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Universities and the success of entrepreneurial ventures: evidence from the small business innovation research program

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Abstract There has been little direct, systematic empirical analysis of the role that universities play in enhancing the success of entrepreneurial ventures. We attempt to fill this gap by analyzing data from the US SBIR program, a "set-aside" program that requires key federal agencies (e.g., Department of Defense) to allocate 2.5% of their research budget to small firms that attempt to commercialize new technologies. Based on estimation of Tobit and negative binomial regressions of the determinants of commercial success, we find that start-ups with closer ties to universities achieve higher levels of performance.

Keywords University technology transfer · Small business innovation research program (SBIR) · Commercialization · Entrepreneurship

JEL Classification M13 · O31 · O32 · O38

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1 Background

In the aftermath of the Bayh-Dole Act of 1980, there was a rapid rise in technology transfer from US universities to firms through such mechanisms as patenting, licensing agreements, research joint ventures, and university-based startups. Universities have welcomed this trend because they perceive that technology commercialization can potentially generate large sums of revenue and spawn new firms and create new jobs in the local region. Many cities and regions are increasingly viewing universities as potential engines of economic growth.

In recent years, universities have been placing a stronger emphasis on the entrepreneurial dimension of technology commercialization, which has lead to a substantial increase in the number of university-based startups. This trend has spawned numerous studies on the managerial and policy implications of these ventures and their role in technology transfer (see Siegel and Phan 2005) for a comprehensive review of this burgeoning literature). Many of these studies have focused on institutions that have emerged to facilitate commercialization of the startup's innovation(s), such as university technology transfer offices, science parks, and incubators.

Another strand of this literature focuses more directly on the agents involved in university technology transfer, such as scientists (Zucker and Darby 1996, 2001) academic entrepreneurs (Audretsch 2000; Louis et al. 1989). These papers build on the theoretical analysis of Jensen and Thursby (2001) who demonstrate that inventor involvement in technology commercialization potentially attenuates the deleterious effects of informational asymmetries that naturally arise in technological diffusion from universities to firms.

Unfortunately, there has been little direct, systematic empirical analysis of the role that universities play in enhancing the success of entrepreneurial ventures. Most researchers (e.g., Di Gregorio and Shane 2003; O'Shea et al. 2005) address this issue by estimating regressions, in which success is measured in terms of counts of the number of university-based startups. The unit of observation in such studies is typically the university.[1] The use of numerical startup counts at the university level is problematic for three reasons. First, startup counts are only one metric by which to gauge the extent of academic entrepreneurship at a university. Second, it is also not clear how well this approach measures the market value or outcomes of such activity. Finally, the proper unit of analysis is not the university, but rather the university-based startup, which should be followed over time to determine whether it is successful.

To address these previous limitations, we make use of a database that was constructed for a comprehensive national research council (NRC) study (Wessner 2008). This rich and unique file allows for a significant advance in empirical analysis of the antecedents and outcomes of academic entrepreneurship. Our maintained hypothesis is that an academic founder is an entrepreneurial leader, whose background affects the firm's success. In addition to information on founders, our dataset includes several direct measures of the commercial success of entrepreneurial ventures, including actual sales of products, processes, and services, expectations of future sales, domestic and foreign agreements, and job creation. The dataset also contains the following measures of intellectual property creation: patents, copyrights, trademarks, and licensing agreements.

The remainder of the paper is organized as follows. In the following section, we describe the small business innovation research (SBIR) Program and the resulting dataset

[1] Some researchers have used the firm as the unit of observation. However, these studies have been based on startups from a single university (e.g., Shane (2002)).

from the NRC survey of awardees. Section 3 presents a brief review of two related literatures that provide a motivation for our empirical analysis. We then outline the econometric framework, while simultaneously providing a theoretical justification for the arguments of these equations. Specifically, we test several hypotheses relating to the role of universities and academics in enhancing the probability of success, broadly defined. Section 4 contains preliminary empirical findings. The final section presents caveats and preliminary conclusions.

2 SBIR program and the database

Our empirical analysis is based on project-level data from a key federal government program designed to provide financial assistance to firms during the initial stages of their development: the SBIR program. The SBIR program was established in 1982 as a "set-aside" program. In its current version, SBIR requires all federal R&D funding agencies with extramural research programs to allocate 2.5% of their extramural research budgets to fund through a peer-review process R&D in small (less than 500 employees) firms.

Small business innovation research awards consist of three phases. Phase I awards fund the firm to undertake proof of concept, that is to research the feasibility and technical merit of a proposed research project. A Phase I award lasts for 6 months and is less than $75,000. Phase II awards extend the proof of concept to a technological product/process that has a commercial application. A Phase II Award is granted to only the most promising of the Phase I projects based on scientific/technical promise, the expected value to the funding agency, the firm's research capability, and the commercial potential of the resulting innovation. The duration of the award is up to 24 months and generally does not exceed $750,000. Approximately 40% of the Phase I Awards continue onto Phase II. Phase III involves private funding to the firm for the commercial application of a technology; no financial award from SBIR is made in Phase III.

The SBIR database that we analyze in this study was constructed by the NRC at the request of Congress for the broader purpose of assessing the net social benefits of the SBIR program. In 2005, an electronic survey was administered to focus on a partially random and stratified sample of Phase II projects from 1992 through 2001 from the Department of Defense (DoD), the Department of Energy, the National Aeronautics and Space Administration, the National Institutes of Health, and the National Science Foundation.

More specifically regarding DoD awards, the focal awards of this paper, an electronic survey was sent to 2,652 identifiable firms that received a Phase II SBIR award. Each firm was asked to respond to one or more surveys specific to a funded project. The total number of projects associated with the 2,652 surveyed firms was 6,415. A total of 1,239 firms responded to the survey, each completing one or more project-specific surveys. The total number of projects associated with the 1,239 responding firms was 1,916. Thus, the firm response rate was 46.72% and the project response rate was 29.87%. The final random sample consists of 920 projects.[2]

The NRC DoD database contains information on numerous performance and commercialization indicators of success of the Phase II project, such as:

[2] See Wessner (2009) for a discussion of the 920 project data set. Only 891 of the projects are random, but for purposes of comparison with the National Academy of Sciences report on DoD, we retained all 920 projects. See Link and Scott (2009, 2010) for a detailed explanation of the data reduction process.

- Sales to date of products, processes, and services from the project, to organizations in what sectors, and how soon after completion of Phase II were sales made
- Expected future sales,
- New employees hired to work specifically on the SBIR project
- Patents applied for/received
- Copyrights applied for/received
- Trademarks applied for/received
- Domestic/international licensing agreements

The database also contains information on the characteristics and activities of the founders of the firms conducting the Phase II research, including their entrepreneurial experience[3] and professional background. We also know the gender of the principal investigator, who may also be the founder. In addition, we can determine whether the founders, whom we conjecture are the entrepreneurial leaders of the firm, have a business or academic background and where the founders were employed before they established their firms. And finally, we have information on whether university faculty members are involved in the funded project.

This article is one of a series of recent papers based on the NRC database (see Link and Scott 2009, 2010; Link and Ruhm 2009, forthcoming). These articles, along with this paper, build on previous studies of the first datasets available to researchers, based on "fast track" SBIR projects at DoD (see Audretsch et al. 2002; Lerner 1999). As members of the NRC research team, we have access to these data.

3 Brief literature review and methodology

Given that our objective is to identify empirically covariates with the success of entrepreneurial ventures, two streams of research are relevant for selecting the variable to consider. In recent years, several authors have assessed the relationship between certain human capital characteristics and industry experience of the founders of high-technology start-up companies and subsequent performance of these firms (see Colombo and Grilli 2005; Vyakarnam and Handelberg 2005; Gilbert et al. 2006; Shrader and Siegel 2007).

Some papers focused on the traits of company founders, while others examine the characteristics of the top management teams of entrepreneurial firms. Most authors report strong positive links between these traits and characteristics, such as the level of education, functional expertise, and industry experience of the founder or members of the top management team, and indicators of new venture performance (e.g., sales growth or the creation of new products). As noted in Vyakarnam and Handelberg (2005), this connection appears to be stronger in high-technology industries, where firms operate under high-velocity or turbulent conditions (see Eisenhardt and Schoonhoven 1990; Finkelstein and Hambrick 1990; Wiersema and Bantel 1992).

More specifically, Shrader and Siegel (2007) analyzed the role of human capital in the growth and development of 198 new technology-based ventures. Their results imply that the fit between strategy and team experience is a key determinant of the long-term performance of these high-tech entrepreneurial firms. These findings demonstrate the importance for technology-based new ventures to select strategies for which they possess the human capital to successfully execute.

[3] See Link and Ruhm (forthcoming) for an analysis of this particular entrepreneurial characteristic.

A related literature focuses more directly on university spinoffs and academic entrepreneurship (Rothaermel et al. 2007). This literature is evolving rapidly and there are several papers that present evidence for a positive relationship between university/faculty involvement and commercialization outcomes (e.g., Shane 2002; Shane and Stuart 2002; Lacetera 2007; Link and Ruhm, forthcoming).

The study that is most germane to our paper is a recent article by Link and Ruhm (2009), which examines commercialization activity resulting from research projects funded through the National Institutes of Health's SBIR program. Link and Ruhm (2009) estimate the determinants of the probability of commercialization, where commercialization is defined as a dichotomous variable, which is equal to one if a project resulted in a commercialized product, process, service or sales of the rights to a technology or licensing revenue. The authors report that university involvement in research enhances the probability of commercialization. The Link and Ruhm study serves as a point of departure for the analysis herein. Our analysis extends their preliminary investigation by considering multiple indicators of success, all of which are related to aspects of commercialization. This broader scope allows us to determine whether university involvement has differential effects on various components of successful commercialization.

In our paper, we estimate a non-linear model of the probability of commercialization as a function of the project's ability to attract additional developmental funding, along with other control variables. We find that university involvement in the underlying research increases the probability of commercialization. We also find that additional developmental funding from non-SBIR federal sources and from own internal sources are important predictors of commercialization success, relatively more so than additional developmental funding from venture capitalists. These factors should be considered by NIH when issuing awards, if increased commercialization is an objective.

To assess the determinants of successful SBIR research projects, we estimate the following econometric model:

$$\text{SUCCESS} = f(\mathbf{X}) \tag{1}$$

where SUCCESS refers to the seven indicators of project success mentioned earlier: (1) actual sales (ACTSALES), (2) expected sales (EXPSALES), (3) new employees (NEWEMP), (4) patents received (PATENTS), (5) copyrights received (COPYRIGHTS), (6) trademarks received (TRADEMARKS), and (7) licensing agreement consummated (LICENSES). **X** is a vector of project, firm, and founder-specific characteristics. Given that our unit of analysis is the project, we will also allow for firm effects, because several firms in the sample have multiple projects, and agency effects (in subsequent research where we include data from multiple agencies). We now provide a rationale for the arguments included in **X**.

The literature on university technology transfer (see Siegel and Phan 2005 for a review of these papers) provides us with guidance on the arguments of Eq. 1. We conjecture that several project-level variables should be included as determinants of success. The first is the size of the project (AWARDSIZE), because larger awards are expected, ceteris paribus, to have greater commercial potential. The availability of additional funds for development of the project (ADDDEV) is also expected to increase the likelihood of success. We also include the age of the project (AGEPROJ), because older projects are more likely to be commercialized.

Consistent with Jensen and Thursby (2001), we hypothesize that university-involvement in the SBIR project (UNIVPROJ) raises the probability of Phase II success. There are two reasons for this. The first is that academic engagement is likely to enable the firm to overcome the technical hurdles associated with commercialization. A second reason was uncovered in the seminal papers by Zucker and Darby and various collaborators, who explored the role of "star" scientists in the life sciences on the creation and location of new biotechnology firms in the US and Japan. Zucker and Darby reported that ties between star scientists and firm scientists have a positive effect on research productivity, as well as other aspects of firm performance and rates of entry in the US biotechnology industry (Zucker et al. 1998a, b). That is because university star scientists have a vast social network of colleagues at other universities, graduate students, post-docs, and former students in industry. This social network has been shown to be extremely useful in the commercialization of research.

Another way to assess the impact of universities on successful commercialization is to directly determine whether the SBIR entrepreneurs have previous had ties to a university (certainly not the university that is involved in the SBIR project being studied). We construct two proxies for such connections: (1) the number of founders of a given SBIR firm who have an academic background (ACADFOUNDER) and (2) a dummy variable denoting whether the most recent employment of the founder was in academia (PRIORACAD).

Several additional control variables that must be included in **X**. The first is a proxy for entrepreneurial experience, which we operationalize as the number of other companies started by the founder (ENTREPEXPER). Other control variables include the gender of the principal investigator (GENDER), firm size (SIZE), and the number of previous SBIR Phase1 (PREVAWARD1) and SBIR Phase 2 awards (PREVAWARD2).

Using the dichotomous or truncated alternative measures of SUCCESS, we will employ the appropriate estimation procedure for each of the limited dependent variables: Tobit, Poisson, or Negative Binomial estimation.[4]

3.1 Tobit regressions

For example, we will employ Tobit estimation for sales and employment-related indicators of success, given that these variables are non-negative. Following Foltz et al. (2005), we estimate a Tobit model, based on partial maximum likelihood estimation, which has optimal asymptotic properties. A useful aspect of this version of the Tobit model is that it does not require strict exogeneity of the independent variables (a rather heroic assumption in this context) and also allows for error terms that are serially correlated.

The Tobit model was developed to accommodate a censored dependent variable, such as sales (or expected sales) and to address the bias associated with assuming a linear functional form in the presence of such censoring. A key assumption of this model is that an unobservable latent framework generates the data. The model incorporates this assumption into the modelling process. In the context of SBIR projects, the Tobit model can be expressed:

$$\text{SUCCESS}^*_{it} = x'_{it}\beta + u_{ti} \quad u_{it} \sim N(0, \sigma^2) \quad i = 1.\dots\dots.n \tag{2}$$

$$\text{SUCCESS}_{it} = \text{SUCCESS}^*_{it} \quad \text{if SUCCESS}^*_{it} > 0 \tag{3}$$

$$\text{SUCCESS}^*_{it} = 0 \quad \text{otherwise} \tag{4}$$

[4] Single equation models are appropriate because, as Link and Scott (2010) has shown response bias is not an empirical issue when using the DoD SBIR data.

where x_{it} is a vector of independent variables relating to the ith SBIR project in year t, SUCCESS_{it} are indicators of success associated with the ith SBIR project in year t and SUCCESS^*_{it} is an unobserved continuous latent variable assumed to determine the value of SUCCESS^*_{it}.

Thus, for successful SBIR projects, the latent variable can only be observed if it is greater or equal to zero. Maximum likelihood estimation yields consistent parameter estimates, if the maintained assumptions of homoscedasticity and normality of the error terms are valid. Based on these assumptions, the cross sectional likelihood function of the Tobit model is:

$$L(\beta, \sigma^2) = \prod_0 \left[1 - \Phi\left(\frac{x_i'\beta}{\sigma}\right)\right] \prod_1 \left[\sigma^{-1}\phi\left(\frac{\text{SUCCESS}_i - x_i'\beta}{\sigma}\right)\right] \tag{5}$$

3.2 Poisson or negative binomial regressions

The rest of our success indicators are count variables, such as patents, copyrights, trademarks, or licensing agreements. Thus, we will consider Poisson and negative binomial, or generalized Poisson, specifications for these versions of Eq. 1. As applied to patents or publications, the basic Poisson model is:

$$\Pr(y) = \frac{\exp(-\lambda)\lambda^y}{y!} \tag{6}$$

where $y =$ patents or publications and $\ln(\lambda) = f(\mathbf{X})$, the deterministic function of $\mathbf{X}$ from Eq. 1. The Poisson distribution has the following property: $E(y) = \text{Var}(y) = \lambda$, conditional on $\mathbf{X}$. This restrictive distributional assumption is relaxed in the negative binomial distribution, which allows $\text{Var}(y) > E(y)$, the property known as "over-dispersion" or "extra-Poisson variation." The negative binomial specification generalizes λ to be distributed as a Gamma random variable with parameters $e^{f(x)}$ and a shape parameter α. As shown in Winkelmann and Zimmerman (1995), the resulting likelihood function for y is:

$$L(y) = \binom{\delta + y - 1}{y} p^\delta (1-p)^y \tag{7}$$

where $\delta = 1/\alpha$ and $p = (1 + \alpha(\exp^{f(x)}))^{-1}$. The Poisson distribution (and hence the property of no over-dispersion) corresponds to the special case of $\alpha = 0$. For each negative binomial regression, we will compute the χ^2 statistic (with one degree of freedom) to test the null hypothesis that $\alpha = 0$; that is, that the data are distributed as Poisson (conditional on $\mathbf{X}$).

4 Empirical results

Descriptive statistics for the variables used in the Tobit and negative binomial regressions are presented in Table 1. As a first cut, we have analyzed data from a single agency, the Department of Defense.[5] Recall that we seven indicators of success and therefore, seven dependent variables: (1) actual sales, (2) expected sales, (3) new employees, (4) patents applied for, (5) copyrights applied for, (6) trademarks applied for, and (7) licensing agreements consummated.

[5] As shown in Link and Scott (2010), sample selection is not a problem with the Department of Defense data, because the data file constitutes a random sample.

Table 1 Descriptive statistics for key variables in the regression analyses

Variable	Definition	Unit of analysis	Mean
ACTSALES	Actual sales (100 K)	Project	1,422.76
EXPSALES	Expected sales (100 K)	Project	1,029.65
NEWEMP	New employees	Project	2.5
PATENTS	Patents	Project	0.909
COPYRIGHTS	Copyrights	Project	0.077
TRADEMARKS	Trademarks	Project	0.229
LICENSES	Licensing agreement	Project	0.190
AWARDSIZE	Amount of phase two SBIR award	Project	727.78
ADDDEV	Amount of additional development funding for this project	Project	9.232
AGEPROJ	Age of the project (in months)	Project	84.25
UNIVPROJ	University involvement in the project	Project	0.103
GENDER	Dummy variable if PI is a woman	Founder	0.04
ENTREPEXPER	Number of other companies started by a founder	Founder	1.00
ACADFOUNDER	Number of founders who have an academic background	Founder	0.66
PRIORACAD	Dummy variable denoting whether the most recent employment of the founder was in academia	Founder	0.36
PREVAWARD1	Number of previous phase 1 awards	Firm	14
PREVAWARD2	Number of previous phase 2 awards	Firm	7
FIRMSIZE	Number of employees	Firm	45.845

Notes:

n = 920 respondents to the project-level survey

n = 1108 respondents to the firm-level survey

Table 2 presents Tobit regression estimates of Eq. 1 the sales and employment indicators of success. Columns (2), (4), and (6) include firm fixed effects for each of the three dependent variables. The models appear to fit reasonably well and the findings are somewhat consistent with our expectations. Not surprisingly, we find that the age of the project (AGEPROJ), entrepreneurial experience of the founder (ENTREPEXPER), and the size of the award (AWARDSIZE) are positively related to actual and expected sales. Contrary to expectations, firm size (FIRMSIZE), additional development funding for the project (ADDDEV), and previous awards (PREVAWARD1 and PREVAWARD2) appear to be insignificantly related to success.

We now focus our attention on the coefficients on the measures of university-involvement in the SBIR project. These variables are found to be positive and significantly related to actual and expected sales: the dummy variable for university involvement in a given SBIR project (UNIVPROJ) and the dummy variable denoting whether the founder was recently employed in academia (PRIORACAD). We also observe a positive and significant relationship between the number of founders who have an academic background (ACADFOUNDER) and the number of new jobs created as a result of the SBIR project (NEWEMP). It is also important to note that the magnitude of the university involvement effect is quite high; in some cases, higher than the marginal effect of increasing the size of the award (AWARDSIZE). University involvement appears to have an especially large positive impact on sales-based measures of project success.

We now turn our attention to commercialization findings related to the creation of intellectual property. Negative binomial regression estimates of the remaining indicators of

Table 2 Tobit regressions of the determinants of SBIR project-level success: actual sales, expected sales, and new employees

Independent variable	Dependent variable					
	ACTSALES		EXPSALES		NEWEMP	
	(1)	(2)	(3)	(4)	(5)	(6)
AWARDSIZE	.245*** (.058)	.178*** (.067)	.355*** (.122)	.210** (.103)	.102 (.080)	.056 (.077)
ADDDEV	.056 (.047)	.103 (.121)	−.034 (.043)	.055 (.099)	.052 (.092)	.023 (.042)
GENDER	−.003 (.004)	.002 (.024)	.102 (.161)	.022 (.028)	.002 (.021)	.001 (.008)
AGEPROJ	.153** (.078)	.142** (.070)	.188** (.092)	.150* (.082)	.134 (.078)	.121 (.074)
UNIVPROJ	.202** (.101)	.187** (.092)	.278*** (.123)	.222** (.107)	.114 (.091)	.101 (.077)
ENTREPEXPER	.177** (.087)	.164** (.082)	.183** (.093)	.203* (.110)	.203** (.033)	.203** (.033)
ACADFOUNDER	.104 (.101)	.115 (.091)	.078 (.083)	.112 (.098)	.211*** (.096)	.174** (.086)
PRIORACAD	.132** (.067)	.122* (.068)	.145** (.070)	.116 (.075)	.078 (.082)	.024 (.045)
PREVAWARD1	.067 (.086)	.055 (.089)	.021 (.069)	.067 (.067)	.055 (.089)	.021 (.069)
PREVAWARD2	.045 (.023)	.021 (.034)	.062 (.113)	.045 (.041)	−.011 (.022)	−.007 (.018)
FIRMSIZE	−.036 (.056)	−.023 (.044)	.017 (.053)	−.036 (.093)	−.003 (.012)	.002 (.013)
Firm effects	No	Yes	No	Yes	No	Yes
Log likelihood	−357.32	−312.45	−342.56	−303.21	−231.11	−201.49

Heteroskedastic-consistent standard errors are reported in parentheses

*** Significant at the .01 level; ** significant at the .05 level; * significant at the .10 level

Table 3 Negative binomial parameter estimates of the determinants of SBIR project-level success: patents, copyrights, trademarks, and licensing agreements

Independent variable	Dependent variable							
	PATENTS		COPYRIGHTS		TRADEMARKS		LICENSES	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AWARDSIZE	.209** (.107)	.198* (.098)	.188** (.093)	.177** (.087)	.099** (.049)	.056* (.030)	.103 (.078)	.095 (.083)
ADDDEV	.056 (.068)	.044 (.062)	.037 (.039)	−.021 (.024)	.011 (.017)	.100 (.009)	−.003 (.087)	.004 (.014)
AGEPROJ	.174** (.083)	.162** (.080)	.156* (.082)	.123 (.091)	.018** (.088)	.159* (.084)	.158 (.101)	.143 (.097)
UNIVPROJ	.224*** (.084)	.217*** (.093)	.183* (.097)	.177* (.089)	.045 (.077)	.065 (.062)	.251*** (.114)	.199** (.097)
GENDER	.003 (.091)	.002 (.002)	−.012 (.078)	.045 (.056)	.028 (.043)	−.001 (.009)	.014 (.021)	.008 (.010)
ENTREPREXPER	.034 (.025)	−.021 (.028)	.104 (.078)	.072 (.056)	.055 (.074)	.042 (.066)	.027 (.073)	.016 (.032)
ACADFOUNDER	.199** (.092)	.188** (.090)	.078 (.065)	.044 (.053)	.033 (.026)	.017 (.023)	.200** (.099)	.176* (.090)
PRIORACAD	.177** (.097)	.162** (.083)	.114* (.064)	.105 (.084)	.112 (.095)	.078 (.065)	.234** (.114)	.221** (.108)
PREVAWARD1	−.008 (.010)	−.003 (.021)	.005 (.009)	−.002 (.021)	.003 (.007)	−.001 (.008)	−.012 (.009)	−.010 (.012)
PREVAWARD2	.017 (.042)	.012 (.016)	.013 (.022)	.010 (.018)	−.007 (.013)	.003 (.006)	.021 (.018)	.014 (.023)
FIRMSIZE	.004 (.017)	.002 (.026)	−.002 (.010)	.001 (.005)	.012 (.021)	.004 (.016)	−.005 (.012)	−.007 (.006)
Firm effects	No	Yes	No	Yes	No	Yes	No	Yes
Log likelihood	−316.21	−304.25	−206.32	−204.45	−210.76	−205.41	−309.75	−304.32
$\chi^2(1)$ ($\alpha = 0$)	42.12***	43.84***	18.12**	17.53**	19.23**	17.94**	40.03***	42.47***

Heteroskedastic-consistent standard errors are reported in parentheses

*** Significant at the .01 level; ** significant at the .05 level; * significant at the .10 level success are presented in Table 3. Columns (2), (4), (6), and (8) include firm fixed effects for each of the three dependent variables. Once again, we find that the models appear to fit fairly well and the findings are somewhat consistent with our expectations, in the sense that larger awards and older projects are more likely to be successful. Most importantly, the indicators of interaction between the firm and the university (i.e., UNIVPROJ, PRIOR-ACAD, and ACADFOUNDER) appear to be positively associated with successful commercialization, especially for patenting and licensing. The findings are weaker are for copyrights and trademarks. Note also that these findings are somewhat stronger when we include firm effects in the regression models.

5 Conclusions, caveats, and extensions

Universities have recently devoted more attention to the entrepreneurial dimension of technology transfer. This has induced the creation of numerous university-based spinouts and connections to local start-up companies founded by academic entrepreneurs or their students. This paper, along with the recent NIH-SBIR study by Link and Ruhm (2009), provides direct, systematic empirical evidence confirming the hypothesis that a university connection to an SBIR project increases the likelihood of successful commercialization. Note that our empirical analysis is based on seven indicators of "success" and several proxies for university-involvement in the SBIR project.

Our empirical findings should be interpreted with caution for two reasons. The first is that we have only analyzed data from a single agency, DoD. A second concern is that there is either a two-stage process, or perhaps a simultaneous process, underlying our statistical analysis. That is, it could be that a faculty member (or other agent of the university) consciously chooses to establish a relationship with private companies that have the highest probability of commercialization. It is conceivable that we are not capturing a firm-level "return" to involvement with the university, but rather a selection process on the part of the university agent. We need to tease this out further in subsequent empirical work.

Still, our empirical results suggest that universities may be adding value along this important dimension of technology transfer/commercialization. This is a spillover mechanism that deserves greater attention in the academic literature. In this study, the nature of the relationship between the startup and the university is measured somewhat crudely. It would be interesting to examine the connection between commercialization success and the closeness of the relationship between the SBIR firm and the university. For this, we need a direct measure of contact between these companies and academics and graduate students. The role of distance also needs to be explored.

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