are also inherently associated with publication counts that proxy for the outcomes of collaboration (Duque et al. 2005).

[6]Although Figure 1 suggests a reversal of the inverted U-shaped association, such a pattern occurs at values that fall outside the applicable range of data. Specifically, for internal resources with the value 5, the maximum number of academic collaborators was 30, so we do not expect abundant internal resources to facilitate a positive association between extensive academic collaboration and knowledge creation as revealed in this figure.

[7]We identified 20 scientists who moved to their current institutions after initiating their research programs elsewhere. On average, scientists spent 96.52% of their time working on their nanotechnology research programs in their current institutions.

[8]Our findings confirm that internal resources mitigate the benefits of academic collaboration at the lower bound rather than simply weaken the propensity to collaborate. Besides the observed negative moderation effect of internal resources, its positive correlation with academic collaboration ($r = 0.40$, $p < 0.001$) suggests that internal resources undermine the effects of collaboration rather than the tendency to engage in collaboration.

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