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University–incubator firm knowledge flows: assessing their impact on incubator firm performance

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Abstract

Technology incubators are university-based technology initiatives that should facilitate knowledge flows from the university to the incubator firms. We thus investigate the research question of how knowledge actually flows from universities to incubator firms. Moreover, we assess the effect of these knowledge flows on incubator firm-level differential performance. Based on the resource-based view of the firm and the absorptive capacity construct, we advance the overarching hypothesis that knowledge flows should enhance incubator firm performance. Drawing on longitudinal and fine-grained firm-level data of 79 technology ventures incubated between 1998 and 2003 at the Advanced Technology Development Center, a technology incubator sponsored by the Georgia Institute of Technology, we find some support for knowledge flows from universities to incubator firms. Our evidence suggests that incubator firms' absorptive capacity is an important factor when transforming university knowledge into firm-level competitive advantage.
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1. Introduction

How do technology ventures access university knowledge and how does it affect their performance? Knowledge produced in universities has been studied extensively, as has its impact on industry. Yet, we know little about knowledge flows at the firm level, either in terms of the flows themselves or effects thereof. In part, this is because of the inherent difficulty tracking knowledge created for the public domain, but in part, it is because the firm has not been a common unit of analysis. Moreover, there is mounting empirical evidence that local knowledge spillovers produced by university research are not "free," but depend on contractual agreements. Thursby and Thursby (2002) and Zucker and Darby (1996, 1998) document this. Moreover, Cockburn and Henderson (1998) demon-

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strate that firms must exhibit substantial absorptive capacity to capture and appropriate rents to publicly available knowledge. Cohen and Levinthal (1989) advance the notion of absorptive capacity, which is understood as a firm's ability to recognize, value, and assimilate new external information.

Herein, we attempt to address the two-pronged research question of (1) how knowledge flows from universities to incubator firms and (2) how these flows affect the performance of new technology ventures. As part of the first question, we identify and analyze the effects of different mechanisms through which knowledge flows from universities to incubator firms: university license, and patent backward citations to university research, academic journals, research by the incubator-sponsoring university, and research from other universities than the sponsoring university. Embedded in the second research question is the search for an appropriate performance metric for nascent technology ventures, a significant methodological challenge, which has clearly retarded empirical research in this important area as emphasized by Phan et al. (2004).

Given the dearth on empirical research investigating university knowledge flows and their effect on incubator firm performance, we develop two explorative hypotheses that we subsequently examine econometrically. Firstly, we argue that exclusive knowledge flows in terms of a university license can endow the start-up with a unique resource. Important theoretical work in the strategic management literature has argued that valuable, rare, inimitable, and non-substitutable resources may endow a firm with a competitive advantage that translate to superior performance (Barney, 1991). Secondly, we suggest that university backward patent citations are indicative of a start-up's absorptive capacity that enables it to recognize public knowledge flows emanating from a university, assimilate them internally, and then to apply them to commercial ends (Cohen and Levinthal, 1989). This in turn should lead to a variance in performance among technology ventures with a venture's absorptive capacity being positively correlated with venture performance.

We test these two tentative hypotheses on a sample of 79 incubator firms incubated in the Advanced Technology Development Center (ATDC) at the Georgia Institute of Technology (Georgia Tech (GT)). We follow these firms over the 6-year time span between 1998 and 2003. The use of an annual repeat survey enables us not only to collect fine grained data for nascent technology ventures, but also aids us in overcoming a survivor bias common to research on new technology ventures. Moreover, we attempt to enhance the robustness of the analysis by applying four different performance measures: total revenues, total funds obtained, venture capital (VC) funding obtained, and failure or graduation from the incubator. Applying different outcome variables might aid in identifying an appropriate outcome measure in the new venture context, in particular, when attempting to capture the performance implications of university knowledge flows.

This paper has the following outline. Section 2 reviews prior research on university–industry knowledge flows, and Section 3 develops the hypotheses regarding university licenses, patent citations, and new venture performance. Section 4 discusses the methodology applied, Section 5 presents the empirical results, while Section 6 concludes this paper with a discussion of the results, limitations as well as implications for future research and public policy.

2. University–industry knowledge-flows—prior research

Early work on the industrial impact of academic research includes Adams (1990), who showed that academic knowledge, as measured by publications, was a major contributor to productivity growth for 18 of 20 two-digit U.S. manufacturing industries from 1943 to 1983, albeit with a substantial lag times which varied from 0–10 years for applied sciences and engineering to 20 years for basic science publications. Jaffe (1989) classic study of the real effects of academic research showed that university research had significant effects on the generation of industrial patents at the state level.

With the exception of the work by Zucker and Darby (1996, 1998) and Zucker et al. (2002), which we discuss below, the focus of research in this area is not overall firm performance but the effect of university research on industry R&D output. Even when data were collected by firm, the questions of interest have been variations in the relevance of university research by industry and academic field. For example, both the 1983 Yale Survey and the 1994 Carnegie Mellon Survey of R&D managers asked the relevance of university research for technical progress in their industry (Klevorick et al., 1994; Cohen et al., 1998). Mansfield's survey of R&D executives of 66 firms examined the perceived impact of university research on the firm's ability to develop new processes and products in a timely fashion (Mansfield, 1995). Not surprisingly, all of this work finds the most pervasive effects of university research are in the drug, chemical, and electronics industries.

This prior research demonstrates that knowledge flows from universities tend to be mitigated by geographic distance, which of course suggests that academic publications alone cannot be the sole means by which firms gain access to university knowledge. Researchers have used a variety of methods to examine the channels by which university knowledge is transferred to industry, including interviews and survey research, citations to academic publications and patents, collaboration patterns in academic publications and patents, as well as information on formal contracts such as licenses or sponsored research. The most comprehensive survey in this regard is the Carnegie Mellon Survey of 1478 R&D laboratories which asked R&D managers the importance to them of 10 channels of knowledge flow (patent, publications, meetings or conferences, informal channels, hires, licenses, joint ventures, contract research, consulting, and personal exchange). Of these publications, public meetings and conferences, informal and personal information channels, and consulting contracts appear to be the four most important channels, suggesting a complementarity between publication and other mechanisms involving personal contact (Cohen et al., 1998). The results on consulting support the results from Mansfield (1995) that show a complementarity between consulting and the research agendas of university scientists working with industry.

The use of citation data, either to academic publications or patents, in economics has a rich tradition, not only for examining knowledge flows from universities, but also R&D spillovers in general (Griliches, 1992). With regard to flows from universities, a series of important studies examine a variety of measures of citations to university patents in order to examine issues of localization as well as the importance of university patents (Jaffe et al., 1993; Trajtenberg et al., 1997; Henderson et al., 1998). Branstetter (2004) examines patent citations to academic publications and shows an increasing trend for industrial patents to cite academic science. This work complements that of Agrawal and Henderson (2002) and Murray and Stern (2004) which examines the interaction of academic and industry collaboration and citation patterns. Here, one underlying assumption is that knowledge spillovers tend to be localized, and that being located close to the knowledge source enhances the efficiency and effectiveness of the knowledge transfer. When studying the performance of U.S. university research parks, for example, Link and Scott (2004) found that parks located closer geographically to a research university grew significantly faster.

While much of this literature focuses on knowledge flows as spillovers, some authors have focused on market transactions involving university industry collaboration. Prominent in this stream is the work of Zucker and Darby (1996, 1998) who examine the role of star university scientists in the formation and performance of new firms in biotechnology. Their work points to the importance of star scientist collaboration in the transfer of information to nascent firms. Similarly, Thursby and Thursby (2004) also examine collaboration between scientists and firms but their sample is comprised of firms that license university technologies and their focus is on contractual mechanism of transfer.

3. Knowledge flows and incubator firm performance

In this paper, we build on the ideas from this literature and hypothesize that both contractual and noncontractual mechanisms are important for understanding university–firm knowledge flows and the effects on incubator firm performance.

3.1. University licenses and incubator firm performance

Since the early 1990s, licensing activity in U.S. research universities has increased considerably. Analyzing the growth of university licensing, Thursby and Thursby (2002) draw on data from a survey by the Association of University Technology Managers (AUTM) and state that in 1998 alone, the 132 research universities responding to the survey reported more than 9500 disclosures, more than 4100 new patent applications, and more than 3000 licenses and options executed.

The university licensing process starts with a faculty member disclosing a discovery to the university's office of technology transfer. Some universities, like Georgia Tech, do not wait for faculty to take the first step of disclosing an invention but rather proactively monitor university faculty research and encourage faculty to disclosure inventions. Once a discovery is disclosed, the office of technology transfer evaluates the commercial potential of this invention. If there is some commercial potential and expected licensees are anticipated, the office of technology licensing applies for a patent. Note that not all technology licenses go along with patent protection because many inventions are protected by copyright, for example, software. Yet, university technology licenses are generally exclusive. As a case in point, all of the licenses granted by Georgia Tech to the incubator firms in this study are exclusive.

We suggest that exclusive licenses endow the incubator firm with a unique resource. In a seminal article that laid the theoretical foundation for the resource-based view of the firm, an important framework in strategic management research, Barney (1991, pp. 105–106) posited that for firm resource to have the potential to be the basis of a competitive advantage, "(a) it must be valuable, in the sense that it exploits opportunities and/or neutralizes threats in a firm's environment, (b) it must be rare among a firm's current and potential competitors, (c) it must be imperfectly imitable, and (d) there cannot be strategically equivalent substitutes for this resource that are valuable but are neither rare or imperfectly imitable." Competitive advantage is defined as "a value creating strategy not simultaneously being implemented by any current or potential competitors" (Barney, 1991, p. 102).

We thus posit that a technology license fulfills the attributes discussed by Barney as it is valuable because it allows the firms to exploit a technological opportunity; it is rare because the license is exclusive and contains novel technology; it is generally imperfectly imitable, often protected by legal barriers like patents or copyrights; and there are generally no readily available substitutes. Thus, holding a technology license should aid an incubator firm in achieving superior performance because it can implement a strategy based on this unique resource that its existing or potential competitors cannot readily imitate.

3.2. Patent citations, absorptive capacity, and incubator firm performance

Backward patent citations are references made to prior art in a patent application. Patent backward citations are bibliometric fossils that identify the ideas on which an incubator firm draws when applying for a patent. Being able to draw on past research, albeit public in nature, demonstrates that the incubator firm is endowed with some degree of absorptive capacity which enables it to recognize, assimilate, and exploit external knowledge. Here, it is important to note that university knowledge, albeit publicly available, is far from costless. Firms must build internal capabilities to evaluate external research and apply it to commercial ends (Cohen and Levinthal, 1990). This is often done through hiring intellectual human capital in the form of star scientists (Zucker and Darby, 1996, 1998), through participation in the broader scientific community through journal publications (Henderson and Cockburn, 1994; Cockburn and Henderson, 1998), and/or through strategic alliances with providers of the new technology (Rothaermel, 2001). A firm's absorptive capacity has been shown to enhance a firm's innovative capability (Cohen and Levinthal, 1989), which in turn improves firm performance especially in highly dynamic industries (Rothaermel and Hill, 2005).

We thus suggest that backward patent citations to university research are indicative of an incubator firm's absorptive capacity to recognize, assimilate, and apply university knowledge flows to commercial ends. This is because many capabilities like absorptive capacity cannot be observed directly. Godfrey and Hill (1995) argued that unobservable constructs lie at the core of a number of influential theories in strategic management research. Given this serious challenge impeding empirical research, they suggested that "what scholars need to do is to theoretically identify what the observable consequences of unobservable resources [capabilities] are likely to be, and then go out and see whether such predictions have a correspondence in the empirical world. The analogy here is with quantum mechanics, which has been confirmed *not* by observing subatomic entities (since they are unobservable) but by observing the trail left by subatomic entities in the cloud chambers of linear accelerators" (Godfrey and Hill, 1995, p. 530, italics in original).

We suggest that a firm's absorptive capacity, while an important construct, is not directly observable. Thus, we resort to proxying for absorptive capacity by patent backward citations, which can be understood as indicating the existence of firm-level absorptive capacity deep within the firm. Moreover, absorptive capacity is a firm-level capability that is expected to be heterogeneously distributed among firms and thus should lead to variance in performance. In summary, we suggest that backward patent citations to university research should positively enhance incubator firm performance.

4. Methodology

4.1. Research setting—Georgia Tech's Advanced Technology Development Center

The research setting of this study is the Advanced Technology Development Center, a technology incubator sponsored by the Georgia Institute of Technology. The incubator is located adjacent to the Georgia Tech main campus in midtown Atlanta as part of a US$ 250 million state-of-the-art building complex that houses Georgia Tech's Business School and Economic Development Institute, among others. Besides being sponsored by Georgia Tech, the ATDC also receives legislative and financial appropriations from Georgia's Governor and the General Assembly of the state.

The ATDC was founded in 1980 as one of the first technology incubators in the U.S., and has since generated a cumulative of 4100 jobs and US$ 352 million in total revenues as of December 31, 1998. During our study period, the ATDC member firms had a total of US$ 12 million in annual revenues in 1998, US$ 19 million in 1999, and US$ 18 million in 2000. In the late 1990s, Georgia Tech's ATDC was voted as one of the top incubators in the U.S. based on a survey of peer incubators conducted by *Inc*. magazine (Rosenwein, 2000). The ATDC focuses on incubating early stage companies (0–3 years), with the company's founding date generally coinciding with the firm's admission to membership into the incubator.

The ATDC managers actively solicit applications from new ventures, and admitted, during our study period, between 10 and 20% of their applicants after a fairly stringent, two-staged review process. It is not necessary that the technology underlying the new venture is related to Georgia Tech; yet, it must be proprietary in nature. During the last few years, the size of the full-time professional staff of the ATDC remained, despite turnover, fairly constant at 22 managers. These managers assist the commercialization efforts of the ATDC member firms.

4.2. Sample and data

The sample consists of the population of member firms in the ATDC for the years 1998–2000. A total of 79 firms were tenants of the ATDC during this 3-year time frame. The year 1998 marks the first year detailed data were collected for the firms in the incubator. We drew our sample based on the years 1998–2000 to be able to follow each firm for a minimum of 4 years to assess the performance of the incubator firms. Employing multiple performance measures, we assessed the performance of the newly formed ventures over or at the time period $t+1$, where $t \leq 3$ years. This time window appears to be a conservative one given the fact that incubator tenants tend to graduate from public incubators within 2 years and from private incubators within 1 year (Rosenwein, 2000). While the ATDC has no explicit graduation policy, it attempts to graduate their members in a timely fashion. In the year $t+1$, the technology venture could fall into one of three categories: (1) failure, i.e., the firm ceased to exist due to bankruptcy or liquidation; (2) firm remains in the incubator; and (3) successful graduation, i.e., the firm is a stand-alone going concern or was acquired. We included acquisitions as part of successful graduation based on qualitative assessments made by ATDC managers.

Data for the 79 firms were collected annually for the 6-year time period between 1998 and 2003 through a survey instrument that was administered to all firms in the sample in the spring of every year to collect data for the prior year. Accordingly, data collection began in the spring of 1999 and ended in the spring of 2004. This longitudinal, repeat survey approach allowed us to obtain multiple, ubiquitous performance outcomes for all 79 firms in the initial sample. Thus, our results are not prone to a survivor bias, frequently observed in studies focusing on new venture creation and their early performance.

For the subset of firms based on Georgia Tech technologies, the Georgia Institute of Technology's Office of Technology Licensing provided us with data on relevant patents and founding dates. We augmented the collection of the quantitative data through semi-structured interviews with managers of the ATDC, the Institute's Vice Provost for Economic Development and Technology Ventures, the Institute's Director of the Technology Licensing Office, and the Institute's Director of its VentureLab, a center founded to identify commercializable technologies within the Institute.

A third source of data was the patent database maintained by the U.S. Patent and Trademark Office, an agency of the U.S. Department of Commerce. Here, we accessed all patents awarded to the incubator firms in this sample.

4.3. Measures

4.3.1. Incubator firm performance

Incubator firm performance is the dependent variable of this study. Clearly, assessing the performance of entrepreneurial start-ups, and incubator firms in particular, is a thorny problem retarding empirical research in this important area (Phan et al., 2004). Based on the annual repeat survey instrument underlying the data collection for this study, we are fortunate to assess the performance of incubator firms on multiple dimensions including revenues, total funds raised, venture capital funding obtained, and whether the firm graduated, failed, or remained in the incubator. Assessing the performance of incubator firms along several performance dimensions is particularly salient in this context because the most appropriate performance metrics for nascent technology ventures are less than clear.

4.3.1.1. Revenues. One of the performance metrics we employed is total cumulative revenues obtained by the incubator firms. To enhance the validity of this measure, we did assess it as cumulative revenues accrued over the time period including $t+1$ to avoid dependence on single observations often characterized by high annual fluctuations. While revenues are an accepted performance metric for more mature firms, it is less clear if this measure is suitable for the incubator context. We attempt to shed some more light on this issue. We applied a logarithmic transformation to enhance the normality of this variable.

4.3.1.2. Total funds raised. A second performance metric used is the total amount of cumulative funding the new ventures obtained over the time period including $t+1$. We constructed the *total funds raised* variable by leveraging fine-grained data pertaining to the different financing sources: family and friends, angel investors, venture capitalists, private placements, equity investments, and grants.

4.3.1.3. VC funding. One important milestone in the development of a nascent technology venture is obtaining venture capital funding (Shane and Cable, 2002; Shane and Stuart, 2002). Funding obtained from venture capitalists takes on an important signaling role as it often bestows legitimacy upon the new venture (Stuart et al., 1999). Moreover, some universities, albeit not the focal institution of this study, make obtaining a university license contingent upon having received venture capital. We assessed whether the incubator firms in this sample have obtained venture capital during the time period including $t+1$ by a bivariate indicator variable taking on the value of 1 if the incubator firm received venture capital funding, and 0 otherwise.

4.3.1.4. Failure, graduation, and remain in incubator. As discussed in detail in Rothaermel and Thursby (2005), one of the important milestones in the development of incubator firms is the timely graduation from the incubator. On an average, private incubators expect their tenants to graduate within 1 year, while public incubators expect their tenants to graduate within 2 years (Rosenwein, 2000). To be conservative, we assessed the state of incubator firms in $t+1$, where $t \leq 3$ years. In the year $t+1$, an incubator venture could fall into one of three categories: (1) failure, i.e., the firm ceased to exist due to bankruptcy or liquidation; (2) firm remains in the incubator; and (3) successful graduation, i.e., the firm is a stand-alone going concern or was acquired. We subsumed acquisitions under successful graduation because the few cases in which incubator firms were acquired in this sample (three firms or 4%) reflect successes rather than failures based on the evaluations by ATDC managers. We coded the performance of the new technology ventures in $t+1$ as a multinomial variable with three categories: failure, graduation, and remaining in incubator. Remaining in the incubator serves as reference category.

4.3.2. Knowledge flows from university to incubator firms

The key independent construct of this study concerns knowledge flows from the university to the incubator venture. Here, we hypothesized that exclusive knowledge flows in terms of a university license can endow the start-up with a unique resource that should lead to a superior performance (Barney, 1991). Moreover, we suggested that university backward patent citations are indicative of a start-up's absorptive capacity that enables it to recognize public knowledge spillovers emanating from the university, assimilate them internally, and then to apply them to commercial ends (Cohen and Levinthal, 1989). To obtain a comprehensive and fine-grained assessment of knowledge flows from the university to incubator firms, we employed five distinct variables proxying for different mechanisms through which knowledge may flow from the university to an incubator firm. In particular, we proxied for knowledge flows from the sponsoring university as well as more general university knowledge flows emanating from the broader university community.

4.3.2.1. GT license. One mechanism through which knowledge can flow from a university to an incubator firm is through a licensing agreement. Here, we assessed potential knowledge flows from the sponsoring university, Georgia Tech, to the incubator firms by including a variable that tracks whether the firm in the sample was founded to commercialize a technology invented at Georgia Tech and subsequently licensed it from the Institute's Office of Technology Licensing (1 = *GT license*). These licenses are exclusive in the sense that they are only given to one firm.

4.3.2.2. Backward citations to university research. A second area where knowledge flows from universities to incubator firms should manifest themselves is in the incubator firm's patent citations because all prior art must be credited in the patent application. Patents reflect inventions because they are only granted to processes or products that are novel, non-obvious, and industrially useful as judged by someone possessing proficient knowledge in the relevant technical area (Acs and Audretsch, 1989).

Here, assessing knowledge flows from a university to an incubator firm can be accomplished by analyzing the backward citations to university research in a technology venture's patent portfolio. To do this, we secured copies of all patents that the start-ups in the sample had obtained. We then counted all backward citations to university research in an incubator firm's patent portfolio. University research is defined as either citations to patents granted to universities or citations to academic journals publishing research results. In the final step, we took the ratio of an incubator firm's patent backward citations to university research over its total number of patent backward citations to assess the magnitude to which the new venture is drawing on university research in their own inventions. This measure can be considered as a proxy for knowledge flows from universities to incubator start-ups.

4.3.2.3. Backward citations to academic journals. We suggest that research findings published in academic journals tend to be more embryonic and basic in nature than research that is explicated in university patents, which tend to be more developed and explicit. In general, university faculty tend to first publish research results in academic outlets prior to the university applying for a patent. For example, in 1973, Stanley Cohen (then a professor at Stanford) and Herbert Boyer (then a professor at the University of California, San Francisco) first published their scientific breakthrough in recombinant DNA in the *Proceedings of the National Academy of Sciences of the United States of America* (Cohen et al., 1973). The patent on recombinant DNA, however, was granted 7 years later in 1980, and assigned to Stanford University with Cohen and Boyer listed as inventors (U.S. Patent 4,237,224). Therefore, to assess the potential flow of early stage, basic knowledge to incubator firms, we included a ratio of an incubator firm's patent backward citations to academic journals over its total number of patent backward citations.

4.3.2.4. Backward citations to GT research. Besides highlighting a technology license of the sponsoring university as one possible mechanism through which knowledge from the sponsoring university can flow to an incubator firm, we also assessed the impact of knowledge flows from the sponsoring university by including a ratio of the firm's patent backward citations to Georgia Tech research over its total number of patent backward citations. This measure indicates how much the incubator firm draws on localized knowledge. Georgia Tech research is defined as either citations to patents granted to Georgia Tech or citations to research published by Georgia Tech faculty members.

4.3.2.5. Backward citations to non-GT research. Besides focusing on knowledge flows from the sponsoring university, we also consider the impact of knowledge flows from research universities that are not directly linked to the focal incubator under consideration. Here, we assess the impact of the ratio of firm's patent backward citations to non-GT research over its total number of patent backward citations. Non-GT research is defined as either citations to patents granted to any university other than GT or citations to research published by any person that is not a GT faculty member. Please note that the sum of *backward citations to GT research* and *backward citations to non-GT research* equates to *Backward Citations to University Research*, the first backward citation measure introduced above.

4.3.3. Control variables

We included a number of control variables that theoretically could impact new venture performance.

4.3.3.1. Firm size. When assessing the performance of incubator firms, it is critical to control for their firm size. Because the important assets of incubator firms tend to be intangible in nature, it is more appropriate to use the number of employees as a proxy for firm size (*employees*) as done in prior research focusing on high-technology ventures (Rothaermel, 2002; Rothaermel and Deeds, 2004).

We controlled for firm size effects through the number of employees up to the year prior to which the outcome variable was assessed. Moreover, because newly created ventures tend to be quite small, we collected data not only on the number of full-time employees, but also on the number of part-time employees. Each full-time employee was counted as one employee, while one part-time employee was counted as one-half of a full-time employee.

4.3.3.2. Industry effects. When assessing new venture performance, it is pertinent to control for industry effects. We tracked each incubator firm's industry based on their Standard Industry Classification (SIC) codes. About 60% of the firms were active either in the software industry or the in telecommunications industry. To control for these two most prevalent industries, we inserted two indicator variables in the regression models. The first indicator variable takes on 1 if the incubator firm is a *software* company, and 0 otherwise. The second indicator variable takes on 1 if the incubator firm is a *telecom* company, and 0 otherwise.

4.3.3.3. Time in incubator. While the sample is not prone to a survivor bias, we are faced with the problem of left censoring because the ATDC technology incubator was in existence prior to 1998, the first year of our annual data collections. To ameliorate this problem, we recorded the year that each firm was admitted into the incubator, which generally coincides with the firm's founding date, and the last year the firm remained in the incubator. These two data points enabled us to construct the *time in incubator* variable, which is the number of years the firm remained in the technology incubator, to account for left censoring.

4.3.3.4. Non-GT university link. When assessing the effect of university knowledge flows on incubator firm performance, it is prudent to control for university linkages that the ATDC ventures may have to other, non-sponsoring universities. In fact, the sample firms listed linkages to 11 other U.S. research universities besides Georgia Tech. To isolate the effect of different knowledge flow mechanisms on the performance of ATDC ventures, we created an indicator variable that takes on the value of 1 if the firm had a link to a university other than Georgia Tech. Some ATDC firms in the sample, for instance, maintained a link to a university other than Georgia Tech but did not have a link to Georgia Tech.

4.3.4. Estimation procedures

When assessing the performance of incubator firms, we focus on four different outcome variables: revenues, total funds raised, venture capital obtained, and graduation, failure, or remaining in the incubator. These different dependent variables indicate different estimation procedures. The regression models with revenues and total funds obtained as dependent variables were estimated using ordinary least squares (OLS).

Venture capital obtained is a binary variable taking on 1 if the incubator firm received venture capital, and 0 otherwise. This model indicates logit regression. The outcome variable, $\widehat{Y}$, is the probability of the venture receiving or not receiving venture capital based on a non-linear function with two outcomes. The logit model is estimated with a maximum likelihood procedure and has the following specification:

$$\ln\left(\frac{\widehat{Y}}{1-\widehat{Y}}\right)=\alpha+\sum\beta_j X_{ij},$$

where X_{ij} is a vector of independent variables.

The last performance variable employed in this study can take on three categories: failure, remaining in incubator, and successful graduation. This indicated application of a multinomial logistic regression, estimated with a maximum likelihood procedure. The outcome variable, P_j, is the probability of falling into one of the outcome categories based on a non-linear function with three outcomes (Maddala, 1983):

$$P_j=\frac{e^{\beta_j x}}{D}\quad (j=1,2,\ldots,m-1)$$

and

$$P_m=\frac{1}{D}$$

where

$$D=1+\sum_{k=1}^{m-1} e^{\beta_j x}.$$

5. Results

We assessed the effect of university–incubator firm knowledge flows on 79 firms incubated in the Georgia Tech's ATDC over the 6-year time period between 1998 and 2003. We employed multiple performance measures to reflect the multi-dimensional nature of incubator firm performance. In particular, we assessed the performance of the newly formed ventures over or at the time period $t+1$, where $t\leq 3$ years. Relying on a repeat sample method, we were able to obtain ubiquitous outcome variables on all 79 firms, thus overcoming a potential survivor bias.

We tracked incubator firm performance on four different dimensions. In total, the 79 incubator firms raised over US$ 404 million in funding, with a US$ 193 million (48%) thereof being VC funding. The average incubator firm had revenues of US$ 1.6 million and had raised a total of US$ 5.1 million in funding. Notable is also the high variance in these performance variables. While some incubator firms did not generate any revenues or raised any funding, one firm accrued over US$ 39 million in revenues and another firm raised a total of US$ 36.5 million in funding. Almost one-half of the sample incubator firms (46%) obtained VC funding. In the year $t+1$, 23 firms (29%) had graduated successfully, 15 firms (19%) remained in the incubator, while 41 firms (52%) had failed.

The key independent variables of this study proxy for university–incubator firm knowledge flows. We find that 11 firms (14%) were founded based on a Georgia Tech license. Of the 79 incubator firms, 13 firms (16.5%) had rights (either through a Georgia Tech license or as an assignee themselves) to a total of 35 patents from the U.S. Patent and Trademark Office. It is important to note that the firms founded on GT licenses in comparison to non-GT start-ups that were assigned patents did not differ with respect to the total number of patents granted or any of the four different patent backward citations measures used in this study. This implies that the analysis of university–incubator firm knowledge flows based on patent citation measures is unbiased with respect to the firm having obtained a GT license or not.

Overall, these 35 patents contained 978 citations, splitting into 766 backward citations and 212 forward citations.[1] The 766 backward citations split into 627 non-university (i.e., industry) backward citations (82%) and 139 (18%) university backward citations. Of the latter, 22 (16%) were backward citations to Georgia Tech research.

At the firm level, about 3.3% of all patent citations referenced university research in general, while 2.4% of all patent citations were traced back to academic journals in particular. When dividing the university backward citations in citations to the sponsoring university and citations to other non-sponsoring university research, we find that 0.7% of all backward citations are to Georgia Tech research, while 2.6% of all backward citations are to non-GT university research. The average patent citations to university research are

[1] When analyzing the backward citations, we also coded whether the citation was added by the inventor or by the examiner. Since 2001, patent citations added by the examiner are marked by an asterisk. In this sample, there were 397 backward citations since 2001. We found that only six of these citations (0.15%) were added by the patent examiner. We are thus confident that the results are not materially influenced by patent citations added by the patent examiner.

quite low because most incubator firms (66 firms or 83.5%) did not obtain any patents. Thus, our econometric estimates for university patent citation ratios on incubator firm performance are quite conservative, and potentially biased downward. When assessing the prevalence of university patent backward citations among the firms that have been granted patents, we found that 18% of all their patent citations was to university research, which split into 14% to non-Georgia Tech research and 4% GT research. When considering the more narrow set of academic journal citations, we find that among these firms, 12% of all patent citations are to academic journals. Indeed, some of the firms exhibited very high university backward citations in their patent portfolios. For example, the maximum ratio for overall university backward citations was 83%, for backward citations to academic journals it was 79%, and for backward citations to Georgia Tech research it was 32%.

Noteworthy is also the discriminant validity of the different knowledge flow measures employed in this study. When excluding bivariate correlations that share by definition a significant amount of common variance,[2] and which are not inserted in the same regression models, we find that the bivariate correlations among the different knowledge flow measures are well below the suggested cut-off point of $R = 0.70$, suggesting satisfactory discriminant validity (Cohen et al., 2003).

The control variables reveal that the average incubator firm had about 14 employees and spent 2.4 years in the ATDC. The majority of firms are either active in the software industry (34 firm or 43%) or in the telecommunications industry (13 firms or 17%).[3] A little more than 20% of the firms had a linkage to a research university other than Georgia Tech. Table 1 depicts the descriptive statistics and bivariate correlation matrix, while Table 2 presents the regression results.

We advanced two exploratory hypotheses. We argued that exclusive knowledge flows in terms of a university license can endow the start-up with a unique resource, which can lead to a competitive advantage (Barney, 1991). We also suggested that university backward patent citations are indicative of a start-up's absorptive capacity that enables it to recognize public knowledge flows emanating from a university, assimilate them internally, and then to apply them to commercial ends (Cohen and Levinthal, 1989). A new venture's absorptive capacity is hypothesized to positively affect its performance.

Each of the four different performance measures was assessed in three different regression models. The four different performance dimensions are revenues, funds obtained, venture capital, and graduation from the technology incubator. In the first model of each three-model block, we added the effect of backward citations to university research on incubator firm performance. In the second model, we evaluated the impact of a somewhat more stringent knowledge flow measure, backward citations to academic journals, on incubator firm performance. In the last model of each block, we split the backward citations to university research into backward citations to research by the sponsoring university, Georgia Tech, and backward citations to research by other universities. Each regression model, however, contains the proxy for a GT license.

Models 1–3 evaluate the effect of the five different knowledge flow mechanisms on incubator firm performance proxied by revenues. Here, we find that none of the knowledge flow proxies reach significance. This might be indicative of the fact that revenues is not the most appropriate measure when assessing the performance of nascent technology ventures.

Models 4–6 assess the impact of the different knowledge mechanisms on the total amount of funds raised by the incubator firms. All three models are overall highly significant ($p < 0.001$), and exhibit R^2 values of around 0.36. With respect to individual coefficients, the regression results reveal that backward citations to university research (Model 4), backward citations to academic research (Model 5), and backward citations to non-GT research (Model 6) are each positive and

[2] That is, backward citations to university research and backward citations to academic journals; backward citations to university research and backward citations to non-GT research; backward citations to academic journals and backward citations to non-GT research.

[3] In total, the 79 firms fall into 14 different industries based on four-digit SIC codes. Besides software and telecommunications, there are six firms each in manufacturing and communications (8%), five in healthcare (6%), three Internet businesses (4%), two firms each in agriculture, biotechnology, environmental services, and general services (3% each), and one firm each in microelectronics, paper industry, robotics, and video industry (1% each). We suggest that the results presented below appear not to be directly influenced by the Internet boom and bust during the late 1990s and early 2000s because only three firms in the sample are Internet firms.

Table 1
Descriptive statistics and bivariate correlation matrix

		Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1.	Revenues	1,654,023	5,338,124															
2.	Total funds raised	5,116,468	7,779,855	0.05														
3.	VC funding	0.456	0.501	0.01	0.32													
4.	Failure	0.519	0.503	−0.29	−0.28	−0.19												
5.	Graduation	0.291	0.457	0.25	0.35	0.14	−0.67											
6.	Remain in incubator	0.190	0.395	0.08	−0.05	0.08	−0.50	−0.31										
7.	Employees	13.734	16.152	0.23	0.50	0.41	−0.07	0.30	−0.26									
8.	Software	0.430	0.498	0.03	0.24	0.18	0.02	0.06	−0.09	0.17								
9.	Telecom	0.165	0.373	0.07	0.05	0.21	−0.05	0.09	−0.04	0.25	−0.39							
10.	Time in incubator	2.430	2.164	0.24	−0.33	−0.23	−0.03	−0.28	0.37	−0.25	−0.19	−0.07						
11.	Non-GT university link	0.203	0.404	−0.09	−0.14	−0.02	0.17	−0.32	0.16	−0.14	0.13	−0.22	0.02					
12.	GT license	0.139	0.348	0.05	−0.01	0.00	−0.20	−0.10	0.36	−0.14	−0.28	0.02	0.26	−0.02				
13.	Backward citations to university research	0.033	0.123	−0.03	0.00	0.05	−0.25	−0.07	0.40	−0.11	−0.22	−0.12	0.24	0.30	0.38			
14.	Backward citations to academic journals	0.024	0.101	−0.09	0.01	0.09	−0.19	−0.11	0.37	−0.10	−0.18	−0.10	0.17	0.31	0.24	0.95		
15.	Backward citations to GT research	0.007	0.038	0.10	−0.08	−0.09	−0.19	−0.07	0.32	−0.10	−0.16	−0.08	0.28	0.24	0.36	0.56	0.44	
16.	Backward citations to non-GT research	0.026	0.107	−0.07	0.03	0.09	−0.22	−0.06	0.35	−0.09	−0.20	−0.11	0.17	0.26	0.32	0.96	0.94	0.29

$N = 79$.

Table 2
Regression results assessing the impact of university–incubator firm knowledge flows on incubator firm performance

	Model 1 Revenues	Model 2 Revenues	Model 3 Revenues	Model 4 Funds raised	Model 5 Funds raised	Model 6 Funds raised	Model 7 VC funding	Model 8 VC funding
Constant	3.683**** (0.300)	3.683**** (0.299)	3.683**** (0.301)	5.11E06**** (7.36E05)	5.11E06**** (7.36E05)	5.11E06**** (7.42E05)	−0.184 (0.278)	−0.183 (0.280)
Employees	0.803*** (0.337)	0.803*** (0.334)	0.794*** (0.338)	0.410**** (0.106)	0.414**** (0.106)	0.411**** (0.107)	0.919*** (0.396)	0.934*** (0.398)
Software	0.171 (0.369)	0.142 (0.365)	0.178 (0.370)	0.210** (0.116)	0.206** (0.116)	0.209** (0.117)	0.638** (0.329)	0.644** (0.326)
Telecom	0.086 (0.360)	0.075 (0.356)	0.090 (0.360)	−0.007 (0.115)	−0.014 (0.113)	−0.007 (0.109)	0.610** (0.318)	0.600** (0.317)
Time in incubator	0.930*** (0.326)	0.939*** (0.324)	0.885*** (0.331)	−0.247*** (0.103)	−0.243*** (0.102)	−0.243** (0.105)	−0.469* (0.334)	−0.417* (0.336)
Non-GT university link	−0.112 (0.332)	−0.061 (0.329)	−0.151 (0.336)	−0.152* (0.105)	−0.152* (0.104)	−0.148 (0.106)	−0.005 (0.293)	−0.027 (0.294)
GT license	0.108 (0.342)	0.111 (0.325)	0.056 (0.348)	0.109 (0.108)	0.131 (0.103)	0.114 (0.110)	0.230 (0.293)	0.291 (0.290)
Backward citations to university research	−0.163 (0.362)			0.155* (0.114)			0.441* (0.306)	
Backward citations to academic journals		−0.315 (0.336)			0.150* (0.107)			0.500* (0.340)
Backward citations to GT research			0.233 (0.348)			0.019 (0.110)		
Backward citations to non-GT research			−0.260 (0.344)			0.146* (0.109)		
R^2	0.159	0.167	0.168	0.355	0.356	0.356	0.353	0.363
F-stat	1.921*	2.035*	1.767*	5.586****	5.616****	4.833****		
−2 log likelihood							84.665****	83.859****

	Model 9	Model 10		Model 11		Model 12	
	VC funding	Fail	Graduate	Fail	Graduate	Fail	Graduate
Constant	−0.193 (0.282)						
Employees	0.920*** (0.394)	1.097* (0.676)	1.346** (0.686)	0.749* (0.553)	0.021** (0.564)	3.335** (1.593)	3.610** (1.597)
Software	0.629** (0.328)	−0.612* (0.419)	−0.334 (0.486)	−0.466 (0.385)	−0.268 (0.439)	−0.949** (0.533)	−0.667 (0.603)
Telecom	0.603** (0.318)	−0.483 (0.394)	−0.357 (0.439)	−0.349 (0.372)	−0.316 (0.408)	−0.651* (0.468)	−0.548 (0.517)
Time in incubator	−0.420 (0.333)	−0.300 (0.315)	−1.272*** (0.502)	−0.344 (0.290)	−1.147*** (0.480)	−0.469 (0.379)	−1.608*** (0.583)
Non-GT university link	0.031 (0.297)	0.079 (0.347)	−2.039*** (0.860)	0.136 (0.332)	−1.350** (0.643)	0.023 (0.408)	−5.380*** (2.162)
GT license	0.275 (0.302)	−0.334 (0.365)	−0.514 (0.421)	−0.373 (0.360)	−0.255 (0.383)	−0.929** (0.494)	−1.069** (0.624)
Backward citations to university research		−5.620**** (1.496)	0.507 (0.481)				
Backward citations to academic journals				−4.850**** (1.534)	0.147 (0.950)		
Backward citations to GT research	−0.207 (0.542)					−18.036*** (6.244)	−0.067 (2.077)
Backward citations to non-GT research	0.509* (0.334)					0.775 (1.234)	1.375 (1.175)
R^2	0.363	0.546		0.468		0.654	
−2 log likelihood	83.837****	119.663****		129.753****		103.452****	

Standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.
**** $p < 0.001$.

significant ($p < 0.10$) in predicting incubator firm performance.

The results of the logit estimations, predicting the probability of obtaining VC funding, are displayed in Models 7–9. The results for obtaining VC funding are basically identical to the results when applying total funds raised as dependent variable. All three models are overall highly significant ($p < 0.001$), and exhibit R^2 values of around 0.36. Here again, backward citations to university research ($\exp(\beta) = 1.554$, Model 7), backward citations to academic research ($\exp(\beta) = 1.649$, Model 8), and backward citations to non-GT research ($\exp(\beta) = 1.663$, Model 9) are each positive and significant ($p < 0.10$) in predicting incubator firm performance.

Models 10–12 display the results when assessing the impact of the different knowledge flows on the incubator firm's probability of failure and graduation, while remaining in the incubator serves as reference category. Each of the three models is statistically significant ($p < 0.01$ or smaller), and the R^2 ranges between 0.47 and 0.65. Holding a GT license reduces the probability of outright failure (Model 12: $\exp(\beta) = 0.395$, $p < 0.05$), but also retards timely graduation from the incubator (Model 12: $\exp(\beta) = 0.343$, $p < 0.05$). With respect to backward patent citations, we find that backward citations to university research (Model 10: $\exp(\beta) = 0.004$, $p < 0.001$), backward citations to academic journals (Model 11: $\exp(\beta) = 0.008$), and backward citations to GT research (Model 12: $\exp(\beta) = 1.47\text{E}{-8}$, $p < 0.01$), each significantly reduces the probability of outright failure.

Some of the results for the control variables are also noteworthy. Firms that grow faster in terms of employees perform significantly better along all the different performance metrics used to assess incubator firm performance in this study. Yet, these faster growing firms are also somewhat more likely to fail. The results also manifest consistent industry effects. Software firms tend to perform significantly higher when considering the amount of funding raised, the probability of obtaining VC funding, and exhibit a lower likelihood of outright failure. Telecom firms are significantly more likely to obtain VC funding and less likely to experience failure. Firms that remain longer in the incubator tend to raise fewer funds, are less likely to obtain VC funding, and are less likely to graduate in a timely fashion. Firms that stay longer in the incubator, however, tend to generate significantly higher revenues. Incubator firms that maintain linkages to other research universities than Georgia Tech tend to raise significantly fewer funds and are less likely to graduate within 3 years or less.

5.1. *Robustness checks*

We checked if multi-collinearity could bias the results when applying OLS estimations (Models 1–6). Here, we found that the maximum variance inflation factor was 1.5, well below the suggested cut-off point of 10 (Cohen et al., 2003). Multi-collinearity, however, did appear to affect the results when including an additional control variable for an incubator firm's total number of patents received or a binary indicator variable whether the firm received a patent or not. The results for the probability of obtaining VC funding and the results with respect to failure or graduation remained robust; however, the results for predicting the total amount of funding raised do not reach significance. The overall somewhat weaker results can be explained by the fact that the variable *total number of patents received* and the indicator variable *patent received* (=1) are highly significantly correlated with each of the four backward patent citation measures employed in this study (at $p < 0.01$ or smaller). This high correlation is expected because the firms that obtain patents are the only ones that can cite university research in their patents. Therefore, it appears prudent to not include the patent count or indicator variables thereof simultaneously with the backward patent citations measures in the regression estimations.

6. Discussion

One of the arguments for incubators associated with universities is that knowledge flows from universities should enhance performance of high-technology ventures and that access to this knowledge is not "free," despite the publication norms of science. In this paper, we examined two mechanisms by which incubator firms can access this knowledge. One, which is available to new ventures based on Georgia Tech inventions, is a license to develop and use a university invention. In the case of ATDC firms, all of the licenses to Georgia Tech inventions were exclusive so that the resource-based view of the firm suggested that these licenses provide a unique, performance-enhancing resource (Barney, 1991). The other mechanism we explored was citations to university research found in the patents associated with incubator firms. We argued that this mechanism reflects not only a non-exclusive means for firms to access university knowledge, but also that it reflects the ability of the new venture to utilize university knowledge, and thus could be seen as a proxy for absorptive capacity (Cohen and Levinthal, 1990). We argued that both licenses and backward citations should be positively related to incubator firm performance. A secondary purpose of this study was to examine different performance metrics for evaluating the performance of nascent technology ventures.

We found little support for the unique resource hypothesis because the license variable was in general not significant. Holding a Georgia Tech license had a significant effect only on performance measured by failure and graduation, and then only when the citation ratios were split between Georgia Tech and non-Georgia Tech citations. This result is interesting because this is also the only model for which the localized citation variable, the ratio of citations to Georgia Tech research to all citations, is significant.

We found more consistent support for the absorptive capacity hypothesis as backward citations to university research positively affect three of the performance measures. This was the case both for all university citations and citations to academic publications alone. Notice that the variable backward citations to university research is, ceteris paribus, one minus the ratio of citations to industry patents to all citations (abstracting from non-university and non-industry citations). Thus, the coefficient for the university research variable is the opposite of the coefficient had we entered the ratio of industry citations. A natural interpretation of the university citation variable is that it is a measure, not only of absorptive capacity, but also of how basic are the patents of the new venture. According to this interpretation, our results of citations on the probability of obtaining VC funding suggest that venture capitalists tend to be more likely to back basic inventions rather than those whose prior art arises primarily in industry.

With respect to evaluating different performance metrics for technology ventures, in particular in the context of university knowledge flows, we found that revenues were a poor measure for incubator firm performance. The revenue models explain the lowest amount of variance, and none of the individual proxies for knowledge flows reaches statistical significance. It is not surprising that revenues appear to be an inappropriate measure for assessing the performance of incubator firms because the firms are very young (less than 3 years old) and compete in the high-technology space, where many firms do not generate much revenues initially as they invest to develop the new technology. More promising performance metrics appear to be the total amount of funding obtained, whether the firm was backed by VC funding, and whether the firm graduated from the incubator in a timely manner or failed altogether. The last variable should be applied with caution in future research because many incubators tend to have an explicit graduation policy (not the ATDC) and encourage or expect timely graduation. Thus, total funds obtained or VC funding are market mechanisms that appear to assess the performance of new technology ventures in a satisfactory manner.

6.1. Limitations and future research

One of our more important assumptions underlying this research was that patent citations reflect knowledge flows. While this assumption is based on a long tradition in economics, some recent research has suggested that patent citations may not reflect knowledge flows, since citations are often added by attorneys and patent examiners (Jaffe et al., 2000; Alcacer and Gittelman, 2004; Sampat, 2004). While this is a fundamental challenge to the research relying on patent data when attempting to capture knowledge flows, the recent practice of publishing examiner cites mitigates this problem. Moreover, if patent citations indeed do not truly reflect knowledge flows, future research needs to develop alternate metrics that capture knowledge flows more effectively.

We suggested that firms with a higher ratio of university citations in their patent portfolio achieve higher performance because these firms are based on more basic invention with a greater potential of making a commercial breakthrough. While the ratio of university citations to total citations was a positive predictor of incubator firm performance, especially with respect to total amount of funding obtained and the probability of obtaining VC funding, we need to emphasize that the relationship between the ratio of university citations to total patent citations on firm performance may not be positive and linear because the average firm in this sample exhibited a low level of university citations among its patents. Future research could investigate a potentially diminishing marginal or even diminishing total returns hypothesis for the relationship between university backward citations and firm performance.

Clearly, future research should also address the generalizability of our findings. While we find some support for the absorptive capacity hypothesis, we need to emphasize that our research setting is somewhat unique. While it enabled us to empirically assess interfirm performance differentials among incubator firms, we were limited to firms incubated in the ATDC sponsored by Georgia Tech, a research institute with a clear focus on engineering sciences. Some researchers have begun to compare incubator differential performance (Mian, 1996; Colombo and Delmastro, 2002); however, studies on interfirm differential performance of incubator firms are rare. We hope that future research will be able to apply a repeat survey approach similar to the one used in this study in order to collect fine-grained, longitudinal data on incubator firms across different technology incubators.

6.2. *Implications for public policy*

The results presented in this study seem to indicate that knowledge does flow, via different mechanisms, from universities to incubator start-up firms. While the negative impact of having a link to a research university other than the sponsoring university on firm performance seems to indicate some benefits of being closely located to the sponsoring university, other measures for localized spillovers did generally not reveal significant results. One area of public policy concern could therefore be the enhancement of localized spillovers because many public incubators and other university-based technology initiatives are formed to improve the economic performance of the region. Siegel et al. (2003), for example, showed, when examining the effect of university science parks in the UK on firm research productivity, that firms associated with science parks were more productive than those not so located. The question of how localized spillovers from universities to incubator firms can be enhanced is an interesting one and opens up another promising avenue for future research.

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