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Commercializing Science: Is There a University "Brain Drain" from Academic Entrepreneurship?

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When academic researchers participate in commercialization using for-profit firms, there is a potentially costly trade-off—their time and effort are diverted away from academic knowledge production. This is a form of brain drain on the not-for-profit research sector that may reduce knowledge accumulation and adversely impact long-run economic growth. In this paper, we examine the economic significance of the brain drain phenomenon using scientist-level panel data. We identify life scientists who start or join for-profit firms using information from the Small Business Innovation Research program and analyze the research performance of these scientists relative to a control group of randomly selected research peers. Combining our statistical results with data on the number of university spin-offs in the United States from 1994 to 2004, we find the academic brain drain has a nontrivial impact on knowledge production in the not-for-profit research sector.

Key words: academic entrepreneurship; SBIR; NIH; brain drain; research productivity; university mission
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1. Introduction

There is now a convincing body of evidence describing the convergence and coevolution of scientific and commercial opportunities in the life sciences and the adoption of entrepreneurial attitudes and behaviors by academic life science researchers (Seashore et al. 1989; Dasgupta and David 1994; Powell and Owen-Smith 1998; Etzkowitz 1998, 2003; Stephan 1996; Murray 2002; Stuart and Ding 2006). Academic scientists participate in a wide spectrum of entrepreneurial behaviors, and their choices are influenced by university organizational mechanisms and public policies that shape incentives (Lach and Schankerman 2004, Toole and Czarnitzki 2007). Of particular note is the expanding practice by university administrators of accepting equity in lieu of licensing fees and investing directly in entrepreneurial companies (Desruisseaux 2000, Feldman et al. 2002, Di Gregorio and Shane 2003, Shane 2004). When combined with the growing use of venture capital and small firm financing programs such as the U.S. Small Business Innovation Research (SBIR) Program, life scientists and other university faculty members are increasingly involved in the most extreme form of entrepreneurial behavior—working part time or full time on commercialization using for-profit firms (often with an equity interest).[1] To the extent that these academic entrepreneurs devote significant time and cognitive effort to the firm, their contribution to academic knowledge accumulation is likely to be less—a potentially costly "brain drain" on the not-for-profit research sector.[2]

This paper explores the economic significance of the brain drain phenomenon by assessing how founding or joining a for-profit firm affects a scientist's academic research performance. University administrators and public policy makers should consider the potential sacrifice of academic knowledge production when designing and evaluating alternative modes of technology transfer. Effective technology transfer involves understanding and managing the incentives that determine how faculty members allocate their time, effort, and commitments to external

[1] Throughout the paper we will use "university" as shorthand for all not-for-profit research institutions and "faculty" as shorthand for researchers who work in the not-for-profit research sector.

[2] Although the concept of an academic brain drain could be applied very broadly to include, say, consulting with private industry, we see full-time or part-time employment with a vested interest in the firm, either temporary or permanent, as the form of private sector involvement that will induce an academic brain drain.

organizations. Promoting spin-offs relative to patenting or licensing may unintentionally jeopardize the university's research and educational missions. For policy makers, the costs of the academic brain drain stem from its harmful effects on the accumulation of public scientific knowledge and the role this knowledge stock plays in economic growth. Several empirical studies support the view that academic research is an important factor-fueling industry innovation and productivity. Jaffe (1989) presents evidence that university research contributes to state-level corporate patenting. Adams (1990) shows that cumulative stocks of academic research stimulate productivity growth in manufacturing industries. Toole (2009) finds that university research makes a significant contribution to drug innovation in the pharmaceutical industry.

Using a case-cohort sampling design, we compiled a scientist-level panel database to examine four indicators of academic research performance: journal publications, impact factor-weighted publications, U.S. National Institutes of Health (NIH) research grants, and university patents. For each of these indicators, the empirical analysis addresses two specific questions. First, how does the research performance of NIH academic entrepreneurs differ from a randomly selected control group of their NIH research peers during their careers in academe? If the most productive academic researchers are the ones taking employment positions at for-profit firms, the academic brain drain will be larger. Answering this question also provides one way to estimate the magnitude of the brain drain phenomenon. Assuming a one-time permanent employment transition to industry and immediate replacement at the university by an NIH research peer, it can be measured as the relative difference in research performance between the two groups over the period following the employment transition.[3] Second, how does the academic research performance within the group of NIH academic entrepreneurs change once they decide to participate in commercialization by joining a for-profit firm? Answering this question provides an alternative way to estimate the magnitude of the brain drain phenomenon. It accounts for part-time or temporary employment transitions by incorporating their academic research performance before and after their decision to start or join a firm.

The results show that life scientists who commercialize through the SBIR program perform better (on average) than their NIH research peers during their careers in academe. This holds for journal publications, impact factor-weighted publications, the value of NIH research awards, and university patents. We also find a significant decrease in the research performance within the group of NIH academic entrepreneurs after they begin working in for-profit firms for all indicators except university patenting. These results are robust to a variety of changes in the econometric specifications and to scientist unobserved heterogeneity, which may stem from their innate research ability or taste for scientific puzzles or commercialization (Levin and Stephan 1991, Stern 2004).

Assuming a one-time permanent employment transition to industry and immediate replacement at the university by an NIH research peer, the brain drain costs *per academic entrepreneur* are 26% fewer journal publications per year and 183% fewer patents per year. To assess the broader economic significance, we compared the cumulative publication and patent output of the Massachusetts Institute of Technology (MIT) with estimates of the academic brain drain costs for the period 1994–2004. Over this period, numbers equivalent to 81% of MIT's cumulative output of journal publications and 163% of MIT's cumulative output of approved patents were lost because of the academic brain drain. Although provocative, this "back-of-the-envelope" estimate is subject to a number of caveats, as described in §4.

The rest of this paper proceeds as follows. Section 2 provides a brief overview of the literature supporting the emergence of an academic brain drain phenomenon. Section 3 describes the data and career life cycle models we estimate. Section 4 presents the empirical results and estimates of the economic significance of the academic brain drain along with the limitations of our approach and assumptions. Section 5 discusses some of the implications of our findings.

2. Prior Literature

Our search of the literature revealed that Zucker and Darby (1996), Stephan and Levin (1996), and Powell and Owen-Smith (1998) expressed similar concerns about the movement of academic scientists and its potentially detrimental impact on academic research. Zucker and Darby (1996) note that knowledge transfer in people imposes a real cost because it requires a significant redirection of time and energy. Stephan and Levin (1996) emphasize the differences in property rights regimes between academe and industry, highlight the shortened lag between basic research discovery and commercialization, and provide a number of interesting anecdotes. Powell and Owen-Smith (1998) suggest that changing reward systems within academic research institutions could speed up the outflow of life scientists and weaken the traditional educational and research missions.

[3] This thought experiment assumes a perfectly elastic supply of academic researchers with the same career tenure.

The following review of prior research is organized around three observations that form the basis of our concern about an emerging academic brain drain.

The first observation is that academic faculty participation is critical to successful commercialization and that faculty effort devoted to this process increases with economic incentives. Based on survey data from 62 universities, Jenson and Thursby (2001) found that 71% of university inventions required continued faculty participation to have a reasonable chance at successful commercialization. Lowe (2001) and Shane (2004) make this point using case studies of academic spin-offs from the campuses of the University of California and MIT, respectively. Agrawal (2006), also using a sample drawn from MIT, shows that greater faculty-inventor involvement leads to an increased likelihood and degree of commercialization success. With respect to faculty effort, Lach and Schankerman (2004) find that university licensing income increases with faculty royalty rates. They suggest that higher royalty rates increase faculty effort devoted to commercialization. Thursby et al. (2007) use life cycle models of faculty behavior to show that licensing not only increases total research effort but also increases the ratio of applied to basic research. Because most of this increased effort comes at the expense of faculty leisure time, they do not believe that licensing activities are detracting from university knowledge production.

The second observation is that the most productive academic life scientists are the ones involved in the commercialization process with private industry. An influential stream of research suggests that "star" scientists transfer new and valuable academic knowledge to for-profit biotechnology firms (Zucker and Darby 1996; Zucker et al. 1998, 2002a, b; Toole and Czarnitzki 2009). For a sample of life scientists, Stuart and Ding (2006) examine the factors associated with when scientists choose to become entrepreneurs. Using a hazard model, they find that both cumulative publication counts and patent counts are positively related to when a life scientist founds a new biotechnology firm or joins a scientific advisory board. Lowe and Gonzalez-Brambila (2007) find that biomedical faculty entrepreneurs publish significantly more than their graduate school peers but significantly *less* than their coauthor peers.

The third observation is that more and more entrepreneurial life scientists are choosing employment in firms, either part time or full time, as their commercialization vehicle. As the most extreme form of faculty entrepreneurial behavior, firm employment involves the strongest economic incentives pulling life scientists to venture completely into the private sector. Audretsch and Stephan (1999) find that 50% of the scientific founders in their sample of biotechnology firms had prior careers in academe. Of these academic founders, 30% had transitioned to full-time employment at the firms and 70% maintained part-time employment. Using the Venture-One database, Zhang (2007) identified 903 venture capital-backed academic entrepreneurs who founded or cofounded a firm between 1992 and 2001. Toole and Czarnitzki (2007) identified 337 NIH academic scientists involved in commercialization through the SBIR and Small Business Technology Transfer Programs between 1983 and 1996. Their data show an upward trend in life scientist entrepreneurship since 1991.

Taken together, these observations suggest that a growing number of the most productive academic life scientists are participating in commercialization using for-profit firms and provide a compelling basis for concern about an emergent academic brain drain. Based on the literature, we expect to find that NIH academic entrepreneurs are more productive than their NIH research peers. We also expect to find a decrease in research performance for these entrepreneurial scientists after they become employed at for-profit firms.

3. Data and Methods

3.1. Data

We constructed a novel scientist-level database using a case-cohort sampling design. As discussed in Stuart and Ding (2006), this sampling design is used by epidemiologists to study rare diseases. To implement the case-cohort design, all of the observed cases of interest in the population are identified and grouped into cohorts. A random sample is drawn from each cohort, and this constitutes the control group that is compared to the cases of interest. As described below, the statistical analysis weighted each case and cohort observation by the inverse probability of being selected into the sample. Thus, using the case-cohort sampling design allows one to generalize the statistical findings to the original population.

The population for this study is defined to be all academic life scientists in the fields of biology, chemistry, and health sciences who were principal investigators (PIs) on at least one research award from the NIH between 1972 and 1996. We identified all individuals in this population using the NIH Computer Retrieval of Information on Scientific Projects (CRISP) database. Over this period, the population contains about 61,000 individual life scientists. For each scientist in the population, this database provides name, grant history, institutional affiliation, award amounts, award years, and NIH national institute code.

NIH-supported academic life scientists who undertook commercialization by starting or joining a for-profit firm are the entrepreneurial cases of interest.

Generally, identifying these individuals in a systematic and consistent way is a barrier to research. To overcome this barrier, we developed a method that exploits the information contained in the SBIR program. All SBIR grants have principal investigators who are the scientific and technical project leaders at the firm. For each academic scientist in the NIH researcher population, we looked up whether that individual also served as a PI on one or more SBIR commercialization grants.[4] If the academic scientist received NIH research grant(s) at a not-for-profit institution and *later* received SBIR grant(s) at a for-profit firm, then he or she is an academic entrepreneur. This procedure identified 213 NIH academic entrepreneurs in the SBIR program between 1983 and 1996. It was further required that the academic entrepreneurs have degrees in the fields of biology, chemistry, or health sciences and have available data on their degree institutions and years from the ProQuest UMI Dissertation Publishing database or the Internet. The final sample consists of 89 NIH academic entrepreneurs.

Using the SBIR program to identify NIH academic entrepreneurs has both advantages and disadvantages. One advantage is that the SBIR program is an attractive route for academic entrepreneurship. It targets small for-profit firms and has grown into the largest commercialization program in the United States.[5] Furthermore, it is the only public data source that identifies the principal investigators involved in the firm's research. This principal investigator information provides the link between the not-for-profit and for-profit sectors. To qualify as an SBIR PI, individuals must be employed full time at the small business at the time of award and throughout the duration of the project(s).[6] This requirement provides assurance that we are studying academic entrepreneurs who make nonnegligible commitments to their firms as opposed to providing advising or other arms-length services.

Notwithstanding these advantages, the SBIR information is subject to some important limitations. One limitation is that the SBIR program represents only one of several modes of commercialization available to NIH-backed academic scientists. For instance, NIH scientists can start or join companies supported by other modes of financing such as venture capital, personal assets, friends and family, and so forth. Using only the SBIR commercialization mode, we are undercounting the actual number of NIH research scientists who choose to leave the academic environment or devote significant effort to entrepreneurial ventures. At this time, little is known about the population of NIH-supported academic entrepreneurs or about the population of academic entrepreneurs more broadly. In this sense, one should be cautious about generalizing our findings to scientists who are not supported by NIH research grants or who work in different academic fields. Further, the SBIR program identifies a financing point in the entrepreneurship process. The receipt of funding necessarily follows the decision to found or join a firm. The next section describes how we address the possibility that the academic entrepreneurs' initial decisions to leave academe might be related to their academic research performance.

To form the random control group of NIH research peers, the observed cases of NIH academic entrepreneurs were allocated to medical cohorts defined by 15 NIH national institutes, such as the National Cancer Institute, the National Eye Institute, and so forth. We drew a total random sample of 1,500 researchers from the population of NIH principal investigators with at least one research award from any of the 15 national institutes after excluding the NIH academic entrepreneurs. It was further required that the NIH research peers have degrees in the fields of biology, chemistry, or health sciences and have available data on their degree institutions and years from the ProQuest UMI Dissertation Publishing database or the Internet. These restrictions reduced the control group to 444 life scientists. In the final sample, the ratio of controls to NIH academic entrepreneur cases is about 5:1.

To complete the database, we collected information on each scientist's publication and patenting history. Journal publications were collected from PubMed using the PublicationHarvester software for the period 1972–1996 (Azoulay et al. 2006). For each article, journal impact factors were collected from the Institute for Scientific Information (ISI) Web of

[4] Matching PIs by name is notoriously difficult and requires cross-referencing information to eliminate false matches. This process was facilitated by using specialized software developed by Thorsten Doherr at the Centre for European Economic Research, Mannheim, Germany, for text field matching and by exploiting the internal consistency of the NIH CRISP database, which includes information on all NIH research project grants and NIH SBIR grants. Each academic entrepreneur in our final group was manually verified.

[5] Authorized by Congress in 1982, the SBIR program awarded about $1.78 billion in subsidies in 2008 across 11 participating agencies. The NIH, the second largest agency after the Department of Defense, awarded 1,617 grants worth $559 million in 2008. NIH (2003) and the National Research Council (2009) provide overall descriptions of the firm age, size, and industry distribution for the NIH SBIR program. Toole and Czarnitzki (2007) consider the merits of the SBIR program as a policy fostering academic entrepreneurship.

[6] Based on the SBIR eligibility rules, the NIH scientists who venture into commercialization spend at least 51% of their time at the for-profit firms at the moment of award and throughout the duration of their projects. We do not observe whether the SBIR academic entrepreneurs hold equity, found new firms, or join established firms.

Knowledge.[7] Searches of the NBER patent database identified all patents assigned to universities on which the scientists are listed as inventors (Hall et al. 2001).[8] The final scientist-level panel database has 89 NIH academic entrepreneurs and 444 NIH research peers covering the years 1975–1996.

There are two primary explanatory variables in the database. First, to analyze performance differences between NIH academic entrepreneurs and their NIH research peers while in academe, we specified a dummy variable, *AEIN*, which takes the value of one for all NIH researchers who eventually become employed at a for-profit firm as indicated by winning an SBIR commercialization grant. This variable is constant over their careers in academe and captures differences in research performance levels between the NIH academic entrepreneurs and the control group. Second, because we are interested in examining changes in research performance once an NIH researcher becomes an academic entrepreneur, we specified a dummy variable *AEOUT*, which switches from zero to one in the year the NIH researcher becomes an academic entrepreneur through the SBIR program. Clearly, the NIH researchers in the control group never became academic entrepreneurs and these observations cannot be used in this part of our analysis. Using the *AEOUT* variable, we only look *within* the group of NIH academic entrepreneurs to analyze differences in research performance due to starting or joining a for-profit firm.

Table 1 presents descriptive statistics for our sample of NIH academic entrepreneurs and their NIH research peers. The top panel summarizes the time-constant variables for each group. The bottom panel shows the time-varying variables by group and employment status.[9] Looking at the bottom panel reveals that NIH academic entrepreneurs perform better than their research peers (on average) across all research indicators during their careers in academe. This is consistent with prior findings that the most productive academic life scientists are the ones involved in the commercialization process. Comparing academic entrepreneurs before and after they leave academe shows a decrease in research performance across all indicators except university patenting. Interestingly, some academic entrepreneurs have more university assigned patents *after* they have ventured into private industry. This suggests that some NIH academic entrepreneurs do not permanently leave the not-for-profit research sector, but leave temporarily or maintain part-time positions at their universities. We attempted to systematically track the 89 academic entrepreneurs using Internet searches to find out how many leave permanently versus temporarily. Although not completely successful, we determined that 27% left temporarily (four years or less), 38% left permanently, and 35% could not be determined.[10]

3.2. Methods

To analyze the counts of publications and patents, we use a Poisson model where the conditional mean is an exponential function of the explanatory variables. The value of NIH research grants and impact factor weighted publications are zero for a nontrivial number of observations. We treat these as corner solution and data-censored outcomes and estimate Tobit models.

The literature on life cycle models of researcher productivity informs our model specifications (Diamond 1986, Levin and Stephan 1991, Turner and Mairesse 2005, Hall et al. 2007, Lowe and Gonzalez-Brambila 2007). In addition to exogenous time effects, this literature suggests that scientists' age and graduation cohort may have an important influence on their research performance. We include time and graduation cohort dummies in the analysis. Age is defined to be career age, which is equal to the number of years elapsed since the scientists received their advanced degrees. Career age is usually entered as a quadratic to allow for a nonlinear profile. Also, there may be unobserved heterogeneity among individual scientists because of differences in their abilities or tastes for research. This suggests controlling for scientist fixed effects in the empirical analysis.

The next section presents regression results for both pooled and unobserved-effects Poisson and Tobit models. An advantage of the pooled models over the unobserved-effects models is that they do not impose the assumption of strict exogeneity. This assumption rules out feedback from current realizations of the dependent variable to future values of the explanatory variables. Unobserved-effects models impose the

[7] The ISI Web of Knowledge is a selective database. In the sample, 69% of the journals were successfully matched to the ISI database.

[8] To identify the scientist's patents, a name match was performed based on the inventor name and assignee name of the not-for-profit institutions where the scientists where employed during their career (obtained from the NIH CRISP database). This search also used the text field search engine developed by Thorsten Doherr. Given our focus on the costs of the brain drain on the not-for-profit research sector, the patent variable does *not* include patents invented by these scientists and assigned to firms.

[9] We only have time-varying data on 87 of the 89 NIH academic entrepreneurs for the period *after* they become associated with for-profit firms. Two NIH academic entrepreneurs exited at the end of their careers, which in our analysis is 35 years after their receiving their advanced degree.

[10] As suggested by an anonymous referee, the observations for NIH academic entrepreneurs who left temporarily were dropped as a robustness check for the within regressions that use *AEOUT*. The results presented in the next section continued to hold.

Table 1 Descriptive Statistics

Variable	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
	Time constant variables; Control sample: $N = 444$				Time constant variables; Academic entrepreneurs: $N = 89$			
degree year	1974	9.2	1951	1991	1973	7.9	1954	1991
cohort dummy 1951–1960	0.0721	0.259	0	1	0.0449	0.208	0	1
cohort dummy 1961–1965	0.113	0.316	0	1	0.124	0.331	0	1
cohort dummy 1966–1970	0.171	0.377	0	1	0.191	0.395	0	1
cohort dummy 1971–1975	0.164	0.371	0	1	0.27	0.446	0	1
cohort dummy 1976–1980	0.178	0.383	0	1	0.225	0.42	0	1
cohort dummy 1981–1985	0.169	0.375	0	1	0.101	0.303	0	1
cohort dummy 1986–1991	0.133	0.34	0	1	0.0449	0.208	0	1
field dummy: Biology	0.459	0.499	0	1	0.337	0.475	0	1
field dummy: Chemistry	0.3	0.459	0	1	0.461	0.501	0	1
field dummy: Health sciences	0.241	0.428	0	1	0.202	0.404	0	1
female (dummy)[a]	0.218	0.414	0	1	0.0787	0.271	0	1
Ph.D. (dummy)	0.899	0.302	0	1	0.944	0.232	0	1
foreign degree (dummy)	0.0405	0.197	0	1	0.0225	0.149	0	1
public school (dummy)	0.505	0.501	0	1	0.562	0.499	0	1
medical school (dummy)	0.119	0.325	0	1	0.124	0.331	0	1

Variable	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
	Time-varying variables; Control sample: $NT = 7{,}779$				Time-varying variables; Academic entrepreneurs *while in academe*: $NT = 1{,}044$				Time-varying variables; Academic entrepreneurs *after leaving academe*: $NT = 628$			
# journal publications	2	2.73	0	27	2.23	2.49	0	17	1.74	2.66	0	19
ISI journal impact factor-weighted publications	9.539	16.670	0	216.243	10.509	17.217	0	167.965	7.012	14.475	0	116.676
NIH awards (in 1,000 US$, prices of 1996)	122	255	0	3,955	134	193	0	1,462	48.1	145	0	935
# academic patents	0.0179	0.157	0	3	0.0556	0.357	0	7	0.104	0.506	0	7
lagged # journal publications (sum of $t-1$, $t-2$, $t-3$)	5.56	6.86	0	72	6.02	5.82	0	41	5.79	6.93	0	44
lagged NIH grants (sum of $t-1$, $t-2$, $t-3$, and $t-4$ in million US$, prices of 1996)	0.434	0.86	0	10.7	0.469	0.651	0	5.45	0.288	0.564	0	3.69

Note. The regressions will include career $AGE = t -$ degree year; *cohort, field, Ph.D., public school* and *medical school* are dummy variables corresponding to the characteristics of the scientists' academic degree.
[a]Gender was determined by the first name of the researchers and Internet searches.

strict exogeneity assumption but have the advantage of controlling for unobserved time-constant heterogeneity. As pointed out by Wooldridge (1997), unobserved-effects estimators are not more robust than pooled estimators, but they impose a different set of assumptions.

To obtain estimates of the time-constant explanatory variables for publications and patents when controlling for fixed effects, we follow Turner and Mairesse (2005) and use a two-step estimation method. The first step regresses the performance measure on the time-varying explanatory variables using the fixed-effects Poisson quasi-maximum likelihood (QML) estimator. In the second step, the unexplained variation in the dependent variable is regressed on the time-constant variables using nonlinear least squares.[11] The model can be formulated as

$$\text{First step:}\quad E(y_{it} \mid X_{it}, \alpha_i) = \exp(X_{it}\beta + \alpha_i),\quad \text{where } \alpha_i = \mu + Z_i; \quad (1)$$

$$\text{Second step:}\quad y_{it}/\exp(X_{it}\hat{\beta}) = \exp(\mu + Z_i\gamma) + \varepsilon_{it}, \quad (2)$$

where y_{it} is the performance measure for individual i at time t, X_{it} are the time-varying explanatory variables, Z_i are the time-constant explanatory variables, and α_i is the unobserved effect for individual i.

To control for correlated unobserved effects in the models for impact factor-weighted publications and NIH grants, we used an unobserved-effects Tobit

[11] To get consistent estimates of the time-constant explanatory variables, this method assumes that all correlation between the unobserved effects and the explanatory variables is due only to the time-varying explanatory variables and not to the time-constant variables, Z_i.

model suggested by Wooldridge (2002). Unlike the usual random-effects Tobit, this model allows the unobserved effect to be correlated with the explanatory variables. Under appropriate assumptions we can write

$$y_{it} = \max(0, \mu + X_{it}\beta + \overline{X}_i\delta + \alpha_i + \varepsilon_{it}), \tag{3}$$

$$\varepsilon_{it} \mid X_i, \alpha_i \sim N(0, \sigma_\varepsilon^2), \tag{4}$$

$$\alpha_i \mid X_i \sim N(0, \sigma_\alpha^2), \tag{5}$$

where y_{it} is the performance measure for individual i at time t, X_{it} are the time-varying explanatory variables, $\overline{X}_i$ are the within averages of the time-varying explanatory variables, and α_i is the unobserved effect for individual i.

Throughout the empirical analysis we assume the control variables satisfy the appropriate exogeneity assumptions for the methods used. Looking back at Table 1, this assumption is reasonable because most of the explanatory variables are either predetermined or not under the control of the academic scientists. For instance, the *career age, degree year, degree institution,* and the *gender* variables are all strictly exogenous. *Lagged publications* and *lagged NIH awards* are predetermined. That is, they can be assumed to be exogenous in the pooled regression models but may not be strictly exogenous as required for the unobserved-effects models.

The exogeneity of our key explanatory variables, *AEIN* and *AEOUT*, is more complicated because these variables are determined from the observed behavior of the NIH scientists. Life cycle models provide some insight into the scientist's decision to found or join a firm (Levy 1988, Levin and Stephan 1991). In these models academic scientists build their reputations over time by accumulating human capital through various means, such as publications, grants, and patents. At any point, these scientists may choose to "cash in" on their accumulated human capital by founding or joining a firm in the private sector. Holding past research performance constant, this framework suggests that the decision to pursue entrepreneurship depends on the scientist's expected (or future) human capital accumulation. Unobserved shocks to expected human capital accumulation might influence *when* the scientist chooses cash in, as captured by *AEIN* and *AEOUT*, and may also be related to contemporaneous research performance.

For analyzing research performance differences between NIH academic entrepreneurs and their peers while in academe using *AEIN*, the sample observations for the academic entrepreneurs after the date of their first SBIR commercialization grant were dropped. This avoids confounding their research performance while in academe with their research performance after they leave. However, one may be concerned that academic entrepreneurs experience an unobserved positive shock to their research productivity just prior to leaving that induces an upward bias on our estimate of their relative research performance using *AEIN*. To examine the sensitivity of our results to this possibility, we lagged the date of their first SBIR award by one, three, and five years. This effectively drops the NIH academic entrepreneurs out of academe one, three, and five years earlier than their observed date of leaving. Our results using *AEIN* were not sensitive to these changes in the timing of when the NIH academic entrepreneurs leave academe.

For our analysis of changes in academic research performance within the group of NIH academic entrepreneurs using *AEOUT*, the sample includes all annual observations before and after receipt of scientists' first SBIR commercialization grant. In this setup, an unobserved shock to their expected research productivity could be related to both the timing of their decision to cash in as captured by *AEOUT* and their contemporaneous research performance. To address this possibility, we performed tests for endogeneity in the regression models using *AEOUT*. The tests were based on the two-step method introduced by Smith and Blundell (1986) for Tobit models and adapted to count data models as shown in Wooldridge (2002). We identified instrumental variables that would be uncorrelated with individual-specific shocks to expected academic research productivity, but correlated with *AEOUT*. Lagged regional variables appeared to be good candidates because shocks to an individual's scientific research may not be related to regional economic activity, whereas their opportunity to found or join a firm would be.[12] We collected information on venture capital investment, population, income, total SBIR funding, and total NIH investment by national institute for both local and state regional aggregations. SBIR funding and NIH funding per capita at the state level were jointly significant in the first-stage regressions using *AEOUT*, but the residuals-based test in the second stage did not reject exogeneity of *AEOUT*. Based on these results, we do not believe *AEOUT* suffers from significant endogeneity bias. As reported in the appendix, we employed

[12] As an example, consider the joint discovery of the recombinant DNA technique for gene splicing by Herbert Boyer of the University of California at San Francisco and Stanley Cohen of Stanford University. This discovery was unanticipated but led to Herbert Boyer's decision to cofound Genentech with venture capitalist Robert Swanson. In this case, our identification strategy assumes the discovery of gene splicing is uncorrelated with regional economic activity, but Professor Boyer's decision to pursue entrepreneurship is correlated with regional activity such as venture capital investment.

a conditional difference-in-difference approach as an alternative estimation method that does not require instrumental variables. The results reaffirm the findings presented in §4.

4. Empirical Results

This section presents the regression results for each of the four indicators of research performance. Recall that we are interested in two specific questions regarding these indicators: (1) How does the research performance of NIH academic entrepreneurs differ from a randomly selected control group of their NIH research peers during their careers in academe? (2) How does the academic research performance within the group of NIH academic entrepreneurs change once they decide to participate in commercialization by joining a for-profit firm? We begin by discussing the statistical findings for each indicator. This is followed by an exploratory estimate of the costs of academic brain drain to the not-for-profit research sector.

4.1. Analysis of Journal Publications

Our first indicator is a scientist's journal publications per year. This is a traditional measure of academic research performance and captures aspects of both knowledge production and dissemination in public science. Models 1–3 of Table 2 correspond to the pooled and fixed-effects Poisson QML estimators for the number of journal publications per year. The results incorporate sampling weights and account for heteroscedasticity as well as arbitrary within-group correlation of the error terms. This method adjusts the standard errors for any overdispersion in the data. Using the pooled estimator, Model 1 shows the key variable *AEIN* is positive and significant at the 5% level. Relative to the control group of NIH research peers, NIH academic entrepreneurs publish about 26% more articles per year on average during their careers in academe. Consistent with the life cycle productivity literature, the results for career age show a concave publication profile. NIH researchers reach their peak number of publications nearly 19 years after they earn their advanced degree. The cohort dummy variables based on degree year were never significant and were dropped from the model. The value of NIH research awards, which enters the regression specification as a lagged sum of NIH awards over the previous four years, significantly increases journal publications per year. Among the time-constant explanatory variables, NIH researchers with degrees from medical schools and foreign institutions publish more journal articles. NIH researchers with Ph.D. degrees publish significantly less than those with M.D. degrees.

The next two columns in Table 2 report the results for Model 2, which uses the two-step fixed-effects Poisson QML estimator. This method allows for unobserved scientist heterogeneity, which may stem from a scientist's innate ability or taste for research but imposes strict exogeneity on the explanatory variables. For our key variable, *AEIN*, the results are robust and continue to show that NIH academic entrepreneurs publish more journal articles on average than their NIH research peers during their careers in academe. Their academic publication profile is the same as in Model 1. The coefficient on lagged NIH research awards is positive and significant but quite a bit smaller than in Model 1. The cohort dummy variables based on degree year were jointly significant and included in the second step estimation. For the time-constant explanatory variables, NIH researchers with Ph.D. degrees continue to publish significantly less than those holding M.D. degrees. Degrees from foreign institutions are no longer associated with publishing significantly more, and degrees from medical schools are only marginally significant and positive. Interestingly, after controlling for unobserved scientist heterogeneity, the female indicator became negative and significant at the 5% level. This result is consistent with a number of prior studies that find a gender gap in scientific publication. Although the reasons underlying this gap remain unclear, Xie and Shauman (1998) suggest that this "productivity puzzle" is largely due to differences in personal and structural characteristics such as marital status and teaching hours.

Model 3 examines how annual journal publications of NIH academic entrepreneurs change after they become employed at a for-profit firm. The estimates are based on the Poisson QML fixed-effects estimator using only the scientist-year observations on the NIH academic entrepreneurs. The key explanatory variable, *AEOUT*, is negative and significant at the 5% level. On average, NIH academic entrepreneurs reduce their journal publications per year by about 19% after they join for-profit firms. Their career publication profile is concave and reaches its peak just under 20 years after they earn their advanced degree. Past NIH research awards are associated with more journal publications at the 10% level of significance.

Models 4–6 of Table 2 correspond to the pooled and unobserved-effects Tobit estimators for the number of weighted publications. Each journal article was assigned the ISI impact factor of the journal in which it was published. Publications in non-ISI journals received a weight of zero. The results are consistent with those found using the Poisson models for the count of journal publications. The pooled Tobit Model 4 shows the key variable *AEIN* is positive and significant at the 1% level. The marginal

Table 2 Poisson and Tobit Models of Journal Publications per Year (1975–1996)

Dependent variable	*Number of journal publications*				*ISI journal impact factor-weighted publications*		
	Full sample			AE sample	Full sample		AE sample
	Model 1	Model 2		Model 3	Model 4	Model 5	Model 6
		Fixed-effects estimation					
Variable	Pooled cross-sectional Poisson	Step 1 time-variant: Fixed effects Poisson model	Step 2 time constants: Nonlinear LS	Fixed-effects Poisson model for AE = 1	Pooled cross-sectional Tobit	Random-effects Tobit	Random-effects Tobit for AE = 1
AEIN	0.227**		0.235***		4.378***	3.754**	
	(0.096)		(0.090)		(1.695)	(1.849)	
AEOUT				−0.216**			−3.868**
				(0.097)			(1.740)
AGE	0.075***	0.075***		0.078**	0.501**	0.482	0.062
	(0.012)	(0.018)		(0.040)	(0.210)	(0.328)	(0.752)
AGE^2	−0.002***	−0.002***		−0.002**	−0.020***	−0.024***	−0.023***
	(0.000)	(0.000)		(0.000)	(0.006)	(0.003)	(0.008)
lagged NIH grants	0.200***	0.135***		0.180*	7.117***	3.373***	4.802***
	(0.035)	(0.030)		(0.099)	(1.393)	(0.368)	(1.111)
field: chemistry	−0.091		−0.068		−0.440	0.000	3.618
	(0.113)		(0.089)		(1.774)	(1.604)	(3.088)
field: health sciences	0.008		0.181		−1.563	1.341	9.405**
	(0.139)		(0.113)		(2.463)	(1.880)	(4.094)
female	−0.079		−0.256**		−1.679	−3.642**	−8.279
	(0.157)		(0.115)		(2.040)	(1.780)	(5.246)
Ph.D.	−0.543***		−0.416***		−9.790***	−6.621**	−14.931**
	(0.155)		(0.134)		(3.209)	(2.901)	(6.812)
foreign degree	0.354*		0.260		2.364	−1.378	−10.011
	(0.208)		(0.190)		(3.882)	(3.657)	(10.067)
public school	−0.123		−0.071		−4.366***	−3.108**	3.046
	(0.087)		(0.071)		(1.537)	(1.370)	(2.695)
medical school	0.256**		0.217*		1.621	0.713	−0.494
	(0.130)		(0.119)		(2.200)	(2.207)	(4.308)
intercept	0.546***		0.510**		9.268**	3.597	7.209
	(0.202)		(0.253)		(3.859)	(6.324)	(13.848)
mean(AGE$_i$)						−0.021	0.611
						(0.427)	(0.929)
mean(lagged grants$_i$)						6.976***	−1.666
						(1.077)	(3.676)
mean(AEOUT$_i$)							−10.516
							(7.546)
time dummies	Yes	Yes	No	Yes	Yes	Yes	Yes
cohort dummies	No	No	Yes	No	No	No	No
N	8,823	8,674	8,674	1,672	8,823	8,823	1,672
(McFadden) R^2	0.107	0.388	0.444	0.319	0.022	0.071	0.057

Notes. Fully robust standard errors are in parentheses for all models except random-effects Tobit. *** (**, *) indicate the 1% (5, 10%) significance level. Models 5 and 6: The *mean*(·) variables are the individual specific means of the time-varying covariates that are added to the Tobit panel estimations to allow for correlation of the individual specific effects and the explanatory variables (see Wooldridge 2002). LS, Least squares; AE, academic entrepreneur.

effect indicates that NIH academic entrepreneurs publish in journals that receive about 2.6 more citations per article than their NIH research peers. In the unobserved-effects Tobit shown as Model 5, *AEIN* is also positive and significant. Both sets of estimation results show a concave journal impact factor profile over the scientists' careers. Further, the value of NIH research awards is positively associated with publishing in journals that receive more citations per article. Life scientists with Ph.D. degrees and those who have degrees from public institutions publish in journals that receive fewer citations per article. As found in the analysis of publication counts, after controlling for unobserved scientist heterogeneity, the female indicator is negative and significant, which suggests that women NIH scientists publish in journals with fewer citations per article. This appears to be another dimension of the gender productivity puzzle mentioned above.

Looking at the change in weighted publications within the group of academic entrepreneurs, Model 6 shows the key variable *AEOUT* is negative and significant at the 5% level. After founding or joining a for-profit firm, NIH academic entrepreneurs publish in journals that receive fewer citations per article than during their careers in academe. *AGE* and AGE^2 are always jointly significant, even though *AGE* is not individually significant in Model 6. Among the time-constant variables, academic entrepreneurs with a health sciences degree publish in higher-impact journals than those holding degrees in biology. Life scientists with Ph.D. degrees publish in journals that receive fewer citations per article. The female indicator is negative but not significant.

4.2. Analysis of NIH Awards

Our third indicator is the value of the life scientist's NIH research awards per year. This indicator is relevant for two reasons. For individual life scientists, NIH funding is an important source of research support, and grantsmanship is often linked to academic promotion. Further, universities collect revenue from the indirect costs included in most grants. Table 3 reports the pooled and unobserved-effects Tobit estimators explaining the log of annual NIH research awards to individual NIH scientists.[13] The pooled Tobit results in Model 1 show that *AEIN* is positive and significant at the 1% level. This finding is confirmed using the unobserved-effects Tobit as shown in Model 2. On average, NIH academic entrepreneurs win more NIH research awards than their NIH research peers during their careers in academe. Each of these models indicates a concave career profile. Lagged journal publications, measured as the sum of publications over the previous three years, significantly increases NIH research awards in both regression models. In the pooled model, NIH scientists who have a degree from a foreign institution and in the field of health sciences (relative to biology) win less NIH grant money. Controlling for unobserved heterogeneity eliminates these effects, but having a Ph.D. relative to an M.D. degree becomes associated with larger NIH grants.

Model 3 of Table 3 shows the change in the value of NIH research awards received by NIH academic entrepreneurs after starting or joining a firm. The key variable *AEOUT* is negative and significant at the 1% level. On average, grantsmanship through the NIH drops after academic entrepreneurs take employment positions in the private sector. As before, more journal publications are associated with greater NIH awards. For NIH academic entrepreneurs, none of the

Table 3 **Tobit Models of NIH Research Awards per Year (1975–1996)**

	Dependent variable: ln(1 + *amount of NIH grants per year)*		
	Full sample		AE sample only
	Model 1	Model 2	Model 3
Variables	Pooled cross-sectional Tobit	Random-effects Tobit	Random-effects Tobit
AEIN	1.342*** (0.444)	1.141*** (0.397)	
AEOUT			−4.989*** (0.507)
AGE	0.716*** (0.124)	0.597*** (0.094)	0.344 (0.264)
AGE^2	−0.022*** (0.002)	−0.022*** (0.001)	−0.017*** (0.002)
lagged publications	0.250*** (0.031)	0.167*** (0.012)	0.235*** (0.031)
field: chemistry	0.481 (0.476)	0.341 (0.277)	−0.340 (0.684)
field: health sciences	−0.917* (0.537)	−0.135 (0.373)	0.985 (0.892)
female	0.135 (0.421)	0.229 (0.303)	1.459 (1.117)
Ph.D.	0.409 (0.713)	1.139** (0.521)	−1.239 (1.395)
foreign degree	−1.510* (0.871)	−0.727 (0.467)	−2.184 (2.386)
public school	−0.444 (0.385)	−0.073 (0.234)	0.740 (0.595)
medical school	0.343 (0.607)	−0.688 (0.433)	−1.347 (0.927)
mean(lagged publications$_i$)		0.143*** (0.023)	−0.128 (0.084)
mean(AGE$_i$)		0.103 (0.143)	0.801** (0.375)
mean(AEOUT$_i$)			−3.225* (1.820)
intercept	−4.619* (2.428)	−5.609* (2.894)	−16.313** (7.854)
time dummies	Yes	Yes	Yes
cohort dummies	Yes	Yes	Yes
(McFadden) R^2	0.055	0.122	0.140
N	8,823	8,823	1,672

Notes. Fully robust standard errors are in parentheses pooled cross-sectional Tobit. *** (**, *) indicate the 1% (5, 10%) significance level. Models 2 and 3: The *mean*(·) variables are the individual specific means of the time-varying covariates that are added to the panel estimations to allow for correlation of the individual specific effects and the explanatory variables (see Wooldridge 2002). AE, Academic entrepreneur.

[13] Because the value of NIH awards to a scientist can be zero in any given year, we add one to all scientist-year NIH award amounts to allow the natural log transformation.

Table 4 Poisson Models of the Number of Patents (by Application Date) per Year (1975–1996)

	Dependent variable: Number of patent applications			
	Full sample			AE sample
	Model 1	Model 2		Model 3
		Fixed-effects estimation		
Variable	Pooled cross-sectional Poisson	Step 1 time variant: Fixed-effects Poisson model	Step 2 time constants: nonlinear LS	Fixed-effects Poisson model for AE = 1
AEIN	1.039** (0.427)		1.601*** (0.309)	
AEOUT				−0.306 (0.435)
AGE	0.115 (0.130)	0.193 (0.141)		−0.047 (0.146)
AGE^2	−0.007** (0.003)	−0.006*** (0.002)		−0.007*** (0.003)
lagged publications	0.056*** (0.013)	0.030 (0.020)		0.051* (0.030)
field: chemistry	0.670 (0.434)		1.614*** (0.504)	
field: health sciences	−0.242 (0.503)		1.027* (0.538)	
female	−1.417*** (0.524)		0.272 (0.523)	
Ph.D.	1.300 (1.040)		3.306*** (0.768)	
foreign degree	−0.489 (0.720)		−0.026 (0.630)	
public school	−0.605 (0.410)		−0.755*** (0.246)	
medical school	−0.321 (0.820)		0.344 (0.411)	
intercept	−5.942** (2.344)		−9.253*** (1.228)	
time dummies	Yes	Yes	No	Yes
cohort dummies	Yes	No	Yes	No
(McFadden) R^2	0.139	0.647	0.148	0.472
N	8,823	1,012	1,012	441

Notes. Fully robust standard errors are in parentheses. ***(**,*) indicate the 1% (5, 10%) significance level. LS, Least squares; AE, academic entrepreneur.

time-constant explanatory variables are significantly related to the value of NIH grants.

4.3. Analysis of Patents

Our final indicator of research performance is the number of patents assigned to universities on which the NIH scientist appears as an inventor. This is the least traditional indicator of academic performance, but it has become increasingly important as university attitudes and policies have become more supportive of commercialization activities. Nevertheless, patenting appears less important than journal publications as an indicator of academic knowledge accumulation. For MIT, Agrawal and Henderson (2002) find that professors place much greater emphasis on academic papers in spite of the fact that MIT is one of the most prolific patenting academic institutions. Over the 15 year period in their study, almost half the faculty never patented and only 10%–20% of the faculty actively patented in any year. In our sample of 89 NIH academic entrepreneurs, only 27% were granted patents in any year.

Model 1 of Table 4 shows the results using the pooled Poisson QML estimator for the number of university patents. The key variable *AEIN* is positive and significant at the 5% level. The results from the two-step Poisson fixed-effects estimator in Model 2 show that *AEIN* is positive and significant at the 1% level. Relative to the control group of NIH research peers, NIH academic entrepreneurs patent more per year (on average) during their careers in academe. Both sets of estimation results show a concave patenting productivity profile over careers. *AGE* and AGE^2 are jointly significant even though *AGE* is not individually significant. Lagged journal publications are positive in the pooled model but insignificant in the fixed-effects model.

Among the time-constant covariates, the pooled and two-step fixed-effects models show different results. The pooled model finds that female NIH researchers patent significantly less than males. Ding et al. (2006) examine gender differences in scientific patenting and suggest that male scientists have more exposure to industry and view patenting as complementary to their university careers and commitments. The gender gap, however, disappears after controlling for fixed effects. The fixed-effects model finds several other time-constant variables to be statistically significant. Life scientists with degrees in chemistry and health sciences patent significantly more than those with degrees in biology. In addition to their field of degree, life scientists with degrees from public universities patent significantly less, whereas those having a Ph.D. patent significantly more than life scientists with M.D. degrees.

Model 3 of Table 4 shows the fixed-effects Poisson QML results using only observations of NIH academic entrepreneurs. Unfortunately, the sample size for this regression is inadequate because it relies on information from only 24 NIH academic entrepreneurs who have at least one patent in the sample period. The key variable *AEOUT* is negative but insignificant.[14] The patenting career profile does not have the same shape. Both *AGE* and AGE^2 are jointly significant and negative. Patenting is relatively new to the academic environment and has not been part of the expected research output of older life scientists, so it is not surprising that patenting decreases with career age among academic entrepreneurs.

4.4. Economic Significance of the Academic Brain Drain

Our objective in this subsection is to estimate the costs of the academic brain drain for the *whole* not-for-profit research sector. A major component of these costs is the lost research output due to the employment of academic researchers at for-profit firms. We calculate the lost research output for journal publications and patents.[15] Our objective requires us to generalize our regression results and impose a number of fairly strong auxiliary assumptions. As will be clear, estimating the costs of the academic brain drain phenomenon introduces a number of unresolved conceptual and measurement issues. For this reason, the reader should be cautious when interpreting the broader cost estimates, because they are exploratory and speculative. Nevertheless, the estimates allow us to gauge the order of magnitude of the academic brain drain and obtain a sense of its economic significance.

Our starting point is to assume that NIH academic entrepreneurs make a one-time permanent employment transition to industry and are replaced immediately at the university by an NIH research peer.[16, 17] The lost research output is given by the marginal effect of the *AEIN* variable from the pooled models in Tables 2 and 4. From these models, each NIH academic entrepreneur publishes 25.5% more in journals per year (0.51 more articles) and patents 183% more per year (0.033 more patents) than their NIH research peers.[18] As we used sampling weights in the regression analysis, these estimates are statistically valid for the target population considered in this study, namely the 61,000 life science researchers in the fields of biology, chemistry, and the health sciences who won at least one research award from the NIH between 1972 and 1996.

To obtain broader estimates of the brain drain costs for the life science segment of the not-for-profit research sector, we would like to know how many individuals in the population of 61,000 life scientists chose to start or join for-profit firms. Unfortunately, such data are not available for the life science segment or for any other segment of academic researchers in the not-for-profit research sector. The only systematic data source we could find is the annual surveys of universities conducted by the Association of University Technology Managers (AUTM). These surveys ask universities to report the annual number of companies formed around a license of intellectual property from the university, a relatively narrow

[14] As a robustness check, we reestimated the fixed-effects model with patents assigned to both universities and firms. The *AEOUT* variable remained insignificant.

[15] Research funding from grant agencies supporting academic research, such as the NIH, is not necessarily lost because most of these funds are likely to be reallocated within the not-for-profit research sector.

[16] An alternative way to interpret this assumption is as follows: NIH academic entrepreneurs continue working at the university, but their academic research performance falls to the level of their NIH research peers because of their commitments to the for-profit firm.

[17] This is a conservative method for estimating the cost of the academic brain drain phenomenon because it assumes, unrealistically, that the NIH academic entrepreneur is replaced by an existing NIH research peer with the same career age (i.e., a perfectly elastic supply). Because of employment flows, a more realistic assumption would have the NIH academic entrepreneur replaced by a life scientist from outside the not-for-profit research sector such as a newly minted academic life scientist or an industry life scientist.

[18] The marginal decrease in journal publications from the fixed-effects regression using only NIH academic entrepreneurs is about 19% (0.424 fewer articles).

Table 5 Academic Brain Drain Costs to the Not-for-Profit Research Sector

Year	Number of U.S. university spin-offs (AUTM)[a]	Brain drain lost journal publications	Brain drain lost university patents	MIT journal publications[b]	MIT patents[c] (by grant date)	Brain drain as percentage of MIT pubs (%)	Brain drain as percentage of MIT patents (%)
1994	212	1,994	129	3,360	99	59	130
1995	192	1,806	117	3,520	104	51	112
1996	202	1,900	123	3,440	119	55	103
1997	275	2,586	167	3,502	102	74	164
1998	306	2,878	186	3,648	138	79	135
1999	294	2,765	179	3,682	142	75	126
2000	424	3,987	258	3,701	113	108	228
2001	426	4,006	259	4,011	125	100	207
2002	401	3,771	244	3,955	135	95	181
2003	374	3,517	228	4,296	127	82	179
2004	462	4,345	281	4,540	132	96	213
Total loss	3,568	33,555	2,171	41,655	1,336	81	163

[a]University spin-offs were obtained from a survey by the Association of University Technology Managers (AUTM 2005).
[b]MIT annual publications were obtained from searches using the ISI Web of Science. The searches specified the English language, the year, and the institution name.
[c]MIT patents were obtained from the online report by the United States Patent and Trademark Office (2007).

definition. These data cover all university spin-offs regardless of whether they are life science related, engineering related, or something else.

Given this data constraint, to obtain exploratory estimates of the brain drain costs for the whole not-for-profit research sector, we impose four assumptions. First, the marginal differences in research output of NIH academic entrepreneurs found in this study are representative of the marginal differences in research output for all academic entrepreneurs in all fields of study. Second, the average career age at which NIH academic entrepreneurs choose employment at for-profit firms is the same for all academic entrepreneurs in all fields. In our study, the average career age at exit is 16.56 years after the entrepreneurs earn their advanced degrees.[19] Assuming a 35-year career for each academic researcher implies the not-for-profit research sector loses 18.44 career years for each academic entrepreneur. Third, all university spin-off companies have one academic entrepreneur. Fourth, the AUTM data are accurate.

Under these assumptions and using AUTM data on university spin-offs for 1994 through 2004, Table 5 reports the annual and cumulative brain drain costs for journal publications and university patents.[20] Also included in this table are the annual journal publications and patents by faculty at MIT. MIT serves as a benchmark to help interpret the relative magnitudes of the academic brain drain loses. We chose MIT because it is a preeminent American university that performs well in both publishing and patenting. The estimated brain drain costs are expressed as a percentage of MIT's annual publication and patent output in the last two columns. Over the 11-year period shown in the table, a number equivalent to 81% of MIT's cumulative output of journal publications is eventually lost due to the academic brain drain. For university patenting, a number equivalent to 163% of MIT's cumulative output of approved patents is eventually lost to the academic brain drain.[21] These figures suggest the academic brain drain may have a nontrivial impact on knowledge accumulation in the not-for-profit research sector.

Although provocative, a number of unresolved conceptual and measurement issues need to be addressed in future research to improve on these estimates. First, it is clear that our estimates do not measure a net loss to social welfare because we cannot measure the value created by the exiting scientists in the private sector. The social cost of this form of academic entrepreneurship may be offset by the social benefit created through their work in the private sector. Second, it remains unclear how to monetize the loss of academic publications and patents when calculating the cost to the not-for-profit research sector. Third, our estimates of lost academic knowledge accumulation are based on a select group of NIH academic

[19] Ding and Choi (2008) find the hazard for founding a company peaks at about 12 years after the Ph.D. is granted.

[20] For example, the 212 spin-offs reported in the AUTM data for 1994 correspond to 3,909 lost academic career years (212×18.44 years), about 1,994 lost journal publications ($3,909 \times 0.51$) and about 129 lost university patents ($3,909 \times 0.033$). Over the time period from 1994 to 2004, the number of lost academic career years accumulates to more than 70,000.

[21] If this calculation were based on the fixed-effects regression using only NIH academic entrepreneurs (column 4 of Table 2), 67% of MIT's cumulative publication output would be lost. We do not use the fixed-effects regression for university patents because the sample size of 24 entrepreneurs is too small to be reliable.

entrepreneurs commercializing through the SBIR program. This group may not be representative of the broader population of academic scientists who leave academe for industry. Expanding the research to cover non-NIH scientists and scientists in other academic fields is an important next step. Fourth, there may be other unobserved and unmeasured dimensions of costs to the not-for-profit sector such as the scientists' tacit knowledge or teaching skills, which may have positively influenced future student education as well as the research performance among their academic colleagues.

5. Conclusion

Our analysis highlights an increasing trend among university faculty to pursue commercialization using employment positions at for-profit firms. This is the most extreme form of faculty entrepreneurship because it involves the strongest incentives pulling faculty members' time and effort away from academic research. We argue that this form of academic entrepreneurship trades off academic knowledge accumulation for commercialization activities—an academic brain drain that may adversely affect the organizational mission of universities as well as prospects for long-run economic growth. Based on the data used in this analysis, the academic brain drain appears to be nontrivial and warrants further research to assess its magnitude and implications.

The trade-off between academic knowledge accumulation and commercialization of university-based discoveries has important implications for university administrators as they continue to grapple with how to define and evaluate alternative organizational mechanisms fostering technology transfer. Our results suggest that current practices, particularly related to promoting spin-offs, have not successfully balanced the research and educational missions of the university against the more recent push to foster commercialization. Some sacrifice of academic knowledge production and student training seems unavoidable as faculty members become more involved in commercialization activities. An important part of this involvement, however, appears to be the form of faculty entrepreneurial behavior and the incentives imbedded within these forms. At least among NIH-supported life scientists, our research indicates that active faculty employment in for-profit firms costs the university in terms of journal publications, impact factors-weighted publications, NIH research awards, and patents. Clearly, more research is needed to understand how variations in the form of academic entrepreneurship relate to commercialization outcomes, academic research performance, and successful student training. At this point, we hope university administrators will acknowledge the potential costs of the academic brain drain and incorporate this information into their managerial assessments of the costs and benefits of alternative commercialization mechanisms.

The same can be said about policies intended to promote the commercialization of university-based discoveries at the state and federal levels. When academic scientists use small firm financing programs, the social cost from lost academic research and student training must be weighed against the social benefit derived from commercialization—when it is successful. Once again, the form of faculty involvement is pivotal because it mediates the degree to which the faculty member is drawn away from academic research. At the very least, as entrepreneurship policies grow in popularity around the world, policymakers need to be clear about how the incentive structures in their policies influence the performance of academic research. Although our research has taken an initial step in this direction, we are careful to note (see the discussion at the end of §4) that a number of difficult conceptual and measurement issues remain to be addressed in future research.

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Appendix. Robustness Check Using Conditional Difference-in-Difference

We performed a robustness check to evaluate the productivity of scientists before and after their SBIR involvement using a conditional difference-in-difference design (see e.g., Heckman et al. 1999).[22] Each academic entrepreneur (AE) is matched to the most similar scientist from the control group (nearest neighbor matching) according to their characteristics (fields: chemistry, biology, or health sciences; gender; Ph.D. versus M.D.; degree obtained from foreign or U.S. school; public or private school; medical school or not). The nearest neighbor is the control scientist with the smallest Mahalanobis distance in the vector of matching arguments to the AE under consideration. On these matched samples, we evaluate the productivity of the scientists with respect to publication counts, journal-impact factor-weighed publication counts, patent filings, and NIH grants before and after the SBIR involvement relative to the performance change of

[22] We would like to thank an anonymous referee for suggesting this robustness check.

Table A.1 Conditional Difference-in-Difference Results

Dependent variable	$TT_{\text{CDID}} = a - b$	F-test on $a - b = 0$
# publications	−0.621	5.16**
JIF-weighted # publications	−4.984	8.36***
# patent applications	0.052	1.86
Log(1 + *NIH grants*)	−1.729	28.42***

Notes. The sample comprises of 89 AEs and 89 matched controls, total sample size for the regressions: 3,344 observations. ***(**,*) indicate significance at the 1% (5%, 10%) level.

the drawn control scientist. The comparison is done using fixed effects within regressions:

$$y_{it} = c_i + a * AEOUT_{it} + b * CONOUT_{it} + e_{it},$$

where y is the dependent variable, e is a random error term, and c measures the scientist fixed effect so that the parameter a indicates the change in productivity of the AE after the SBIR award. The variable CONOUT is a dummy for the drawn control observation that switches from zero to one at the same point in time as the matched AE leaves academe. Consequently, the parameter b indicates the difference of productivity of the control for the same time switch as for the AEs. The difference-in-difference, i.e., the treatment of the treated effect, TT, can thus be calculated as $TT_{\text{CDID}} = a - b$. For statistical inference, we simply test whether $a - b = 0$ using an F-test after the within fixed-effects regressions. The results are presented in Table A.1.

The estimated loss of publications is about 0.6 per AE per year, whereas the journal impact factor weighted loss is almost 5. The treatment effect with respect to patent applications is not significant, which coincides with our finding in the fixed-effects regression model using the AE sample only (Table 4). The result that the AEs acquire significantly less NIH grants after leaving academe is also confirmed in the conditional difference-in-difference estimation (Table 3).

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