Commercializing Science: Is there a university "brain drain" from academic entrepreneurship?*

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ABSTRACT

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 creation. This is a form of brain drain on the not-for-profit research sector which 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 (SBIR) 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 U.S. from 1994 to 2004 we find the academic brain drain has a nontrivial impact on knowledge creation in the not-for-profit research sector.

1. Introduction

There is now a convincing body of evidence describing the convergence and co-evolution of scientific and commercial opportunities in the life sciences and the adoption of entrepreneurial attitudes and behaviors among 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). Along with this social transformation, there has been an increase in the number of mechanisms supporting commercialization using for-profit firms. In particular, universities are expanding the practices 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). Academic life scientists are also making use of venture capital investment and small firm financing programs like the U.S. Small Business Innovation Research (SBIR) Program (Zhang 2005; Toole and Czarnitzki 2007).

One consequence of these changes is that university faculty, particularly in the life sciences, 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 fall – a potentially costly "brain drain" on the not-for-profit research sector.[2]

The costs of this academic brain drain phenomenon 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

[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] While the concept of an academic "brain drain" could be applied very broadly to include, say, consulting with private industry, we see full-time employment 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.

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 (2007) finds that university research makes a significant contribution to new drug innovation in the pharmaceutical industry. In turn, greater industry innovation and productivity have been linked to improved economic performance and national welfare. For instance, Lichtenberg (1996, 2001, 2003) links pharmaceutical innovation to lower hospital costs and increased life expectancy. Murphy and Topel (2006) estimate that improvements in life expectancy from progress against diseases added about $3.2 trillion annually to U.S. national wealth since 1970.

The objective of this paper is to explore the economic significance of the academic brain drain by assessing how it impacts academic research performance. The population for this study consists of all university life science researchers in the fields of Biology, Chemistry, and Health Sciences who have received at least one research award from the U.S. National Institutes of Health (NIH) between 1972 and 1996. In this population, we identified NIH scientists who take employment positions in for-profit firms using information from the SBIR program. Based on the SBIR eligibility rules, those NIH scientists who venture into the private sector spend at least 51% of their time at the for-profit firms at the moment of award and throughout the duration of their projects. Using a case-cohort sampling design, we compiled a scientist-level panel database to examine four indicators of academic research performance: journal publications, journal publications weighted by the number of coauthors, NIH research grants, and university patents.

For each of these indicators, our 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] Our second question asks: 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 allows us to account for part-time or temporary employment transitions by incorporating their academic research performance after their decision to start or join a for-profit firm.

Our results show that life scientists commercializing through the SBIR program perform better (on average) than their NIH research peers over their careers in *academe*. This holds for journal publications, 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. 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 Stephen 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 25.9% fewer journal publications per year and 206.2% fewer university patents per year. To assess the broader economic significance, we compare the cumulative publication and patent output of MIT with

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

estimates of the academic brain drain costs for the period 1994 to 2004. Over this period, a number equivalent to 86% of MIT's cumulative output of journal publications and 217% of MIT's cumulative output of approved patents is lost due to the academic brain drain.

The rest of the paper proceeds as follows. The next section provides a brief overview of the literature supporting the emergence of an academic brain drain phenomenon. Section III describes the data and career life cycle models we estimate. Section IV presents the empirical results and estimates of the economic significance of the academic brain drain along with the limitations of our approach and assumptions. The concluding section 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 note that knowledge transfer in people imposes a real cost since it requires a significant redirection of time and energy. Stephan and Levin 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 suggest the changing reward systems within academic research institutions could speed up the outflow of life scientists and weaken the traditional educational and research missions.

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 the university inventions required continued faculty participation to have a reasonable chance at successful commercialization. Lowe (2002) 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.[4] 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. Since most of this increased effort comes at the expense of faculty leisure time, they do not believe licensing activities are detracting from university knowledge creation. However, it is important to point out that their model does not address employment of scientists in private firms.

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; Zucker et al. 2002a; Zucker et al. 2002b). 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

[4] Di Gregorio and Shane (2003) interpret a higher royalty rate as a higher opportunity cost to the faculty member if he or she founds a firm. They find higher royalty rates lead to fewer start-ups using a sample of universities.

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 (SAB). Lowe and Gonzalez-Brambila (2007) examine the academic research productivity of 150 science and engineering faculty entrepreneurs relative to matched control groups of their graduate school peers and their coauthors working at the same institution.[5] They find mixed results across fields. Biomedical faculty entrepreneurs publish significantly more than their graduate school peers but significantly *less* than their coauthor peers. Publishing by chemistry faculty entrepreneurs is not significantly different than their graduate school peers but is significantly more than their coauthor peers. Faculty entrepreneurs in engineering publish significantly more than both their graduate school peers and coauthor peers. They conclude, based on their full sample, that faculty entrepreneurs are more productive researchers (on average).

The third observation is that more and more entrepreneurial life scientists are choosing active 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 more completely into the private sector. Audretsch and Stephan (1999) find that fifty percent of the scientific founders in their sample of biotechnology firms had prior careers in academe. Of these academic founders, thirty percent had transitioned to full-time employment at the firms and seventy percent maintained part-time employment. Zhang (2005) identified 903 venture capital backed academic entrepreneurs who founded or co-founded a firm between 1992 and 2001 using the VentureOne database. Toole and Czarnitzki (2007) identified 337 NIH academic scientists involved in commercialization through the SBIR and Small Business Technology Transfer (STTR) Programs

[5] Their faculty entrepreneurs are full-time faculty members from 12 universities who started a firm based on a university disclosure from their own research.

between 1983 and 1996. Their data show an upward trend in life scientist entrepreneurship since 1991.

Taken together, these observations suggest 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 in journal publications, NIH research grants, and patenting while in academe. 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

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 most often by epidemiologists to study rare diseases. To implement the case-cohort design, all of the observed events 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 which is compared to the "cases" or events of interest. As described below, the statistical analysis weights 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 appropriately 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.[6] Over this period, our target population contains about 61,000 individual life scientists. For each scientist in the population, this database provides their name, grant history, institutional affiliation, award amounts, award years, and NIH organizational code. The NIH organizational codes identify the individual national institutes within the National Institutes of Health such as the National Cancer Institute, National Eye Institute, and so forth. As described below, these organizational divisions allow us to form cohorts by broad therapeutic area for the random selection of the control group used in our analysis.

The cases or events of interest in this study are the NIH supported academic life scientists who undertook commercialization by starting or joining a for-profit firm. Unfortunately, identifying these individuals in a systematic and consistent way has been a significant barrier to research on this form of academic entrepreneurship. To overcome this barrier, we developed a method that exploits the information contained in the SBIR program. All SBIR grants, which are only given to small for-profit firms, have principal investigators who are the scientific and technical project leaders. 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).[7] 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.[8] If the academic scientist

[6] After 1996, the NIH stopped publicly reporting the award amounts in CRSIP for individual grants and contracts.
[7] Based on the SBIR eligibility rules, we know our 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. It is likely that some of the SBIR academic entrepreneurs return to the non-profit research sector after their SBIR experience.
[8] Matching PIs by name is notoriously difficult and requires cross-referencing information in order to eliminate false matches. This process was facilitated by using specialized software developed by Thorsten Doherr at the Center for European Economic Research (ZEW), 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. We manually checked each individual in our final group to verify that they were researchers in the

received NIH research grant(s) at a not-for-profit institution and *later* received SBIR grant(s) at a for-profit firm, then they are an academic entrepreneur. We identified 213 NIH academic entrepreneurs in the SBIR program between 1983 and 1996. For the empirical analysis, however, we further impose the restrictions that these NIH academic entrepreneurs have degrees in the fields of Biology, Chemistry, or Health Sciences, and have available data on their degree year and institution.[9] These restrictions reduce the sample to 89 NIH academic entrepreneurs.

While our usable sample of 89 NIH academic entrepreneurs is small, it is not unreasonably small when compared to prior literature. Using prospectuses of 60 biotechnology firms, Audretsch and Stephan (1999) identified 50 academic founders. Zucker et al. (2002b) identified 207 U.S. "star" scientists either employed at firms or "linked" to firms through co-authorship. Corolleur et al. (2004) identify 132 academic founders associated with 62 French biotechnology firms. Zhang (2005) identifies 294 academic entrepreneurs in the Medical sciences, Bioscience, and Chemistry. This group represents 2.6% of all academic and non-academic firm founders and co-founders backed by venture capital between 1992 and 2001. From SEC filings for 533 U.S.-headquartered biotechnology firms, Stuart and Ding (2006) identified 190 academic founders. Finally, Lowe and Gonzalez-Brambila (2007) observed 54 academic entrepreneurs in Biology, Chemistry, and Medicine who started firms between 1990 and 1999 in their sample of 15 universities.

Using the SBIR program to identify NIH academic entrepreneurs does have some important limitations. First, the SBIR program is only one of several possible 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

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non-profit research environment prior to their first SBIR award and that they were not participating in the Small Business Technology Transfer (STTR) program.

[9] We used the UMI Proquest Dissertation database and web searches to retrieve this information.

assets, friends and family, or some form of internally generated funds. Using only the SBIR commercialization mode, we are significantly undercounting the actual number of NIH research scientists who choose to leave the academic environment or choose to devote significant effort to entrepreneurial ventures. At the present time, little is known about the population of NIH academic entrepreneurs (or about the population of academic entrepreneurs more broadly). Consequently, it is impossible to know if our SBIR-identified "slice" of this population is representative.

A second limitation is that the SBIR program identifies a financing point in the entrepreneurial process that necessarily follows (or lags) the entrepreneurial decision point for the academic scientists. When we observe NIH scientists as entrepreneurs, two decisions have already taken place. First, the academic researchers have already decided to explore their commercialization options outside academe. The reasons underlying this decision are unobservable but might be related to their research productivity in academe. In the next section, we describe how we address this possibility in the empirical analysis. Second, we only observe NIH academic entrepreneurs who were selected by the NIH SBIR program to receive an award. As discussed in the last paragraph, this may affect the representativeness of the group of SBIR academic entrepreneurs.

To form our randomly selected control group of NIH research peers, we allocated the observed cases of NIH academic entrepreneurs to fifteen NIH national institutes. Recall that the individual institutes represent broad therapeutic areas. We drew a total random sample of 1,500 NIH academic researchers from the population of NIH principal investigators with at least one research award from any of the fifteen national institutes (after excluding the NIH academic entrepreneurs). On this random sample of NIH research peers, we impose the restrictions that they have degrees in the fields of Biology, Chemistry, or Health Sciences, and have available data on their degree year and institution. These restrictions reduce the control group to 444 NIH research peers. 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. A count of the scientist's journal publications with coauthors were taken from PubMed using the *PublicationHarvester* software for period 1976 to 2003 (Azoulay et al. 2006). For patenting activity, we use the NBER patent database to identify all patents assigned to not-for-profit institutions on which the scientists are listed as inventors (Hall et al. 2001).[10] Our scientist-level panel database has 89 NIH academic entrepreneurs and 444 NIH research peers covering the years 1975-1997.

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 specify a dummy variable, "*AEIN*," which takes the value of one for all of those 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.[11] Second, since we are interested in examining changes in research performance once an NIH researcher becomes an academic entrepreneur, we specify a dummy variable "*AEOUT*," which switches from zero to one in the year the NIH researcher

[10] 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. Note that our patent variable does *not* include patents invented by these scientists but assigned to firms, as we are interested in the loss of the public sector due to brain drain.

[11] For this part of our analysis, annual observations for NIH academic entrepreneurs *after* they venture into private firms are dropped. This avoids confounding their research performance while in academe with their research performance after they decided to commercialize using a for-profit firm.

becomes an academic entrepreneur through the SBIR program. Clearly, the NIH researchers in the control group never become 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 their time constant variables, and middle panel summarizes their time-varying variables while in academe, and the bottom panel shows the time-varying variables for the NIH academic entrepreneurs *after* they become associated with a for-profit firm.[12] On average, NIH academic entrepreneurs are more productive than their research peers while in academe. Except for their patenting with academic institutions, the research performance of NIH academic entrepreneurs falls on average after taking employment at a for-profit firm. Interestingly, some academic entrepreneurs actually have more patents assigned to universities *after* they have ventured into private industry.[13]

Methods

We examined four scientist-level indicators of annual research performance: the number of journal publications, the number of journal publications divided by the number of coauthors (referred to as "weighted publications"), the value of NIH research awards, and the number of patents invented by the scientists and assigned to universities. To analyze the counts of

[12] 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 is 35 years after their receiving their advanced degree in our analysis.
[13] Clearly, some NIH academic entrepreneurs do not permanently leave the not-for-profit research sector but either leave temporarily or maintain part-time positions at their universities. We attempted to systematically track the academic entrepreneurs to get a sense for how many leave permanently versus temporarily. While not completely successful, we found about one-third leave temporarily, one-third leave permanently, and the other third is unknown.

publications and patents, we use a Poisson model where the conditional mean is an exponential function of the explanatory variables. Using annual data, the value of NIH research grants and weighted publications are zero for a nontrivial number of observations. We treat this as a data-censoring problem and estimate a Tobit model.

We draw from the literature estimating life cycle models of researcher productivity to inform our model specifications (Diamond 1986; Levin and Stephan 1991; Turner and Mairesse 2005; Hall et al. 2007; Lowe and Gonzalez-Brambila 2007). This literature highlights three issues. First, in addition to exogenous time effects, both the scientist's age and gradation cohort may have an important influence on their research productivity. We include time and graduation cohort dummies in the analysis. Since we focus on research productivity during their professional careers, we define age to be "career age," which is equal to the number of years since they received their advanced degrees. Second, career age is usually entered as a quadratic to allow for a nonlinear profile. Third, there may be unobserved heterogeneity among individual scientists due to differences in their "abilities" or "tastes" for research. This suggests controlling for scientist fixed effects in the empirical analysis.

In the next section, we present 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. On the other hand, even though the unobserved effects models impose the strict exogeneity assumption, they have the advantage of controlling for unobserved time constant heterogeneity. As pointed out by Wooldridge (1997), the fixed effects estimator is not more robust than the pooled estimator but imposes a different set of assumptions.

In order 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 model. In the second step, the unexplained variation in the dependent variable is regressed on the time constant variables using non-linear least squares.[14] The model can be formulated as:

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

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

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 fixed effects in the models for weighted publications and NIH grants, we use an unobserved effects Tobit model suggested by Wooldridge (2002, p. 540-1). Unlike the random effects Tobit, this model allows the unobserved effect to be correlated with explanatory variables. Under appropriate assumptions we can write:

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

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

(5) $\alpha_i \mid X_i \sim Normal(0, \sigma_\alpha^2)$

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 time averages of the time-varying explanatory variables, and α_i is the unobserved effect for individual i.

[14] To get consistent estimates of the time constant explanatory variables, this method assumes that all correlation between the unobserved effect and the explanatory variables is due only to the time varying explanatory variables and not due to the time constant variables, Z_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 since most of the explanatory variables are either predetermined or not under the control of the academic scientists. For instance, the career age variables, the degree year and institution variables, and the gender variable are all strictly exogenous. The lagged publications and lagged NIH awards variables are predetermined. That is, they can be assumed to be exogenous in the pooled regressions models but may not be strictly exogenous as required for the fixed effect models.

The exogeneity of our key explanatory variables, *AEIN* and *AEOUT*, is more complicated since these variables are defined using the observed behavior of the NIH scientists. As described above, each of the academic entrepreneurs chose to leave academe to pursue commercialization in the private sector. One may be concerned that *when* these NIH scientists chose to apply to the SBIR program is related to their academic research productivity. In other words, the critical aspect of their choice which is potentially endogenous is the timing of their move from academe to industry.

For our analysis of research performance differences between NIH academic entrepreneurs and their NIH research peers while in academe using *AEIN*, the sample observations for the academic entrepreneurs after they venture to private firms are dropped. In this setup, one may be concerned that the academic entrepreneurs have an uncharacteristic "burst" of research productivity just prior to leaving which induces an upward bias on our estimate of their average research performance. 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 they decide to participate in commercialization. In this setup, one may be concerned that the timing of their decisions to commercialize are related to their expected research productivities. For instance, an academic scientist may experience an unobserved "shock" to his or her university research productivity (either positive or negative) that precipitates their decision to leave. 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 show in Wooldridge (2002). As instruments, we used lagged values of venture capital investment, income per capita, and population in the scientists' geographic regions. This approach assumes that lagged economic activity in the scientists' regions is uncorrelated with any shock to their academic research productivity, but is correlated with their decision to pursue entrepreneurship.[15] These regional variables were highly correlated with *AEOUT* in the first stage regressions. Since none of the tests found statistically significant evidence of endogeneity, we did not pursue the issue further in our empirical analysis.

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

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. 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? 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? We begin by discussing the statistical findings for each indicator. This is followed by exploratory estimates of the academic brain drain costs and a discussion of their limitations.

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 creation and dissemination in public science. Models 1-3 on the left side of Table 2 correspond to the pooled and fixed effects Poisson estimators for the number of journal publications. The estimations account for sampling weights and heteroscedasticity as well as arbitrary within-group correlations of the error terms. Using the pooled estimator, Model 1 shows the key variable *AEIN* is positive and significant at a 5% level. Relative to the control group of NIH research peers, NIH academic entrepreneurs (on average) publish more per year during their careers in academe. Consistent with the life cycle productivity literature, the results for career age show a concave publication productivity profile. NIH researchers appear to reach their peak number of publications nearly nineteen years after their advanced degree. The degree-year cohort dummies 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 three years, significantly increases journal publications. Among the time-constant scientist variables, the only variables significantly affecting journal publications are related to medical degrees (MDs) and medical schools. Those life scientists with MDs publish more than those with PhDs and those who graduated from a medical school publish more than those with degrees from non-medical schools.

The next two columns in Table 2 report the results for Model 2 which uses the two-step fixed effects Poisson estimation method. 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 in journals on average than their NIH research peers during their careers in academe. Their academic publication productivity profile is the same as in Model 1. The degree-year cohort dummies were jointly significant and included in the second step estimation. The coefficient on lagged NIH research awards is positive and significant but quite a bit smaller than in Model 1. It is not possible to tell whether this is due to controlling for scientist fixed effects or failure of the strict exogeneity assumption. For the time-constant explanatory variables, female life scientists publish significantly less than males and graduating from a medical school is no longer significantly related to journal publications.

Model 3 in column 4 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 fixed effects estimator using only the scientist-year observations on the NIH academic entrepreneurs. The key explanatory variable is *AEOUT*, which changes from zero to one on the first year the scientist is observed as a PI on an SBIR commercialization award. This variable is negative and significant at a 1% level. On average, NIH academic entrepreneurs have fewer journal publications after they join for-profit firms. Their career publication profile is concave and reaches its peak about twenty-one years after their advanced degree. The lagged value of NIH research awards significantly increases journal publications.

Our second indicator is a scientist's annual journal publications divided by the number of coauthors on the publication ("weighted publications"). This indicator is motivated by the possibility that laboratory size or composition may influence a scientist's annual number of journal publications.[16] Models 4-6 on the right side of Table 2 correspond to the pooled and unobserved effects Tobit estimators for the number of weighted publications. The results are consistent with those found using the Poisson models for the count of journal publications. The pooled Tobit, Model 4 in column 5, shows the key variable *AEIN* is positive and significant at a 5% level. In the unobserved effects Tobit, as shown in column 6, *AEIN* is also positive and significant. These results confirm the earlier finding that NIH academic entrepreneurs (on average) publish more per year during their careers in academe than their NIH research peers. Looking at how weighted publications change after the NIH academic entrepreneur joins a firm, column 7 reports a negative and significant effect. Adjusted for coauthors, NIH academic entrepreneurs still publish less after taking employment in a for-profit firm. The other findings are broadly similar to those reported above.

<u>Analysis of NIH Awards</u>

Our third indicator is the value of the life scientist's NIH research awards per year. This indicator is relevant for two reasons. First, for individual life scientists, NIH funding is an

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[16] See Turner and Mairesse (2005) and Carayol and Matt (2006) for some evidence on how laboratory size and composition may influence an individual scientist's research productivity.

important source of research support and grantsmanship is often linked to academic promotion. Second, the 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.[17] The pooled Tobit results in column 1 show that *AEIN* is positive and significant at a 1% level. This finding is confirmed using the unobserved effects Tobit as shown in column 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. In the pooled model, NIH supported researchers reach their peak level of awards about seventeen years following their advanced degree. Controlling for unobserved scientist effects, NIH awards peak a little earlier at about fourteen years following their advanced degrees. Lagged journal publications, measured as the sum of their publications over the previous three years, significantly increases NIH research awards in both regression models. Among the time-constant explanatory variables, the gender dummy is marginally significant and positive in the unobserved effects regression.

Column 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 a 1% level. Controlling for fixed effects and looking within the group of NIH academic entrepreneurs shows the value of NIH research awards drops significantly after joining a firm. The career profile for NIH funding is concave and reaches a peak value of awards about ten years following their advanced degree. As before, lagged journal publications and being female significantly increases the value of NIH research awards.

[17] Since 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.

Analysis of University Patents

Our fourth indicator of research performance is the number of patents invented by the scientists and assigned to universities. 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, university patenting appears less important than journal publications as an indicator of academic knowledge accumulation. For the Massachusetts Institute of Technology (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 fifteen 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% patented with a university in any year.

Column 1 of Table 4 shows the results using the pooled Poisson estimator for the number of university patents. The key variable *AEIN* is positive and significant at a 1% level. The results from the two-step Poisson fixed effects estimator in columns 2-3 also show *AEIN* is positive and significant at a 1% level. Relative to the control group of NIH research peers, NIH academic entrepreneurs (on average) patent more per year during their careers in academe. Both sets of estimation results also show a concave patenting productivity profile over their careers. *Age* and *Age2* are jointly significant even though *Age* is not individually significant. Lagged journal publications are positive in both models but only marginally significant in the fixed effects model.

Among the time-constant covariates in the patent regressions, the pooled and two-step fixed effects models show different results. First, the pooled model finds that female NIH researchers patent significantly less. This result, however, does not carry over to the fixed effects model. The two-step fixed effects model also finds several other time-constant variables statistically significant. Life scientists with degrees in Chemistry and Health Sciences patent significantly more relative to those with degrees in Biology. The Health Sciences area is only marginally significant. In addition to their field of degree, those life scientists with degrees from foreign schools and private U.S. schools patent significantly more.

Column 3 of Table 4 shows the fixed effects Poisson results using only those observations on NIH academic entrepreneurs. Unfortunately, the sample size for this regression is inadequate since it relies on information from only twenty-four NIH academic entrepreneurs. The key variable *AEOUT* is negative but not statistically significant. The patenting career profile does not have the same shape. Both *Age* and *Age2* are jointly significant and negative. Since patenting is relatively new to the academic environment and has not been part of the expected research output of older life scientists, it is not surprising to find that patenting decreases with career age in our sample.

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 university patents.[18] 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

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

of unresolved conceptual and measurement issues. For this reason, the reader should be cautious when interpreting the broader cost estimates since 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 for 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.[19,20] 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 25.9% more in journals per year (0.543 more articles) and patents 206.2% more per year (0.044 more patents) than their NIH research peers.[21] 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, this type of data is 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 comes from the

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[19] An alternative way to interpret this assumption is: NIH academic entrepreneurs continue working at the university but their academic research performance falls to the level of their NIH research peers due to their commitments to the for-profit firm.
[20] This is a conservative method for estimating the cost of the academic brain drain phenomenon since 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.
[21] The marginal decrease in journal publications from the fixed effects regression using only NIH academic entrepreneurs is 16.7% (0.373 fewer articles).

annual surveys of universities conducted by The Association of University Technology Managers (AUTM). Their surveys ask universities to report the annual number of companies formed around a license of intellectual property from the university. 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 their advanced degree. 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.[22] 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

[22] For example, the 212 spin-offs reported in the AUTM data for 1994 correspond to 3,909 lost academic career years (212 times 18.44 years), about 2123 lost journal publications (3909 times 0.543), and about 172 lost university patents (3,909 times 0.044). Over the time period from 1994 to 2004, the number of lost academic career years accumulates to more than 70,000 years.

a percentage of MIT's annual publication and patent output in columns 7 and 8. Over the eleven year period shown in the table, a number equivalent to 86% of MIT's cumulative output of journal publications is lost due to the academic brain drain. For university patenting, a number equivalent to 217% of MIT's cumulative output of approved patents is lost due to the academic brain drain.[23] These figures suggest the academic brain drain has a nontrivial impact on knowledge accumulation in the not-for-profit research sector.

While 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 since we cannot measure the value created by our exiting scientists in the private sector. The social cost from 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 appropriately value lost academic publications and patents when calculating the cost to the not-for-profit research sector. The economic value distributions for academic publications and patents are likely to be highly skewed (Scherer and Harhoff 2000). One approach would be to weight publications and patents by forward citations, however, this requires a long time series and the citation data are not available for this study. Third, our estimates of lost academic knowledge accumulation are based on a select group of NIH academic entrepreneurs commercializing through the SBIR program. This group may not be representative of the broader population of academic scientists who leave academe for industry. 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

[23] If this calculation were based on the fixed effects regression using only NIH academic entrepreneurs (column 4 of Table 2), 59% of MIT's cumulative publication output would be lost. We do not use the fixed effects regression using only NIH academic entrepreneurs for university patents because the sample size of twenty-four entrepreneurs is too small to be reliable.

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 since it involves the strongest set of incentives drawing the faculty member's 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 which may adversely affect prospects for long-run economic growth. Based on the data analyzed in this paper, the academic brain drain imposes a nontrivial reduction in academic knowledge accumulation.

The trade off between academic knowledge accumulation and commercialization of university-based discoveries has important implications for university policy. Our results suggest these policies have not successfully balanced the educational mission of the university against the more recent push to foster commercialization. Some sacrifice of academic knowledge creation 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, 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 from the academic brain drain and will incorporate this information into their assessments of the costs and benefits of alternative commercialization policies.

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's 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. While our research has taken an initial step in this direction, we are careful to note (see the discussion at the end of section IV) that a number of difficult conceptual and measurement issues remain to be addressed in future research.

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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	.0721	.259	0	1	.0449	.208	0	1
Cohort dummy 1961-1965	.113	.316	0	1	.124	.331	0	1
Cohort dummy 1966-1970	.171	.377	0	1	.191	.395	0	1
Cohort dummy 1971-1975	.164	.371	0	1	.27	.446	0	1
Cohort dummy 1976-1980	.178	.383	0	1	.225	.42	0	1
Cohort dummy 1981-1985	.169	.375	0	1	.101	.303	0	1
Cohort dummy 1986-1991	.133	.34	0	1	.0449	.208	0	1
Field dummy: Biology	.459	.499	0	1	.337	.475	0	1
Field dummy: Chemistry	.3	.459	0	1	.461	.501	0	1
Field dummy: Health Sciences	.241	.428	0	1	.202	.404	0	1
Female (dummy)	.185	.388	0	1	.0674	.252	0	1
Gender missing (dummy)*	.0878	.283	0	1	.0899	.288	0	1
Ph.D. (dummy)	.899	.302	0	1	.944	.232	0	1
Foreign Degree (dummy)	.0405	.197	0	1	.0225	.149	0	1
Public School (dummy)	.505	.501	0	1	.562	.499	0	1
Medical School (dummy)	.119	.325	0	1	.124	.331	0	1
	Time varying variables; Control sample: NT = 7779				Time varying variables; Academic Entrepreneurs *while being in academia*: NT = 1044			
# Journal Publications	2	2.73	0	27	2.23	2.49	0	17
# Journal Pub./ #authors	.675	.964	0	11.2	.768	.906	0	6.31
NIH Awards (in 1,000 US$, prices of 1996)	122	255	0	3955	134	193	0	1462
# Academic Patents	.0179	.157	0	3	.0556	.357	0	7
Lagged # journal publications (sum of t-1, t-2, t-3)	5.56	6.86	0	72	6.02	5.82	0	41
Lagged NIH grants (sum of t-1, t-2, t-3 and t-4 in million US$, prices of 1996)	.434	.86	0	10.7	.469	.651	0	5.45

Table 1 continued				
	Time varying variables; Academic Entrepreneurs *after leaving academia*: NT = 628			
# Journal Publication	1.74	2.66	0	19
# Journal Pub./ #authors	.506	.847	0	8.25
NIH Awards (in 1,000 US$, prices of 1996)	48.1	145	0	935
# Academic Patents	.104	.506	0	7
Lagged # journal publications (sum of t-1, t-2, t-3)	5.79	6.93	0	44
Lagged NIH grants (sum of t-1, t-2, t-3 and t-4 in million US$, prices of 1996)	.288	.564	0	3.69

Notes: 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.
Accounting for 4 years of NIH grants as control variable is motivated due to the fact that the average project duration is around 4 years.
* Gender was determined by the first name of the researchers and internet searches. When we were not confident of the researcher's gender based on this information, we coded the gender as missing.

Table 2: Count data models on publication activity per year (1975-1996)							
Dependent Variable	Number of journal publications				Number of publications weighted by number of co-authors		
	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	Time-Variant: Fixed Effects Poisson Model	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	0.230**		0.260***		0.230***	0.216**	
	(0.097)		(0.090)		(0.102)	(0.089)	
AEOUT				-0.183***			-0.224**
				(0.045)			(0.097)
AGE	0.075***	0.075***		0.083***	0.060***	0.035**	0.034
	(0.012)	(0.016)		(0.025)	(0.013)	(0.016)	(0.041)
AGE^2	-0.002***	-0.002***		-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.0002)	(0.0004)
Lagged NIH grants	0.201***	0.136***		0.180***	0.406***	0.271***	0.261***
	(0.035)	(0.011)		(0.026)	(0.080)	(0.021)	(0.062)
Field: Chemistry	-0.089		-0.079		-0.124	-0.082	0.142
	(0.117)		(0.095)		(0.102)	(0.075)	(0.151)
Field: Health Sciences	0.008		0.180		-0.004	0.140	0.731***
	(0.140)		(0.115)		(0.136)	(0.100)	(0.203)
Female	-0.057		-0.216*		0.005	-0.123	-0.423*
	(0.166)		(0.115)		(0.124)	(0.088)	(0.234)
Gender missing	-0.010		0.056		-0.061	-0.021	-0.002
	(0.230)		(0.198)		(0.223)	(0.112)	(0.186)
Ph.D.	-0.545***		-0.410***		-0.623***	-0.419***	-0.580***
	(0.156)		(0.137)		(0.210)	(0.137)	(0.202)
Foreign degree	0.344		0.216		0.423	0.144	-0.731
	(0.221)		(0.208)		(0.319)	(0.156)	(0.479)

Table 2 continued							
Public school	-0.121		-0.078		-0.078	-0.039	0.111
	(0.088)		(0.073)		(0.086)	(0.066)	(0.133)
Medical school	0.255**		0.199		0.291*	0.241**	0.101
	(0.129)		(0.121)		(0.152)	(0.100)	(0.183)
Intercept	0.540***		-0.037		0.562	-0.078	0.555
	(0.197)		(0.285)		(0.243)**	(0.283)	(0.710)
Mean(AGE_i)						0.030	0.020
						(0.020)	(0.050)
Mean(Lagged $Grants_i$)						0.178***	-0.318**
						(0.062)	(0.134)
Mean($AEOUT_i$)							-0.614*
							(0.337)
Time Dummies	YES	YES	NO	YES	YES	YES	YES
Cohort Dummies	NO	NO	YES	NO	NO	NO	NO
N	8823	8674	8674	1672	8823	8674	1672
(Mc-Fadden) R^2	0.107	0.388	0.446	0.325	0.053	0.158	0.126

Notes: Standard errors in parentheses. *** (**, *) indicate a 1% (5, 10%) significance level.
Models V and VI: The Mean(.) variables are the individual specific means of the time-varying covariates which are added to the Tobit panel estimations to allow for correlation of the individual specific effects and the explanatory variables (see Wooldridge, 2002).

Table 3: Tobit regressions on NIH grants 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	1.389***	1.310***	
	(0.444)	(0.334)	
AEOUT			-4.993***
			(0.507)
AGE	0.755***	0.622***	0.352***
	(0.125)	(0.097)	(0.264)
AGE^2	-0.022***	-0.022***	-0.017***
	(0.002)	(0.001)	(0.002)
Lagged publications	0.248***	0.168***	0.235***
	(0.031)	(0.012)	(0.031)
Field: Chemistry	0.476	0.348	-0.368
	(0.474)	(0.309)	(0.680)
Field: Health Sciences	-0.912	-0.271	0.864
	(0.541)	(0.404)	(0.900)
Female	0.170	0.550*	1.979*
	(0.461)	(0.310)	(1.139)
Gender missing	-0.269	0.190	-1.323
	(0.658)	(0.437)	(1.063)
Ph.D.	0.396	-0.204	-0.907
	(0.713)	(0.496)	(1.455)
Foreign degree	-1.455	-0.852	-1.443
	(0.897)	(0.521)	(1.704)
Public school	-0.436	-0.045	0.691
	(0.384)	(0.263)	(0.586)
Medical school	0.322	0.225	-1.147
	(0.605)	(0.391)	(0.936)
Mean(Lagged publications$_i$)		0.073***	-0.108
		(0.023)	(0.086)
Mean(AGE_i)		0.320**	0.806**
		(0.161)	(0.377)
Mean($AEOUT_i$)			-3.393*
			(1.890)
Intercept	-6.979**	-12.209***	-16.351**
	(2.980)	(3.679)	(8.028)
Time dummies	YES	YES	YES
Cohort dummies	YES	YES	YES
Mc-Fadden R^2	0.056	0.122	0.141
N	8823	8823	1672

Notes: Standard errors in parentheses. *** (**, *) indicate a 1% (5, 10%) significance level.
Models II and III: The Mean(.) variables are the individual specific means of the time-varying covariates which are added to the panel estimations to allow for correlation of the individual specific effects and the explanatory variables (see Wooldridge, 2002).

Table 4: Count data models on the number of patent applications 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 part with Poisson Model	Step 2: Time constant part with Nonlinear LS	Fixed Effects Poisson Model for AE = 1
AEIN	1.119***		1.466***	
	(0.422)		(0.324)	
AEOUT				-0.281
				(0.243)
AGE	0.106	0.193		-0.058
	(0.131)	(0.149)		(0.150)
AGE^2	-0.007**	-0.006***		-0.007***
	(0.003)	(0.001)		(0.002)
Lagged publications	0.055***	0.030*		0.060***
	(0.013)	(0.016)		(0.014)
Field: Chemistry	0.727*		1.555***	
	(0.430)		(0.513)	
Field: Health Sciences	-0.254		1.006*	
	(0.506)		(0.556)	
Female	-1.238**		-0.149	
	(0.522)		(0.530)	
Gender missing	-2.033***		-1.885**	
	(0.718)		(0.661)	
Ph.D.	1.232		3.277***	
	(1.024)		(0.816)	
Foreign degree	-0.468		2.151***	
	(0.742)		(0.745)	
Public school	-0.597		-0.751**	
	(0.410)		(0.260)	
Medical school	-0.369		0.432	
	(0.832)		(0.443)	
Intercept	-5.710**		-9.048	
	(2.384)		(1.271)	
Time Dummies	YES	YES	NO	YES
Cohort Dummies	YES	NO	YES	NO
(McFadden) R2	0.147	0.647	0.151	0.650
N	8823	1012	1012	441

Notes: Standard errors in parentheses. *** (**, *) indicate a 1% (5, 10%) significance level.

Table 5: Academic Brain Drain Costs to the Not-for-profit Research Sector							
Year	Number of U.S. University Spin-offs (AUTM)(1)	Brain Drain Lost Journal Publications	Brain Drain Lost University Patents	MIT Journal Publications(2)	MIT Patents (grant date)(3)	Brain Drain as Percentage of MIT Pubs	Brain Drain as Percentage of MIT Patents
1994	212	2123	172	3352	99	63%	174%
1995	192	1922	156	3518	104	55%	150%
1996	202	2023	164	3440	119	59%	138%
1997	275	2754	223	3499	102	79%	219%
1998	306	3064	248	3646	138	84%	180%
1999	294	2944	239	3675	142	80%	168%
2000	424	4245	344	3699	113	115%	304%
2001	426	4266	346	4002	125	107%	277%
2002	401	4015	325	3954	135	102%	241%
2003	374	3745	303	4295	127	87%	239%
2004	462	4626	375	4532	132	102%	284%
Total Loss	3,568	35,726	2895	41612	1336	86%	217%

(1) University spin-off were obtained from the AUTM U.S. Licensing Survey: FY 2004

(2) 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.

(3) MIT patents were obtained from the online report "US Colleges and Universities- Utility Patent Grants, 1969-Present," downloaded from the United States Patent and Trademark Office website.