Trickle-Down Entrepreneurship: Prior Mentorship and the Formation of Academic Entrepreneurs

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November 3rd, 2008 Version

ABSTRACT

People select one another in professional relationships for a variety of reasons. We hypothesize that individuals match to their associates along a set of prominent dimensions, and in so doing, expose themselves to many unanticipated social influences. To examine the inter-generational transmission of traits in the context of scientific mentorship, we collect a novel dataset tracking the training and professional activities of elite young scientists. We show that scientists-in-training choose their mentors along scientific dimensions, but subsequently adopt their prior advisor's commercial orientations. We draw upon qualitative evidence in the form of oral histories, as well as the implementation of inverse probability of treatment weights (IPTW) to estimate causal treatment effects. Taken together, we propose an atypical model of structural influence whereby career paths are opened through prior professional relationships, but the dimensions by which we assess influence are neither deliberately formed nor the outcomes of standard assortative matching. We propose that this model of structural influence may exemplify a common social dynamic.

Keywords: Social Structure, Biotechnology, Academic Entrepreneurship

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INTRODUCTION

People select one another in professional relationships for many reasons. They match based on characteristics such as common professional interests and ambitions, similarities in sociodemographic characteristics and their respective positions in status hierarchies, spatial proximity, and referrals from mutual acquaintances. Most professional relationships, we believe, form through a matching process in which individuals choose to pair on a limited number of high priority dimensions. Although these dimensions surely differ across dyads and settings, the actual ties that emerge among the immense array of connections that possibly could have occurred do so because of matches between individuals in a small set of especially meaningful characteristics.

Despite the fact that people form relationships based on a limited number of attributes, each of us in our totality possesses a great variety of characteristics. This creates an interesting situation in its own right and, we argue, a strategic research site—we may consciously match to our associates along a set of prominent dimensions, but in so doing, we then expose ourselves to many, unanticipated social influences that arise from the many attributes of our friends and professional associates that we never considered when we chose to associate. Moreover, these attributes are often orthogonal to the characteristics that first gave rise to the relationship. In hypothetical terms, when two people form a bond because they share a small set of attributes X, it may be that some set of additional characteristics Z, which was never considered when a choice was made to develop the relationship, prove to be of consequence in the social transmission of attitudes and behaviors.

This is in fact exactly what we find in an analysis of professional choices in a context of considerable sociological interest. We examine the underpinning and consequences of matching between postdoctoral candidates and their faculty advisors for Pew Searle scholars, a prominent group of academic life scientists. Exploiting an extensive quantitative database and a fascinating archive of oral histories, we find that two factors dominate in the formation of matches between post-docs and their advisors: geographic location driven by personal constraints, and overlapping scientific interests. We find a high degree of consensus between coding of Pew Searle's scholars' recounting of the rationales for their choices of postdoctoral opportunities and coefficient estimates from a dyad-level matching model between post-doc candidates and advisors.

In a second-stage analysis, we then show that whether or not the postdoctoral advisor had engaged in patenting during or before the time that a candidate arrives in his/her lab has a strong, long-term effect on whether the advisee subsequently becomes a patenting scientist. By estimating this effect in a two-stage framework and by relying on the qualitative evidence in the oral histories, we are able to show that postdoctoral candidates *do not* consider the advisors' patenting behavior when establishing the match. Thus, insofar as an advisor's values or actions transmit to his or her mentees, this diffusion of behavior is a pure social influence effect: it is causal, rather than being driven by a commonality in interests that underlies the matching of candidates to advisors.

Our work is at the interstices of three literatures in sociology. First, the substance of our findings contributes to a growing body of work on the conditions under which academic scientists choose to pursue the commercial potential of their scientific discoveries (Etzkowitz; Owen-Smith and Powell; Evans; Stuart and Ding). As these authors have observed, the decision to patent scientific findings and advise or even start for-profit companies is influenced by factors as diverse as scientists' perceptions of scientific norms, to peer and employer influences, to the reach of their social networks across the now-porous boundary between academic and commercial science. To this work we contribute empirical findings showing the imprints of graduate school and postdoctoral advisers on the later-career choices of the students that travel through their laboratories. Second, our project is inspired by the burgeoning literature on career sequences (abbott; blair loy; others). Distilled, our findings suggest that the mentors one encounters early in a career have consequences not only along the anticipated dimensions that serve as the basis for mentorship dyads, but sometimes they cause unplanned detours in career trajectories. This is a structural influence of an atypical sort; it is structural because scientist-in-training career paths are opened by the professional relationships they form, but *on the dimension on which we assess influence*, these matches are neither deliberately formed nor are they the outcomes of standard assortative matching processes we so commonly observe. Of course, our findings too that in the specific case we study, relationships formed for one reason have long-term consequence for an unanticipated, second event. There is no doubt in our minds that this is a common dynamic.

Third, we present a novel methodological approach for empirically establishing credible evidence of a social network effect. A growing chorus of authors have critiqued many studies in the social networks literature because of its inattention to the challenges of empirically establishing causal network effects (see, e.g., Meow, Reagans and Zuckerman, Sorenson and Stuart), which stem from the fact that actors' positions in social networks so rarely are exogenous to the outcomes that interest researchers. If we have any reason to believe that actors are deliberate in seeking professional relationships and that they have at least some discretion in the matches they form, then underlying individual differences—in intelligence, charisma, strategic orientation, perhaps even physical attractiveness—will influence and therefore correlate with network positions. In outcome regressions investigating social influence processes and other consequences of network position, separating the true effect of a set of social ties from the factors that cause the ties to come to be in the first instance then becomes difficult.

Our study offers a two-pronged approach to addressing this challenge. First, we rely on Pew Searle scholars' oral histories to identity the bases for the choices they made in matching with specific graduate school and post-doctoral advisers. These data convincingly show that matches are independent of the adviser's views on commercializing academic science. This fact on its own goes a long way to addressing the problem of the endogeneity of network positions and, indeed, reliance on qualitative and survey data to establish the exogeneity of matches relative to a focal dependent variable may offer a quite general strategy for estimating valid network effects. Second, we have constructed a dyad-level regression model that predicts the formation of matches between candidates and advisers, which in turn enables us to employ a modification of inverse probability of treatment weighting (IPTW), a relatively recent approach developed by biostatisticians to estimate causal treatment effects. This approach amounts to estimating the effect of a postdoctoral adviser's influence on a candidate in a regression in which observations are inversely weighted by the probability that each observed post-doc-mentor dyad was formed. Subject to satisfying a few (untestable) assumptions of IPTW estimators, this procedure will recover a causal social influence effect.

Within sociology, debate marches on between structural and individual approaches to the study of careers. On one hand, individuals clearly are not passive actors in the unfurling of their careers; we all recognize, especially within professional labor markets, that individuals actively pursue career strategies, albeit with varying levels of energy and degrees of success. People are not simply passive actors who regimentally respond to external forces; they are dynamic agents seeking to strategically shape their futures. On the other hand, the guiding hands of often-rigid job ladders (internal labor markets) within firms; the gender-typing of work roles and, more broadly, the effects of multiple ascriptive characteristics on distributing labor market opportunities; are but a few among many potent structural forces that mold the progression of individuals' careers.

If much of the diversity in the multiple sequences observed in empirical studies of professionals' career trajectories (B-L, Ab) may be attributed to the influence of early career mentors, a set of questions come to the fore. What systematic factors influence the matches formed between mentors and trainees? At one extreme, are these pairings chance occurrences? At the other, are they predestined to follow well-trodden pathways determined by class structures, status processes, ascriptive characteristics, or some other dimension? Or, are they simple products of individual preferences?In any particular research context, the analyst must develop a rich understanding of this matching process before it because possible to attribute any causal role to mentors in the career progression of those whom they influence.

We explore questions such as these in context of long-standing sociological interest: scientific careers. Using extensive qualitative and quantitative data, we explore the formation of pairings between an elite group of scientists-in-training with their post doctoral advisors. Within the literature on scientific careers, it is widely understood that postdoc advisors are critical influences at the formative career stage. We then examine the long-term consequences of these matches for a professional outcome of growing interest: the propensity of academic scientists to commercialize their discoveries. There are a few reasons for this choice. 1) recent work on the subject. 2) Attitudes toward this outcome are fractured within the scientific community, and the formation of views likely to be influenced by scientific models exhibited during training Liperiods. 3) Very important – it is not one of the dimensions of grad student - post-doc matching.

In the next section, we provide an overview of our empirical approach. Section III describes out choice of a population-at-risk, empirical methodology, as well as variable construction. Section IV presents descriptive statistics and our econometric results. Section V concludes.

RISK SET IDENTIFICATION, METHODOLOGY, AND DATA CONSTRUCTION

Risk-Set identification

This project explores the role of prior mentorship on an individual's subsequent decision to transition to entrepreneurship. To explore transitions to entrepreneurship, it is first necessary to identify a set of individuals who are at risk of commercialization. These individuals must not only have knowledge that is commercially relevant, but there must also remain sufficient variation in the individual's decisions to adopt or defer opportunity exploitation. To explore prior mentorship, an unambiguous identification of influential prior mentors is a must. With these criteria in mind, we choose to focus on academic life scientists. The life sciences have come to dominate academic entrepreneurship in the past several decades, suggesting that opportunities for commercialization abound in this sector (Mowery, Nelson, Sampat, & Ziedonis, 2004). Furthermore, the training of life scientists is long, typically consisting of six-years of pre-doctoral training as well as three or more years of post-doctoral training (Stephan & Levin, 2001). These lengthy tenure terms allow ample opportunities for a mentor's preferences and behaviors to be transmitted to the trainee. Furthermore, the two-stage training of life scientists (as a pre-doctoral and then post-doctoral student) presents an opportunity to empirically control for matching between students and mentors. Lastly, the pedigree (or prior training environments) of a life scientist plays a prominent role throughout his or her career[1], suggesting both the importance of training environments as well as easing data collection.

The matching process between mentors and trainees is far from random. However, the choice of graduate advisors does entail elements of whimsy. A typical junior scientist finishes his university degree (B.A. or B.S.) with limited laboratory experience and enters directly into a graduate program. The individual has acquired basic technical skills, but has not been fully exposed and socialized to the scientific profession (Abbott, 1988). This individual is not yet ready to be an independent scientist, a skill he hopes to acquire in graduate school. The individual typically applies (and is accepted) to an array of schools and chooses a graduate institution based upon a limited set of factors. These factors may likely include 1) number of promising mentorship options 2) personal geographic preferences (i.e. sun vs. snow) 3) prior relationships (family proximity, partners, etc.). Once at a university, the typical graduate student spends a year in coursework while concurrently "rotating" through three different laboratories over the first calendar year. Only after these rotations, is the student allowed to formally choose a laboratory[2]. This choice of graduate advisor is largely determined by scientific research agenda as well as interpersonal congruity. Students almost never choose co-graduate advisors.

After graduating with a PhD, life scientists must undergo post-doctoral training[3]. Typically, individual scientists choose a post-doctoral research stream that builds upon their prior graduate research. After post-doctoral training, scientists apply for an academic

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[1] Paula Stephan, personal communication.
[2] Forbidding graduate students to commit to a laboratory before their second-year forces students to broadly explore their laboratory choices. Furthermore, this system disinclines excessive competition and gaming for popular laboratories with limited space.
[3] In our elite sample described below, only 2% of individuals did not have some sort of post-doctoral training.

appointment (or exit science). Only after choosing a faculty appointment do life scientists start their "independent" research career. Total time as both a graduate student and post-doctoral trainee can easily exceed a decade, encompassing many opportunities for the transfer of preferences from mentors to students (Merton, Reader, & Kendall, 1958). These highly scripted sequences in career training: multiple stages, a prolonged process of professionalization, and distinct mentor/student relationships make life scientists ideal subjects to study the inter-generational transfer of preferences.

Within the universe of academic life scientists, we focus on the population of individuals who have been selected as either Pew Scholars or Searle Scholars (subsequently called PS Scholars). PS Scholar awards are the most elite prizes given early in a life scientist's independent career. Unlike other prestigious accolades in the sciences (such as the Nobel Prize or a National Academy of Sciences nomination), PS awards are given for the anticipation of future research productivity. When the awards are received, awardees have little, if any, track-record of independent research. Thus, the criteria for receiving the award is based upon both research conducted when the recipient was a student as well as future scientific promise.

Pew Searle Scholars conduct scientific research that is relevant to the biotechnology industry. Scholars explore questions in the sub-disciplines of the life sciences that have the most potential to inform the biotechnology industry, such as molecular and cancer biology. The intent of the Pew awards is to "support young investigators of *outstanding promise* in the basic and clinical sciences *relevant to the advancement of human health* [italics added][4]. Furthermore, PS awards constitute only limited financial assistance, approximately $250k over 3-4 years[5], which is generally insufficient to change the recipient's scientific research trajectory. Instead, these

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[4] Quoted from the Pew Scholars Program Description at http://www.futurehealth.ucsf.edu/biomed/scholdes.html. Accessed Sept. 30, 2007

[5] In the year 2007.

awards confer significant status to PS Scholars. Lastly, the inception of PS Awards is fairly recent (1981 for Searle Awards and 1985 for Pew Awards). Thus, our focus on PS Scholars lends insight into the generation of life scientists that came of age during the recombinant biology revolution (Henderson, Orsenigo, & Pisano, 1999). By tracking the activities of PS Scholars, we may glean insights into not only the inter-generational transmission of entrepreneurial norms, but also into the social structure of the nascent biotechnology industry (Powell, Koput, & Smith-Doerr, 1996).

It is worth noting at this point that by exclusively focusing on the population of Pew and Searle Scholars, we are introducing a strong selection bias into our sample. Although we make no apologies for this selection bias, the exact nature of this selection bias is worth elaboration. By focusing on PS Scholars, we limit our sample to the best young academic researchers in each given year. PS Scholars exhibit strong promise with regard to academic scientific publications. As a result, these individuals lie in the far right "tail" of the scientific productivity distribution. For young academic entrepreneurs, novel scientific discoveries often serve as the foundations for new, commercial initiatives, such as patenting or company founding (Azoulay, Ding, & Stuart, 2007). Thus, we are selecting for a sample that has the *potential* to impact the pharmaceutical and biotechnology industries. However, by focusing solely on PS Scholars, we are in no way selecting for "commercialists" or those scientists with entrepreneurial proclivities. On the other hand, we may actually be selecting *against* pure commercialists as those individuals may have chosen to exit and immediately pursue a career in the private sector instead of starting an academic laboratory. By focusing on the population of PS Scholars, we select for those individuals who have not only self-selected to be academics, but also have the potential to become entrepreneurs. It is this transition from academic to academic entrepreneur that we hope to assess.

Both Pew and Searle Scholars are distributed across a broad range of US research institutions. In the year 2007, the Pew Foundation solicited a single nominee from each of 148 United States research institutions. Twenty Pew Scholars were ultimately selected from this cohort of elite individuals. For year 2007 Searle Scholars, 182 individuals who were recently appointed assistant professors, were nominated by 120 universities and research institutions. Fifteen Searle Scholars were ultimately selected. For the past two decades, there have been approximately 35 PS Scholars in each year. We have identified the names of all Pew or Searle Scholars from the inception of the awards through the year 2000. For each and every PS Scholar from the year 1981-2000, we have either received CVs or constructed CV equivalents from both public and private data sources. In all, we have collected data on all 642 PS Awards through the year 2000. From this population of Scholars, we dropped a number of individuals whom were peripheral to the core disciplines relevant to the biotechnology industry. These disciplines included population and field biologists, chemists, materials scientists, and clinical psychologists. Furthermore, one Scholar was dropped due to a precipitous retirement and another succumbed to cancer in his mid-30s, within two years of receiving his award. In all, 583 PS Scholars (90.2% of our original risk-set) were retained for analysis.

The median PS Scholar received his award in the year 1991. This prototypical individual has a PhD in biology and did both graduate and post-graduate training. He began his doctoral studies in the early 1980s and received his doctorate in 1986. Between 1986 and 1991 (when he started his independent career), the individual trained in one post-doctoral lab for five years. In summary, we track each Scholar's activities backwards in time prior to the PS award to identify potential influences during the Scholar's training period and also forward to identify their activities in the independent portion of their career. For the most recent year 2000 PS Scholars, we have the ability to track 7 years of their commercial activities after entering the risk set. For earlier PS Scholars, we track significantly more time at risk for academic entrepreneurship. This dataset is ultimately comprised of 583 PS Scholars and 10,398 years of their independent research and commercial activities.

Utilizing both the paper co-authorship record and the Proquest Dissertation database, we have identified all graduate and post-graduate mentors for these PS Scholars. These 583 PS Scholars were trained in the laboratories of 803 unique graduate or post-graduate laboratories. In all, we have identified 1,158 dyadic mentor/trainee relationships for these 583 PS Scholars[6]. Where a PS Scholar has multiple post-doctoral training environments, we only include the post-doctoral advisor just prior to the Scholar's tenure-track position. Seventeen Scholars stay in the same laboratory for post-graduate work[7] and 13 begin an independent career directly after graduate work. In all, our dataset includes 535 graduate advisor/Scholar dyads and 547 post-doctoral advisor/Scholar dyads. Four hundred and ninety-nine Scholars have both a graduate and a post-doctoral advisor.

Empirical Methodology

Estimating the causal effect of prior mentorship on subsequent transitions to entrepreneurship must confront a basic selection problem: students (and mentors) choose their professional relationships, resulting in a two-sided match. As a result, econometric techniques which assume a random exposure to "treatment", in our case mentorship, cannot recover causal

[6] We identify almost 100% of the mentor/trainee dyads for this population. This does not equal twice the number of Scholars due to individuals who do multiple post-docs, go straight to professorship, or have MDs (and therefore only have one post-doc advisor).
[7] For these individuals, we count the mentor only once, as a graduate advisor. As a result, we do not consider that the trainee has a post-doctoral advisor.

effects. A standard econometric approach for this type of problem is instrumental variable estimation, which depends upon the validity of the exclusion restriction(s). Unfortunately, the choice of academic mentors is not a setting that provides credible sources of exogenous variation across students. For example, a desirable characteristic of a mentor such as high scientific productivity (or status) almost certainly correlates with an increased risk to commercialize scientific discoveries. As a result, we assume that no valid instrument is available.

To address this difficulty, we utilize a novel mix of quantitative and qualitative analysis to begin to overcome the matching issue, as well as the multi-staged nature of career paths in the life sciences. We use an extensive archive of oral histories to probe the causal processes underlying early career decisions of our subjects (i.e. choosing a graduate university and advisor). After graduate training, students purposively match to a post-doctoral advisor. We draw upon both qualitative and quantitative analysis to empirically observe prominent dimensions by which students match to particular post-doc advisors. Importantly, neither oral histories nor probit models suggest that self-selection to particular post-doc advisors is along any (observable) dimension of commercial interests. Thus, we propose that students are randomly exposed to a particular treatment regime: the commercial orientation of their chosen post-doc advisors.

To estimate selection into the second, post-doctoral stage of training, we create a synthetic risk-set of potential post-doctoral mentors. After identifying graduate and post-doctoral advisors, as well as PhD graduation dates for each student, we bin each student into discrete cohorts based upon their graduation date. These cohorts all made a transition from graduate to post-doctoral training within the same timeframe. Thus, we consider each student at risk for matching to any within-cohort, observed post-doctoral advisor. We artificially generate this list of potential post-doctoral advisors, as well as a number of dyad-level (for the potential student/post-doctoral advisor pair) variables. We then use a probit model to estimate the dimensions along which post-doctoral advisor and students self-select one another. Importantly, we find no evidence for matching along commercial lines to post-doctoral advisors.

To estimate the causal effects of post-doctoral advisor patenting on subsequent student commercialization, we make use of a novel empirical approach that has gained acceptance in both biostatistics and economics: Inverse Probability of Treatment Weighted (IPTW) estimation (Azoulay, Ding, & Stuart, 2006a; Robins, Hernán, & Brumback, 2000). These estimators are similar in spirit to propensity-score matching techniques in that they make the (untestable) assumption that selection into treatment is based on observables and extend that methodology to time-varying treatments effects. In particular, IPTW estimation allows one to recover average treatment effects even in the presence of time-varying confounders.

Past research in the program evaluation literature has shown that selection on observables perform well when 1) researchers richly (and correctly) model the probability of treatment 2) units are drawn from similar labor markets 3) outcomes are measured in the same way for both treatment and control (Dehejia & Wahba, 2002). Our dataset construction as well as our rich collection of covariates goes a long towards satisfying these conditions. With regards to condition 1, which is largely unmeasurable, we have supplemented our quantitative analysis with qualitative evidence through oral histories. Both out qualitative and quantitative analysis are consistent with one another.

We implement IPTW estimation in first predicting a student's propensity to match to a given treatment regime (post-doctoral advisor). We then weight the subsequent estimates with the inverse probability of the first-stage (Azoulay et al., 2006a), which places *greater* emphasis on the treatment regimes which are *less* probable. As a result, we are parsimoniously creating a dataset that simulates experimental program treatment. We also supplement our analysis with both unweighted regression estimates as well as a Heckman selection framework.

To estimate the effects of post-doctoral advisor commercialization on subsequent student commercialization, we use a discrete time-hazard model framework with yearly spells (Allison, 1982; Cox, 1972). As patenting is an infrequent event, we use a logistic regression function to link the hazard rate with time and explanatory covariates. In practice, we estimate a logit of Scholar commercialization decisions, with observations after the first commercialization event dropped from the estimation sample. Advisor characteristics are set as initial conditions and are time-invariant.

Data Construction

Using CV, public, and private data sources we have compiled detailed career histories of both PS Scholars and their prior mentors. We have collected measures of commercial orientation in the form of patenting, founding companies, serving on scientific advisory boards, and academic exit to industry jobs. We have also collected both research and commercialization measures at the institution level. Furthermore, our focus on life scientists allows the collection of large-scale bibliometric data (Azoulay, Stellman, & Zivin, 2006b). This allows year-by-year observation of not only the quantity and quality of scientific output, but also an analysis of the nature of the work itself. In particular, we measure the latent patentability of each individual's research stream. Lastly, bibliometric data allows us to quantify changes in research streams over time.

Dependent (Commercialization) Variables

To assess similarities or dissimilarities in academic entrepreneurship between PS Scholars and their post-doc advisors, we collected a number of commercialization measures. For both Scholars and advisors, we collected all of their issued patents and generated year-by-year measures of patenting flows. We assigned all co-patents between advisors and Scholars to advisors. To supplement the patenting data with a separate measure for commercial interaction, we collected data on company foundings and Scientific Advisory Board membership. For each Initial Public Offering prior to 2001 by a nascent biotechnology firm, we have collected S1 filings from the SEC. From these S1s, we have identified both individual founders and also scientific advisory boards. This public data is supplemented by a dataset of founders and scientific advisors for all venture capital backed biotech firms from 2001 to present[8]. Due to extensive faculty patenting in the life sciences, the primary focus of this paper is on Scholar patenting as a proxy for academic entrepreneurship. We also present results using Scholar membership of Scientific Advisory Boards as an indicator of commercial proclivities. Data on company foundings and individual industry exit is too thin to draw any meaningful conclusions.

Control Variables

We have collected a number of demographic variables for PS Scholars and their prior advisors. The gender of each individual was assigned through CV or public sources. Where the gender of an individual's name was ambiguous, gender was assigned through a photo where possible and/or a sexed reference. In the sole case of a transsexual, the final gender was assigned. All PS Scholars have either a PhD and/or an MD. For all Scholars, we identified the year when they received their highest degree.

[8] http://www.growthinkresearch.com/

We created a dataset tracking year-by-year training and employment of each PS Scholar. Consistent with naming PS Scholars at the inception of their career, the first academic appointment year almost perfectly correlates with the year of a PS award (R-squared = 0.98). The norms regarding academic entrepreneurship have changed dramatically from the year 1980 through the year 2000 (Owen-Smith & Powell). As a result, we expect strong cohort effects on academic entrepreneurship, which we control for through (every other) year cohort dummy variables in our regression models.

We have also collected the institutional employment of each advisor and Scholar. All Scholars were tenure-track professors at a research institution when they were named a PS Scholar early on in their academic careers[9]. We control for the research intensity of each Scholar university with the logged flow of total NIH grant dollars received for each employing university[10]. We control for the commercial intensity of each Scholar university with the logged stock of university assigned patents.

As a control, we bin each Scholar into one of four levels of research, depending on the complexity of their subject material. These dummy variables indicate if the Scholar primarily uses macromolecules, cells, organisms or human beings as the primary experimental subject of their scientific research. Although the scientists in our risk set all investigate questions concerning "modern molecular biology" and thus, have at least some relevance to the biotechnology industry, we control for varying differences in the commercial relevance of scientific research using the Scholar's journal commercialization factor score, as well as each scientist's research patentability score (described below).

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[9] Tenure-track professorship is a pre-requisite for both Pew and Searle Award nomination.
[10] Deflated to year 2003 dollars.

We explicitly omit measures of scientific productivity as independent variables, such as a count of Scholar publications, as these covariates are likely to correlate with Scholar commercialization and will confound our results.

Dyad-Selection Variables

To implement a selection on observables framework, it is important to richly model the probability of matching to particular post-doctoral advisors (treatment regimes). As mentioned earlier, we collected commercialization variables for both graduate and post-doc advisors.

To account for Scholar/post-doc advisor homophily, we generated a number of variable controlling for gender and birthplace. We generated indicator variables for both Scholar and post-doc advisor being the same sex, as well as being both female. We also identified the birth-country and the undergrad institution of the Scholar. We generated an indicator variable if the Scholar's undergraduate institution and the Post-doc advisor's research institution were in the same (US) State to account for a possible tendency of Scholar's to remain near their birthplace. To account for sorting along ethnic lines, we generated an indicator variable if the Scholar and Post-doc advisor were born in the same country. To tease out non-US homophilic tendencies, we generated a dummy variable if the Scholar was not born in the US and interacted this variable with the same-country variable above.

We suspect that status differentials may be an important variable in matching to specific Post-doc advisors (Merton, 1968). As a result, we generated quartile dummies for the difference in prior publication count between the Scholar's graduate advisor and a post-doc advisor. To account for matching to higher productivity post-doc advisor, we include a count of post-doc advisor publications. We also collected data for advisor membership in the US National Academy of Sciences[11].

Lastly, we suspect that there is strong matching between a Scholar' prior (graduate) research trajectory and subsequent (post-doc) research trajectory. To control for matching along scientific content, we turn to Medical Subject Heading (MeSH) article keywords[12]. MeSH headings are expert curated keywords that comprise the National Library of Medicine's (NLM) "controlled vocabulary thesaurus." In 2008, these ~25,000 distinct descriptors are used by the NLM to index all journal articles in Medline/Pubmed, the NLM's library. As a result, each life science article collected from Medline will have a discrete number of MeSH keywords associated with it. Concomitant with our collection of each scientist's publication list from PubMed, we have also collected MeSH keywords.

We use the MeSH keywords in two ways. First, we use the MeSH keywords to control for the underlying research patentability of each scientist's productive output. We collected all MeSH keywords from a set of highly-productive "superstar" scientists, with PS Scholars excluded (Azoulay, Superstar Extinction paper ref). Superstar scientists were merged with patenting data and scientist-years were binned into those which had patented in the past and those which had not. MeSH keywords associated with either the patenting or non-patenting regime were then assigned a weight proportional to their frequency of occurrence in either regime[13]. Of note is that each MeSH keyword was assigned a research patentability for each year the keyword occurred, allowing for endogenous changes in patentability over time.

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[11] We also collected a number of other accolades, including Nobel prizes, Lasker awards, etc. These prizes were highly correlated with NAS membership.
[12] http://www.nlm.nih.gov/mesh/
[13] For full data construction reference, see Appendix I in Azoulay, Ding, Stuart, JIE forthcoming)

Our second use for MeSH keywords is to measure scientific research proximity between two individual scientists. Given two scientists' publications, we generate a count of the number of overlapping, unique MeSH keywords. This number, divided by the sum of each advisor's total MeSH headings constituted a symmetric measure of scientific overlap between the graduate and post-doctoral advisor. We generated four dummy variables corresponding to each quartile of scientific overlap. To account for both differences in research productivity and cohort effects, we included only advisor MeSH keywords from publications prior to the end of the PS Scholar's graduate training.

As we have detailed training histories for each PS Scholar, we are able to glean approximate times when the Scholar and Advisor were co-localized. For PhD advisors, we infer co-localization as the six years prior to when the degree was issued. For post-doctoral advisors, we infer co-localization as the time period from the award of a PhD until the PS Scholar starts as an assistant professor[14]. If the advisor has been issued a patent PRIOR to the time when the Scholar departs and co-localization ends, we set an advisor patenting dummy variable to 1. For advisor commercialization variables, we do not include advisor commercialization behavior subsequent to Scholar departure.

Not all scientific research is equally relevant to the commercial sector. Following (Lim, 2004), Azoulay, Stuart and Ding compared the journal names of patenting and non-patenting scientists to identify the venues where commercialists prefer to publish their scientific research (Azoulay et al., 2007). As a result, they empirically derived a time-varying Journal Commercialization Factor for each life sciences journal-year. After collecting each Scholar's

[14] For Scholars with multiple post-doctoral advisors, we infer that the Scholar spent equal time training with each post-doctoral advisor.

and Advisor's publications list from MedLine[15] using Publication Harvester (Azoulay et al., 2006b), scientific paper output was weighted by the Journal Commercialization Factor. For both graduate and post-doctoral advisors, we compute the average JCF score for publications in all years PRIOR to the Scholar's departure. Thus, we are measuring the commercial relevance of each advisor's research agenda only for those years that potentially influence the Scholar. The advisor and Scholar's publishing years do not overlap.

RESULTS

Descriptive Statistics

Our culled dataset is comprised of 583 Pew Searle Scholars. These Scholars are 21% female, and are primarily composed of scientists who earned PhDs (See Table 1). About six percent of the Scholars only have an MD. All Scholars have a higher degree (either MD and/or a PhD). The median Scholar received a PhD in 1986 and began an independent academic career in 1990. Only 9% of the Scholar's work in clinical, translational research. Consistent with the elite nature of the PS Awards, many Scholars are academic entrepreneurs. Just fewer than 40% of the Scholars are issued a patent by year 2007. Furthermore, 15% of the Scholars are identified as either a founder or a member of the Scientific Advisory Board of a biotechnology firm. As expected, each Scholar's scientific research is more similar to their Post-doctoral advisors than their Graduate advisors (Table 1).

For these 583 Scholars, we have identified 535 graduate advisor/Scholar and 547 post-doctoral advisor/Scholar dyads. There are 448 unique graduate advisors, as well as 377 unique post-doctoral advisors [see Figure 2 & Figure 3 for advisor/trainee counts and prominent names].

[15] http://www.ncbi.nlm.nih.gov/sites/entrez

It is interesting to note that this list of prominent graduate and post-doctoral advisors does not overlap. Furthermore, there is striking diversity in types of research by these prominent advisors. Lastly, note that this list of individuals comprises pre-eminent academic scientists, not pre-eminent commercialists. For example, Stanley Cohen and Herbert Boyer, credited with initiating the biotechnology industry and Genentech, Inc., are not even on our list of 803 unique advisors. At the time, Cohen and Boyer were running laboratories at Stanford and UCSF, respectively, placing them at risk for mentorship[16].

Both graduate and post-doctoral advisors are 6% female, a far lower percentage than Scholars. One out of eight post-doctoral advisors is a Nobel laureate (Table 1, Panel C). Nearly one-third are members of the Howard Hughes Medical Institute and nearly two-thirds are members of the US National Academy of Sciences. The average post-doctoral advisor has trained 2.5 Pew Searle Scholars. For each of these measures, graduate advisors are not as prestigious as post-doctoral advisors (Table 1, Panel B). Nonetheless, these descriptive statistics strongly suggest that these graduate and post-doctoral advisors represent an elite cohort of academic scientists. Lastly, many advisors are academic entrepreneurs. Over 20% of graduate advisors and over 45% of post-doctoral advisors had been issued a patent by the time the Scholar finished his/her training period.

Each Scholar's choice of academic institution also does not appear to be random. Most striking is the geographic concentration of graduate and post-doctoral institutions. Five of the seven most prevalent graduate universities are located in Boston and San Francisco (Figure 4). Aggregated by state, more than 50% of PS Scholars who trained as graduate students in the US were at institutions in California or Massachusetts (see Table 2). For post-doctoral institutions,

[16] Note that Stan Cohen won the Nobel Prize in Medicine in 1986. However, both this highest accolade as well as widespread eponymy as a patentor was insufficient for him to train a future Pew or Searle Scholar.

the addition of New York and Maryland (i.e. NIH) comprised over 75% of the Scholars. For post-doctoral appointments, five institutions clearly comprise the universities of choice for Pew Searle Scholars (Figure 5). This incredible institutional concentration of mentorship and human capital is consistent with the central role these two cities play in the biotechnology industry (Kenney, 1999). Furthermore, we note that there is significant variation in the proportion of advisors at each institution who are patentors. Unsurprisingly, there are significantly patent intensive universities such as MIT and Stanford. Conversely, institutions such as the National Institutes of Health, and Yale are less-commercial. It should be noted that Pew Searle Scholars choose to patent in very high numbers across all institutions, suggestive of changing community norms (Figure 6) (Etzkowitz, 1998).

Qualitative Analysis

Our qualitative analysis is summarized in Table 3 & Table 4. Representative quotes for each category are included in each table. We bin each student's motivations to select a particular graduate university (and/or graduate advisor) along personal, institutional, and advisor characteristics. The vast minority, only XX%, of students considered one graduate program over another due to specific advisors at that institution. In XX number of these cases, the student had been awarded a country-specific (i.e. Rhodes fellowship) that required the student to find a specific thesis advisor. European (vs. US) doctoral students apply directly to an individual scientist's laboratory, rather than to a university graduate program. The majority of students (XX%) chose their graduate program due to either personal (relationship or geographic) preferences and/or the status of the graduate institution. In no instance did any Scholar mention future entrepreneurial activities as a factor in their choice of either graduate institution, graduate advisor, or post-doctoral advisor.

On the other hand, matching to post-doctoral advisors was largely purposive. The student had a more sophisticated understanding of the costs/benefits to specific mentors. These decisions were most strongly influenced by the Scholar's personal scientific trajectories (building upon their graduate work) and developing interests. Furthermore, the reputation of the post-doctoral advisor, as well as personal (relationship or geographic) constraints on the part of the Scholar were prominent dimensions to select post-doctoral advisors (see Table 5 for a quote). With the choice of a post-doctoral advisor, scientific fit between the Scholar and post-doctoral advisor was clearly the most dominant advisor characteristic taken into consideration.

Post-doc Advisor Selection Models

To empirically explore the determinants of post-doc advisor selection, we generated a dyad-level risk-set of over 13,000 potential Scholar/post-doc advisor pairs, with 500 dyad-pairs realized in our dataset[17]. In Table 5, we present probit models predicting Scholar matching to particular post-doctoral advisors. Given our emphasis on academic entrepreneurship, we are interested in Scholar/post-doc advisor matching along commercial dimensions. Our qualitative evidence suggests that Scholars do not take (future) commercial interests into account when selecting a post-doc advisor. Furthermore, we are particularly interested in an indicator variable for when ONLY the graduate advisor patents (and the post-doc advisor does not). If our estimates on this indicator variable are negative, this would suggest that graduate advisor commercial orientation is spilling over into Scholar matching preferences.

[17] Expansion of this risk-set to include further include observed post-doctoral advisors in the years adjacent to Scholar graduation resulted in an expansion of the risk-set to >100k potential observations. Using this risk-set did not alter our results.

In the spirit of parsimony, Model 1 presents estimates for Scholar/post-doc advisor matching along commercial lines with no other covariates besides cohort dummies. Although we a marginally significant positive estimate for both advisor patenting, our pseudo-R-squared is very low. As there are multiple positive correlates with patenting (such as research productivity) this result seems within reason. To control for regional propinquity, we see a significant, positive effect for Scholars to stay in the same state as their undergrad institution (Model 2). This effect is largely driven by Scholars who went to undergrad university in California, Massachusetts, and New York, suggesting a disinclination to move between life-science clusters. We also see a propensity for US-born Scholars to selectively work for US-born advisors, as well as foreign-born Scholars to work for post-doc advisor of the same nationality (Model 3). For foreign-born Scholars, this effect is largely driven by Scholars from the UK, not from East Asia. Lastly, we see no propensity to match along gender (Model 4).

The largest determinant of matching between Scholars and post-doc advisors is along scientific lines (Model 5)[18]. As the excluded scientific closeness quartile (# 4) is the quartile with the most scientific overlap between a Scholar's graduate advisor and the post-doc advisor, we see that decreasing scientific closeness (and increasing scientific distance) dramatically lowers the probability of a Scholar matching to that particular post-doctoral advisor. Although in Model 5 we see a significant, negative coefficient on ONLY post-doc advisor patenting, this result is ablated when we take account of scientific productivity and status (Model 6). Consistent with the three quartiles of scientific closeness, we see a slight decrease in matching along research productivity dimensions. In other words, for our elite dataset we do not observe graduate student from high-productivity laboratories selectively matching to other (relatively) high-productivity laboratories. On the other hand, we do see a significant, decreased probability

[18] Note the Pseudo-R-Squares.

of matching to a high-status National Academy of Sciences laboratory if the Scholar's graduate advisor was not a National Academy of Sciences member.

Discrete-Time Hazard Rate Models with Selection

We present discrete time hazard rate models with yearly spells in Tables 6 & 7. We estimate a logit of the decision to commercialize within a given year, for all years up to and including the first commercialization event. Scholars enter the risk-set when they begin their independent careers as professors. Scholars exit the risk-set when they experience their first commercialization event. We proxy for a Scholar's commercial proclivities using Scholar patenting in Table 6 and membership on a Scientific Advisor Board in Table 7. Characteristics of their prior mentors are included as initial conditions and do not vary within each scientist. All hazard rate models include year dummies as well as Scholar cohort dummies. Furthermore, we control for the type of science the Scholar does, as well as both graduate advisor and post-doc advisor's prior commercialization score and depreciated research patentability stock during training.

Table 6 presents hazard rate models of Scholar patenting. Model 1 includes variables commonly thought to be associated with academic patenting. The female scientist dummy has a significant negative effect on the probability of patenting. We estimate that female scientists will become a first-time patenter at 49% the odds of the male scientist. On the other hand, scientists with an MD/PhD will become first-time patenters at 106% the odds of their PhD peers. We see a strong positive effect for universities which are high patenters. A one standard deviation increase in the logged-stock of university patents increases a Scholar's odds of first-patenting by

35%. We do not observe any effects for graduate advisor commercialization behavior on Scholar's subsequent probability of patenting.

Contrary to graduate advisor characteristics, Model 2 shows a strongly significant, positive effect of post-doc advisor patenting on a Scholar's subsequent probability of patenting. Scholars who have been trained in laboratories where the post-doc advisor patented increase their odds of patenting by 102%. In Model 3, we show a similar effect for Scholars who have been training in laboratories where the post-doc advisor served on a Scientific Advisory Board. Post-doc advisor membership on an SAB increases the Scholar's own odds of subsequent patenting by 53%, about half that of patenting. When both SAB membership and patenting are taken into account, the patenting treatment effect dominates (Model 4).

In Model 5 we implement the IPTW methodology using the fully specified probit model in Table 4. Using a probit model to predict Scholar matching to specific post-doc advisors, we predict the probability of observing our realized Scholar/post-doc advisor dyads relative to all potential dyads. The inverse of this probability is then used to weight our regressions in Table 5, Model 5. In essence, we are giving proportionately greater weight to those Scholar/post-doc advisor matches which are less probable, thus constructing quasi-experimental matching between Scholars and post-doc advisors. Implementation of the IPTW methodology increases the probability of Scholar patenting (Model 5).

Reassuringly, having a post-doc advisor who patents (Model 6) or sits on an SAB (Model7) has no effect on subsequent research productivity, as measured through an impact-factor weighted count of published papers. For these Poisson models, female scientists are marginally less productive than their male counterparts, suggesting that gender plays a larger role in commercial outputs than research productivity. As expected, we see no effect in research productivity for MD/PhDs versus PhDs or the patenting intensity of a university.

In Table 7 we run discrete time hazard rate models of Scholar Scientific Advisory Board Membership. As Scholar SAB membership is infrequent, we observe many more right-censored Scholars than in our Scholar patenting panel. In our dataset we observe only 60 events where Scholars are assigned membership to an SAB. Nonetheless, we observe a significant, positive effect of post-doc advisor patenting on subsequent Scholar SAB membership when we account for selection on observables (Model 5). Scholars who have been trained in laboratories where the post-doc advisor patented increase their odds of scientific advisory board membership by 123%. Surprisingly, we see no effect for post-doc advisor SAB membership on subsequent Scholar SAB membership. Neither post-doc advisor patenting nor SAB membership has an effect on subsequent Scholar research productivity (not shown).

DISCUSSION

Our results strongly suggest that prior mentors influence the subsequent entrepreneurial norms of their trainees. Although preliminary, the results presented in this paper provide some evidence that trainees learn much more than job-specific skills from their mentors. Although we commonly conceive of graduate and post-graduate training as a transmission of skills from the mentor to the trainee, our results suggest that a much wider range of behaviors are explicitly and implicitly transmitted from mentors to trainees. In the community of life scientist trainees, students are not only learning mastery of scientific practice, but are also absorbing beliefs about “rules of engagement” with the commercial sector (Merton et al., 1958). As the attitudes of academic scientists towards commercial activities vary widely, replication in behavioral norms between mentors and trainees is likely to have long-term implications that range far beyond scientific research agendas (Owen-Smith et al., 2001).

On the one hand, these results would suggest a particularly slow inter-generational turnover of beliefs, as de novo scientists are strongly imprinted with the beliefs of their predecessors. Only those individuals who choose to flout communal standards, as well as their trainees, are likely to become academic entrepreneurs. On the other hand, if there exists a number of disproportionately influential mentors who are successful at both training academic scientists and engaging in commercial activity (the apparent case with the biotechnology industry), the laboratory structure of the academic life sciences may expedite the diffusion of entrepreneurial norms across generations. Trainees will flock to a select group of advisors for cutting edge science. Tangentially, they will also adopt novel commercialization norms and the adoption of these divergent norms will be expedited.

Lastly, the immediate institutional environment also affects Scholar behaviors, as reflected in our measure of institutional patent stocks. There are a number of possible explanations that may underlie this effect. The most direct explanation is the presence or absence of a Technology Licensing Office. Budding entrepreneurs who produce commercially relevant knowledge and are open to commercial engagement may find themselves stymied through the lack of legal resources (Colyvas et al., 2002). The effects of a university TLO may also be indirect. As more individuals at an institution decide to patent, peer effects may strengthen over time.

It is striking that universities exhibit differing, but stable patent intensities over time. It is not just the elite, life sciences universities which are producing a large number of patents. In the past, a number of elite universities have resisted the trend in the life sciences towards engagement of the commercial sector. This resistance is not just restricted to universities outside of the biotech hubs of Boston and San Francisco, but universities within these cities also exhibit significant variation (Zucker, Darby, & Brewer, 1998). Exploring the causal mechanisms underlying the institutional norms towards commercialization may be a promising avenue of research.

This dataset may be useful for exploring questions complementary to the inter-generational transmission of entrepreneurial norms. In particular, we have coded the employment institution of all our Scholars, including any changes in institutional employment. An interesting, remaining question is the effect of institutional norms relative to prior mentorship norms. For those individuals who did not train under academic entrepreneurs, what are the effects of an institution with strong pro-entrepreneurial norms? Are institution and prior mentorship norms substitutes or complements?

This study comes with many caveats. We begin to get at causality through non-contemporaneous correlations between prior mentors and subsequent trainee behavior. However, matching between mentors and trainees remains a choice. Although we have no silver bullet to address this issue, there are many reasons to suggest that it is not a substantive concern. First, although there is clearly matching between graduate mentors and trainees, scholars in this study appear to have chosen graduate advisors based upon their scientific, not their commercial credentials. The absence of Stan Cohen and Herb Boyer are striking examples of this. Second, the institutional structure of US graduate education in the life sciences discourages rapid commitment between graduate advisors and trainees. Subsequent to co-location at a graduate institution, this partnering is only allowed after a year. Lastly, we find no empirical evidence in our dyad-level models for matching along commercial dimensions. However, these issues require further probing[19].

Furthermore, our dataset currently does not allow us to analyze whether or not trainees explicitly learn *how* to engage the private sector. In this study, we have not explored measures for the commercial success of academic entrepreneurship. Are there antecedents to not only patenting, but also to filing for patents that are subsequently highly-cited? Are the trainees of more *successful* entrepreneurs more successful themselves? To date, we have only explored relatively blunt proxies for commercialization.

Taken together, a novel dataset, a number of new measures, and a careful empirical specification should allow the exploration of norms transmission across successive generations of academic entrepreneurs. By focusing on mentor/trainee relationships, this paper has drawn attention to a key unexplored mediator of entrepreneurship. Furthermore, incorporating mentorship, as well as workplace and institutional factors, may lead to a more complete understanding of both the dynamics of how novel entrepreneurial practices diffuse across industries as well as the origins of entrepreneurs themselves.

[19] A useful resource we are currently exploring is the oral history archive of Pew Scholars, which attempt to qualitatively tease out influential episodes in careers of these life scientists. These 139 oral histories are listed at the following UCLA website: http://unitproj.library.ucla.edu/biomed/histmed/ohistory-pew-n.cfm

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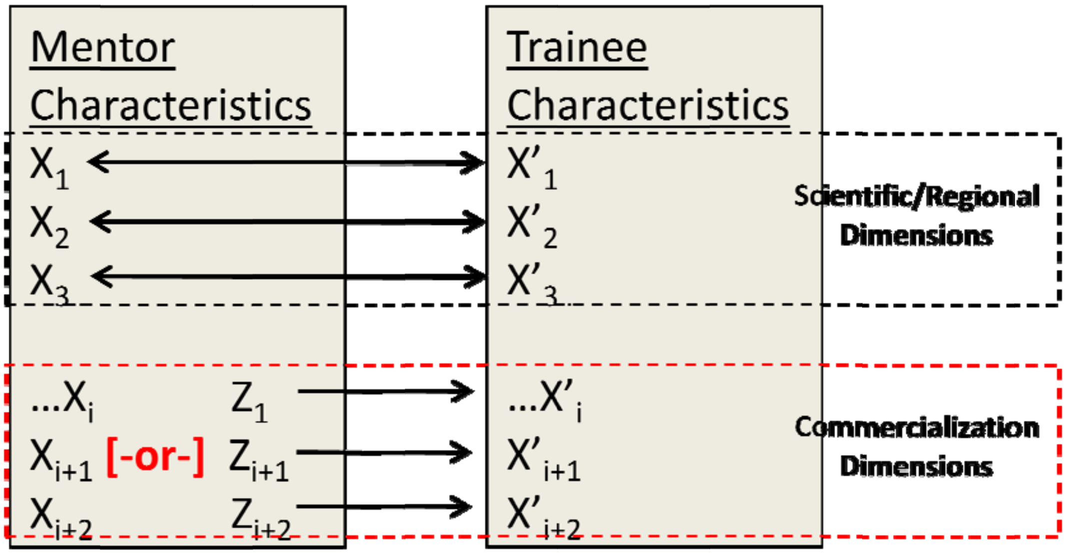
Figure 1: Model of Structural Influence



Legend: Mentors and trainees purposively match to one another along a number of prominent dimensions ("X's"). We propose that as a consequence of this match, trainees inadvertently expose themselves to a wider array of dimensions, which can subsequently shape their behavior.

Figure 2a: Number of Trainees per Graduate Advisor

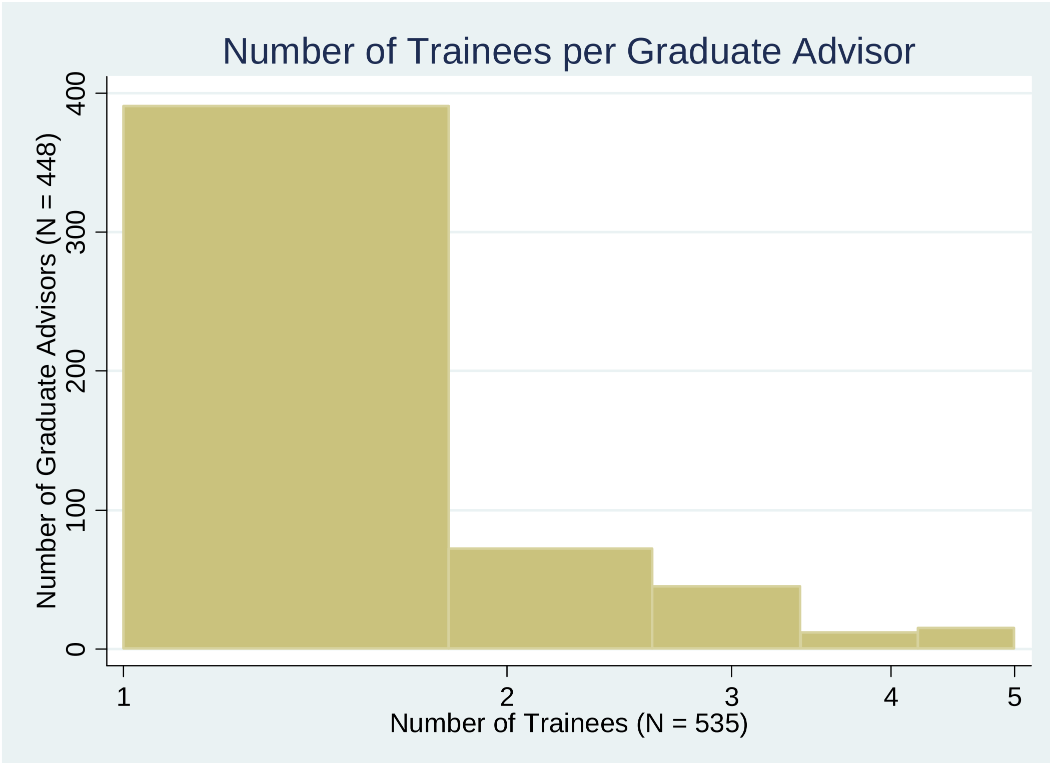
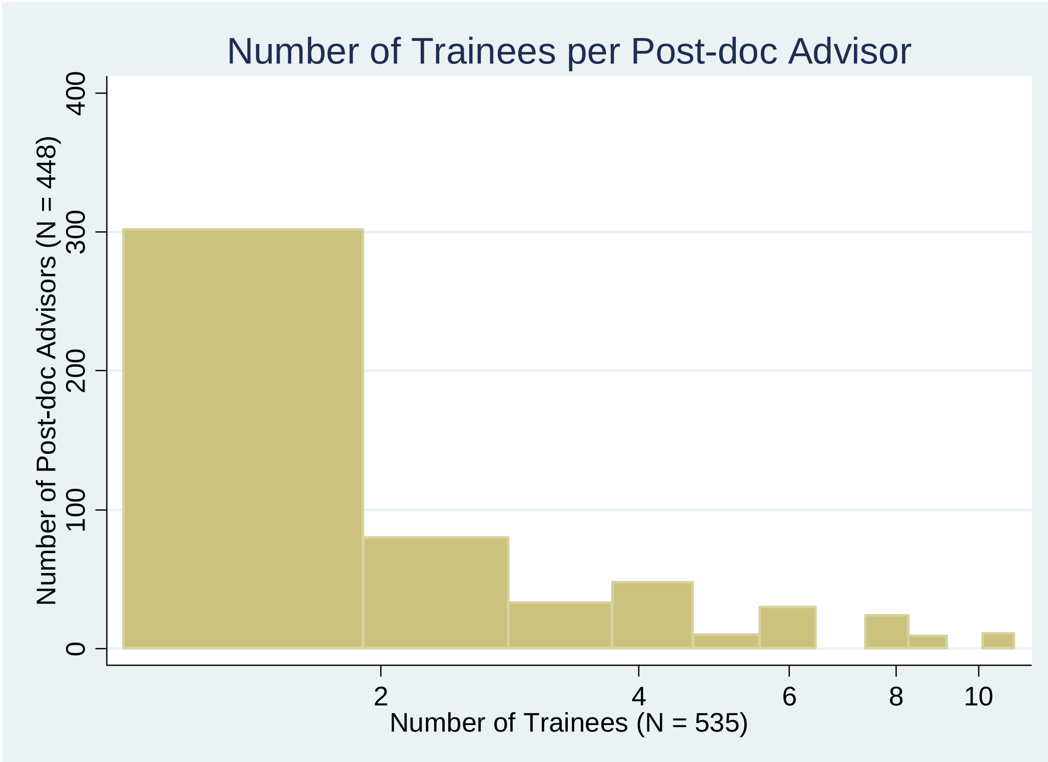


Figure 2b: Names of advisors with 4 or 5 trainees

# of Scholars Trained	**Name**	**University**	**Type of Research**
4	Eric H. Davidson	Caltech	Developmental Biology of Sea Urchins
4	Robert L. Baldwin	Stanford	Biochemistry of Protein Folding
4	Gunter Blobel	Rockefeller	Cell Biology of Yeast Nuclear Transport
5	David Botstein	MIT	Genetics of Baker's Yeast
5	Philip A. Sharp	MIT	Biochemistry of RNA Splicing
5	Jack W. Szostak	Harvard	Genetics of Yeast Chromosomes

Figure 3a: Number of Trainees per Post-doc Advisor



(correct figure, N = 547)

Figure 3b: Names of post-doctoral advisors with 5 or more trainees

# of Scholars Trained	**Name**	**University**	**Type of Research**
5	Ronald W. Davis	Stanford	Molecular Immunology
5	Harold E. Varmus	NIH	Viruses and Cancer
6	Marc W. Kirschner	UCSF/Harvard	Developmental Cell Biology
6	Stanley Falkow	Stanford	Genetics & Microbial Pathogenesis
6	Robert Tjian	UCBerkeley	Biochemistry of Transcription
6	H. Robert Horvitz	MIT	Cell Biology of C. elegans
6	Randy Schekman	UCBerkeley	Vesicle Transport in Yeast
8	Thomas R. Cech	UColBoulder	Biochemistry of Transcription and Splicing
8	Gerald M. Rubin	UCBerkeley	Genetics of the Fruitfly
8	Thomas P. Maniatis	Harvard	Biochemistry of Gene Regulation
9	Richard Axel	Columbia	Genetics of Olfaction
11	David Baltimore	MIT	Molecular Virology

Figure 4: Graduate Advisor Patenting Behavior, Organized by Institution

Notes:

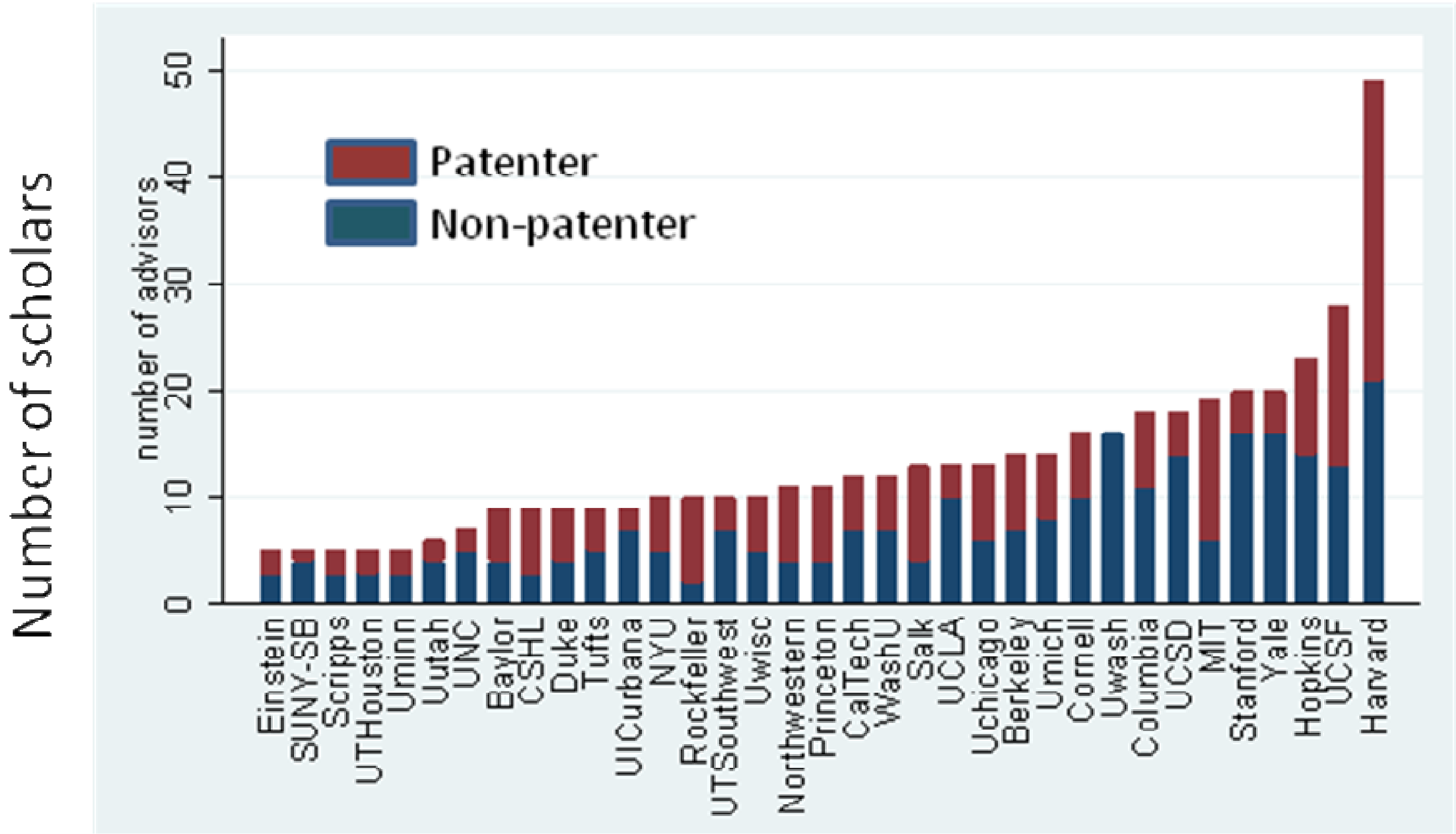
- Only including institutions w/>5 advisors
- Excluding liberal arts colleges

Figure 5: Post-doctoral Advisor Patenting Behavior, Organized by Institution

Notes:

- Only including institutions w/>5 advisors
- Excluding liberal arts colleges

Figure 6: Pew Searle Scholar Patenting Behavior, Organized by Institution



<u>**Notes:**</u>

- Only including institutions w/>5 advisors
- Excluding liberal arts colleges
- Patenting dummy indicates subsequent Scholar patenting

Table 1: Descriptive Statistics

Panel A: PewSearle Scholar Characteristics

Variables	Observations	Mean	Std. Dev	Min	Max
Becomes a Patentor	583	.3979417	.4898936	0	1
Is Identified on an S1	583	.1475129	.354921	0	1
Commercial Relevance Score	583	.0528406	.0131579	.0182131	.1144429
Is Female	583	.212693	.4095637	0	1
Highest Degree Year	583	1985.724	5.069371	1973	1998
Is an MD	583	.0651801	.2470554	0	1
Is a PhD	583	.8027444	.3982686	0	1
Is an MD/PhD	583	.1320755	.3388635	0	1
Year of 1st Academic Appt.	583	1990.165	5.252424	1977	2000
Primarily Studies Macromolecules	583	.3619211	.4809688	0	1
Primarily Studies Cells	583	.2281304	.4199874	0	1
Primarily Studies Organisms	583	.3207547	.4671675	0	1
Primarily Studies Human Beings	583	.0891938	.2852681	0	1
Similarity of Research to Graduate Advisor	535	.321559	.1894119	0	.816
Similarity of Research to Post-doc Advisor	545	.5139115	.1904411	0	.8695652

Panel B: Graduate Advisor Characteristics

Variables	Observations	Mean	Std. Dev	Min	Max
Is Female	535	.0635514	.2441804	0	1
Was a Patentor	535	.2056075	.4045231	0	1
Was Identified on an S1	535	.1401869	.3475058	0	1
Prior Commercial Relevance Score	532	.055933	.0164912	.0157825	.1726375
Number of Publications	583	81.28302	76.42176	0	498
Is an HHMI Investigator	535	.128972	.3354826	0	1
Is a Nobel Laureate	535	.0691589	.2539616	0	1
Is a Nat'l Acad of Sciences Member	535	.4186916	.4938064	0	1
Number of PewSearle Trainees	535	1.482243	.943717	1	5

Panel C: Post-Doctoral Advisor Characteristics

Variables	Observations	Mean	Std. Dev	Min	Max
Is Female	547	.0585009	.234903	0	1
Was a Patentor	547	.4614445	.4957312	0	1
Was Identified on an S1	547	.3199269	.4668749	0	1
Prior Commercial Relevance Score	545	.0536468	.0108415	.0182911	.1039855
Number of Publications	583	106.5557	85.31093	0	514
Is an HHMI Investigator	547	.3144424	.4647184	0	1
Is a Nobel Laureate	547	.1261426	.3323139	0	1
Is a Nat'l Acad of Sciences Member	547	.5886654	.4925261	0	1
Number of PewSearle Trainees	547	2.517367	2.40062	1	11

Panel D: Institution Patenting Characteristics

Variables	Observations	Mean	Std. Dev	Min	Max
Scholar Institution Patenting Intensity	539	1.251889	1.838325	0	13.05524
Graduate Advisor Institution Patenting Intensity	430	1.995241	2.934114	0	16.83056
Post-doc Advisor Institution Patenting Intensity	404	2.048043	2.726643	0	21.11699

Table2a: Geographic Concentration of Graduate Advisors (>=10 Scholars Trained)

US State	# of Scholars Trained	% of US Trained Scholars	Cumulative % of US Trained Scholars
California	120	27.84	27.84
Massachusetts	103	23.90	51.74
New York	51	11.83	63.57
Connecticut	17	3.92	67.52
Missouri	15	3.48	71.00
Wisconsin	14	3.25	74.25
Indiana	13	3.02	77.26
Maryland	13	3.02	80.28
Texas	13	3.02	83.29
North Carolina	12	2.78	86.08
New Jersey	10	2.32	88.4

Note: In total, 431 Scholars receive PhDs from US institutions.

Table2b: Geographic Concentration of Post-doctoral Advisors (>= 10 Scholars Trained)

US State	# of Scholars Trained	% of US Trained Scholars	Cumulative % of US Trained Scholars
California	137	32.39	32.39
Massachusetts	117	27.66	60.05
New York	49	11.58	71.63
Maryland	26	6.15	77.78
Connecticut	21	4.96	82.74
Indiana	13	3.07	85.92
Texas	13	3.07	88.89

Note: In total, 423 Scholars did post-docs in US Institutions

Table 3:
Motivations for Choosing Graduate Institution/Advisor

Motivations underlying choice	% of Scholars
Personal Reasons	TBD
• -Relationship	TBD
• -Preference	TBD
Institution Features	TBD
• -Program Feature	TBD
• -Status	TBD
Specific Advisor	TBD
• -Prior direct experience	TBD
• -Reputation	TBD
• -Fellowship required	TBD

<u>Quotes:</u>
(Personal Reasons; Relationship + Preference)

> "I applied to three programs: Cornell, Wisconsin, and Berkeley. And Davis. I was accepted to all of them, and Berkeley seemed easy. It was quite easy to do. I basically had to drive seventy miles and I was there. And it had enough allure as the name that it was fine. In restrospect, certainly it was, again fairly poorly thought out… I think it was much more of an issue of convenience. I had a girlfriend at the time. How did that work? She was at Davis, and that affected things." -pg 89-90.

(Institutional Features; Status)

> "By the time I decided that [to apply to PhD programs], the application deadlines had passed. I could have gone to University of Minnesota…I felt that it would be in my interest to get the pedigree—to try to go to the best place I could. I decided to wait a year…" –pg21
>
> "Then I went to MIT… I also looked at faculty at the universities throughout the country—where they came from. Almost invariably, it was either Berkeley or MIT; that seemed like a good sign to me." –pg22

(Specific Advisor: Prior direct experience)

> "What happened was I was given a fellowship to come to the United States to work in a research lab in Michigan. This was John Pringle's lab. It was an amazing experience for me. I thought I was coming to the US to just basically see the US and take a vacation and then go back to Ireland and sort of piddle on. But when I came over I just totally fell in love with science… So by the end of the summer it was perfectly obvious to me that this was what I should be doing for a career. I talked with John Pringle… about the possibility of going back for graduate school to his lab, and he said "Yeah, sure". –pg-32

Table 4:
Reasons for Choosing Post-doc Institution/Advisor

<u>Quotes:</u>
Geographical Constraint 1 (Jean Greenberg):

"… I think after about five years in graduate school, I had done quite a lot. I probably could have graduated at the end of five years, but I had not, of course, done any planning. This is the usual. Nobody ever sat me down and said, gee, you've got to plan for the next step… …Adam [Driks] [her husband, who is a biology grad student at Brandeis] and I sat down and we discussed it. We thought, well, probably we should plan to do is either stay in the Boston area or move to California, the idea being the density of research is high in both of those locations and we could probably both find labs that we would both be happy with. So we had this kind of geographical constraint.

Then the ideas was, What am I going to do? [laughs]… …At that period, I think I spend about three or four months reading. I just read everything I could get a hold of, all different articles, all different journals. Went to a lot of seminars and tried to think about what area might be interesting to pursue…" [pg. 43-44]

"In any case, I wrote to Ausubel; he never wrote back to me. I called him up; he said, "There's no room." I sid, "Well, I'm just across the river, what harm would it do? Then at least if you don't have an opening, you could give me some advice about what to do.' I guess I conned him into letting me come to his lab, because once I got the interview, he basically said, "Well, if you can get some money to come here, you can come and work with me…" [pg 45-46]

Table 5: Probit Regressions for Selection Model

	(1)	(2)	(3)	(4)	(5)	(6)
grad and pdoc advisors both patent	0.145	0.154	0.144	0.145	-0.008	0.120
	(0.080)+	(0.080)+	(0.079)+	(0.080)+	(0.087)	(0.086)
ONLY graduate advisor patents	-0.067	-0.063	-0.065	-0.064	-0.142	-0.075
	(0.072)	(0.072)	(0.072)	(0.072)	(0.075)+	(0.075)
ONLY post-doc advisor patents	-0.015	-0.016	-0.017	-0.015	-0.113	-0.041
	(0.034)	(0.034)	(0.034)	(0.034)	(0.039)**	(0.040)
undergrad & pdoc university in the same state		0.162	0.142	0.141	0.164	0.170
		(0.061)**	(0.061)*	(0.061)*	(0.065)*	(0.065)**
schol & pdoc_advisor born in the same country			0.081	0.081	0.071	0.081
			(0.031)**	(0.032)*	(0.040)+	(0.040)*
scholar not born in the US			0.031	0.030	0.045	0.052
			(0.061)	(0.061)	(0.066)	(0.067)
scholar not born in the US & same country as pdoc advisor			0.606	0.604	0.637	0.606
			(0.202)**	(0.201)**	(0.195)**	(0.201)**
scholar and post-doc advisor are the same sex				0.017	0.010	0.028
				(0.049)	(0.051)	(0.053)
scholar and post-doc advisor are both female				0.090	0.059	-0.028
				(0.131)	(0.133)	(0.136)
Grad/Pdoc Scientific Closeness Quartile ==Farthest					-1.038	-1.247
					(0.073)**	(0.082)**
Grad/Pdoc Scientific Closeness Quartile ==Farther					-0.662	-0.763
					(0.058)**	(0.062)**
Grad/Pdoc Scientific Closeness Quartile == Far					-0.424	-0.488
					(0.051)**	(0.053)**
grad and pdoc advisor both nas						-0.025
						(0.089)
ONLY grad advisor is nas						-0.018
						(0.081)
ONLY pdoc advisor is nas						-0.112
						(0.037)**
prior graduate advisor publications-log						-0.151
						(0.033)**
prior post-doc advisor publications-log						-0.089
						(0.018)**
Constant	-1.149	-1.158	-1.231	-1.249	-0.602	0.159
	(0.004)**	(0.007)**	(0.033)**	(0.056)**	(0.104)**	(0.168)
Observations	13335	13335	13335	13335	13334	13334
pseudoR2	0.0126	0.0141	0.0170	0.0171	0.0850	0.0964

Note: Errors are clustered at the Post-doc advisor level. All models include Scholar-cohort dummies. For Grad/Pdoc Scientific Closeness, excluded quartile (4) is the 25% closest dyads. Robust standard errors in parentheses below; + significant at 10%; * significant at 5%; ** significant at 1%.

Table 6: Discrete-Time Hazard Rate Models of Scholar Patenting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model	Logit	Logit	Logit	Logit	Logit	Poisson	Poisson	Poisson
Dependent Var.	Patents	Patents	Patents	Patents	Patents	Papers	Papers	Papers
IPTW Weights	NO	NO	NO	NO	YES	YES	YES	YES
post-doc advisor was a patentor		0.701**		0.635**	0.753**	0.061		0.021
		(0.188)		(0.195)	(0.249)	(0.084)		(0.107)
post-doc advisor was on an SAB			0.425*	0.195	0.349		0.109	0.100
			(0.187)	(0.198)	(0.249)		(0.088)	(0.111)
graduate advisor was a patentor	0.328	0.330	0.286	0.311	0.156	0.013	0.008	0.009
	(0.250)	(0.254)	(0.248)	(0.253)	(0.306)	(0.135)	(0.129)	(0.129)
graduate advisor was on an SAB	-0.166	-0.316	-0.257	-0.344	-0.397	0.104	0.095	0.095
	(0.301)	(0.305)	(0.302)	(0.305)	(0.374)	(0.134)	(0.136)	(0.136)
scholar is female	-0.674*	-0.731**	-0.666*	-0.724**	-1.080**	-0.206+	-0.200+	-0.201+
	(0.267)	(0.271)	(0.267)	(0.272)	(0.338)	(0.113)	(0.111)	(0.114)
scholar degree is an MD/PhD	0.724**	0.584*	0.682*	0.579*	0.693*	0.109	0.117	0.113
	(0.278)**	(0.292)	(0.283)	(0.292)	(0.325)	(0.112)	(0.107)	(0.109)
scholar university flow of NIH dollars (log)	-0.192+	-0.166	-0.163	-0.155	-0.145	0.032	0.043	0.042
	(0.105)	(0.106)	(0.107)	(0.107)	(0.143)	(0.047)	(0.047)	(0.049)
stock of university patents (log)	0.304**	0.292**	0.298**	0.290**	0.267*	0.081	0.075	0.075
	(0.097)	(0.094)	(0.098)	(0.094)	(0.124)	(0.059)	(0.060)	(0.059)
Constant	-0.864	-1.103	-1.417	-1.323	-1.618	2.192*	1.943*	2.011*
	(2.224)	(2.263)	(2.265)	(2.277)	(2.718)	(0.910)	(0.911)	(1.053)
Observations	4307	4307	4307	4307	4307	4518	4518	4518
pseudoR2	0.0859	0.0965	0.0895	0.0971	0.1234			

Note: All models include year dummies, (every other year) cohort dummies, the type of Scholar Research (i.e. molecular, cellular, etc.), as well as both graduate and post-doc advisor's prior commercialization score and research patentability stock during training. Robust standard errors , clustered by Scholar, are in parentheses below; + significant at 10%; * significant at 5%; ** significant at 1%

Table 7: Discrete-Time Hazard Rate Models for Scientific Advisory Board Membership

	(1)	(2)	(3)	(4)	(5)
Model	Logit	Logit	Logit	Logit	Logit
Dependent Var.	Patents	Patents	Patents	Patents	Patents
IPTW Weights	NO	NO	NO	NO	YES
post-doc advisor was a patentor		0.415		0.397	0.802*
		(0.378)		(0.393)	(0.388)
post-doc advisor was on an SAB			0.189	0.082	-0.511
			(0.402)	(0.420)	(0.532)
graduate advisor was a patentor	0.189	0.155	0.148	0.140	0.330
	(0.445)	(0.460)	(0.441)	(0.449)	(0.432)
graduate advisor was on an SAB	0.510	0.410	0.473	0.398	0.468
	(0.498)	(0.510)	(0.524)	(0.530)	(0.555)
scholar is female	-0.582	-0.612	-0.589	-0.614	-1.031+
	(0.464)	(0.466)	(0.466)	(0.467)	(0.544)
scholar degree is an MD/PhD	0.691	0.609	0.659	0.601	0.823
	(0.505)	(0.518)	(0.513)	(0.520)	(0.573)
scholar university flow of NIH dollars (log)	-0.174	-0.170	-0.158	-0.163	-0.129
	(0.201)	(0.201)	(0.211)	(0.210)	(0.211)
stock of university patents (log)	0.305	0.305	0.299	0.302	-0.004
	(0.202)	(0.196)	(0.200)	(0.195)	(0.218)
Constant	-4.708	-5.438	-5.818	-4.855	-3.741
	(3.924)	(4.017)	(4.281)	(4.147)	(3.989)
Observations	4627	4627	4627	4627	4627
pseudoR2	0.1011	0.1040	0.1016	0.1041	0.1432

Note: All models include year dummies, (every other year) cohort dummies, the type of Scholar Research (i.e. molecular, cellular, etc.), as well as both graduate and post-doc advisor's prior commercialization score and research patentability stock during training. Robust standard errors , clustered by Scholar, are in parentheses below; + significant at 10%; * significant at 5%; ** significant at 1%